ABSTRACT

DEMERS, ALIXANDRA. Determining Path Flows in Networks: Quantifying the Tradeoff between Observability and Inference. (Under the direction of George Fisher List.)

With the sensor technology in-place today, it is difficult to correctly predict path utilization coefficients (PUCs: the percentage of an origin-destination (OD) pair's traffic flows traveling on a given path or route) because the problem is hugely underspecified, requiring inference to overcome the under-specificity. The shortcoming of this method, as discussed in detail, is that the inference rules applied may be wrong. In fact, little path flow research has addressed the issues of (a) reliability in the instrumentation, (b) reliability of other input data or models, (c) reliability and confidence level of the path flows solution, (d) the relationship between what is observed and what is inferred, and (e) verifying that defined path flows are those actually occurring in the network (and discerned), which are all directly relevant to the practical application of path flow estimation and to guiding instrumentation research to meet the needs of the evolving world of transportation. Therefore, this dissertation research addresses the key questions of (1) how well can path flow rates be determined from an instrumented network, and (2) how much inference is required to yield reasonable estimates of all path utilization coefficients in a network. It was discovered that observed link flow data are only slightly better than spurious input data for PUC prediction; automatic vehicle identification (AVI) or automatic vehicle location (AVL) data are required to significantly improve predictions. Therefore, significant value is added by collecting AVI and AVL data to estimate PUCs or OD flows. Moreover, if predicting link volumes is desired, then link

volume observations are also necessary – AVI or AVL data are insufficient. Considering these results, all network analyses are critically dependent upon good utilization coefficient estimates to obtain reasonable flows which, in-turn, are essential for decision-makers. This is true whether you are attempting to estimate OD flows or PUCs (say as a modeler), desiring to make good capacity investment decisions, or trying to make real-time network flow management decisions. In all cases, good quality PUCs are necessary; reliance on link flow observations would require heroic inference assumptions so AVI and/or AVL data are better choices for PUC prediction. Within this dissertation are four components to support this research endeavor and the conclusions drawn. First is a discussion of the theoretical constructs involved in the path utilization rate estimation process. Second, a methodology for estimating PUCs is presented. Third, numerical tests of the methodology are conducted on several hypothetical networks. Fourth, throughout this research three data conditions were examined to test the methodology's predictions – error-free data, stochasticity in demands coverage (such as in OD flows, link volumes, *a priori* path utilizations, and *a priori* link utilizations), and stochasticity in the demand measurements.

Determining Path Flows in Networks: Quantifying the Tradeoff between Observability and Inference

by
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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ASCE – American Society of Civil Engineers

ATIS – Advanced Traveler Information System

ATMS – Advanced Traffic Management System

AVI – Automated Vehicle Identification

AVL – Automated Vehicle Location

CV – coefficient of variation

DEA – data envelopment analysis

FIFO – First In, First Out

GIS – Geographic Information System

GLS – Generalized Least Squares

GPS – Geographic Positioning System

ITE – Institute of Transportation Engineers

ITS – Intelligent Transportation System

IVHS – Intelligent Vehicle Highway System

LAD – least absolute differences

LUC – link utilization coefficient

MIMP – Mixed Integer Mathematical Program

MP – mathematical program

MPH, mph – miles per hour

OD – origin-destination node pair

PFE – path flow estimator

PUC – path utilization coefficient

RMSE – root mean square error

SAE – sum of absolute errors

SHAPE – Shortest Augmenting Path Estimation method

SSE – sum of squared errors

TFS – traffic-flow simulator

TRB – Transportation Research Board

TRR – Transportation Research Record

VBA – Visual Basic for Applications

LIST OF SYMBOLS

$\Rightarrow$ - in mathematical terms, this symbol means “implies”

$\forall$ - in mathematical terms, this symbol means “for all”

$\in$ - in mathematical terms, this symbols means “is a member of”

D_{od} - vector of origin-destination flows

v_a - flow on arc a

x_p - percent of OD flow on path p (path utilization coefficient)

y_{oda} - percent of OD flow on arc a (link utilization coefficient)

α_{odp} - incidence matrix of OD pairs to paths

β_{odpa} - incidence matrix of odp triplets to arcs

γ_v, γ_x, γ_y - weighting factors

m = true value of variable m

$\tilde{m}$ = measured value of variable m

$\hat{m}$ = predicted value of variable m

n_A = total number of arcs
va_a = initial volume on arc a
ve_a = final volume on arc a
ca_a = cost per unit capacity added to arc a
cv_a = user cost of arc a
cst_a = total user cost of traversing arc a
cap_a = capacity of arc a
$dcap_a$ = excess or buffer capacity of arc a
dv_a = portion of volume that requires use of the reserve capacity
τ_a = weighting factor; $(1-\tau)$ is the amount of excess capacity that should be maintained above arc a's volume
ψ_a = weighting factor; the additional user cost incurred per unit volume for all volume requiring use of the reserve capacity
μ_1 = scaling factor for cost equation

$d_{i,j}$ = target demand from i to j
$de_{i,j}$ = estimated demand from i to j
$cmin_{i,j}$ = lowest cost path from i to j

$dedev$ = sum of squared errors for OD demands
$vadev$ = sum of squared errors for arc flows

n_P = total number of paths
vp_p = volume on path p
cp_p = cost of path p
pfr_p = path p origin node
pto_p = path p destination node

n_N = total number of nodes

z = objective function value

n_{PA} = total number of path-arc incidences
pk_k = path number associated with path-arc incidence vector index k
ak_k = arc number associated with path-arc incidence vector index k.

n_{ODA} = total number of OD-arc incidences
o_n = origin node associated with OD-arc incidence vector index n.
d_n = destination node associated with OD-arc incidence vector index n.
a_n = arc associated with OD-arc incidence vector index n.
y_n = arc utilization coefficient associated with OD-arc incidence vector index n.

1 INTRODUCTION

Our ability to observe travel is quite dependent on what is being transported (person or freight), the mode of travel, and the transport network utilized. In the freight arena, an entire shipment's trip from manufacturer to retailer can be reconstructed if the necessary information is released by the various stakeholders; however, the exact path traveled is not always known. For example, rail freight movements are known by path because the mode is on a fixed guideway, trains have unique identities, and car switching from one engine set to another is recorded. Similarly, air freight movements are known because the origin destination (OD) pattern is determined by the flight number while the exact path traveled can be determined from the flight plan filed by plane tail number. Moreover, once the flight is complete, information is available about the gate-to-gate and block-to-block times enabling calculation of path travel times over the course of a set time period such as a day or year. Likewise, passenger movements can be tracked through long distance rail, air, and long distance water transport because of ticketing and because the modes are operated in systems that require reservations and the filing of travel plans for coordination, safety, and efficiency of their respective networks. Hence, the above systems have path information embedded with item and/or traveler identification.

Path knowledge lessens when travel on short-distance rail and water trips for passengers (such as rail public transit and ferries) is examined. In the case of rail transit, one may know the rail transit routes but only some systems (like those in Paris and Washington, DC with

distance-based fares) track passenger OD patterns, and possibly time in the system, by requiring tickets for turnstiles at both station entrances and exits. Unfortunately, even with the mentioned systems, path data is unavailable and must be estimated based on the most probable routes and connections from one station to another, plus assumptions are made that people know where they are going and know the proper trains/ directions to travel to reach their destination station, therefore introducing route choice uncertainty into path estimates. Flat fee rail or bus transit systems (such as in New York City) may only collect system entering and exiting flows at each station without OD information, adding one more layer of uncertainty in determining traveled paths, that of uncorrelated travelers (the inability to correlate an alighting passenger at one station with a departing passenger at another station).

Path information often degrades further when one examines both freight and people on the road network for all trip lengths. At its best, researchers can discover the paths traveled because an automatic vehicle location (AVL) device is utilized by a freight carrier or drivers of fleet vehicles. Currently, some long-haul companies use this technology as well as some rental car companies, public transit (bus) agencies, and taxis see (Saricks, Schofer et al. 1997?; Schäfer, Thiessenhusen et al. 2002; Lorkowski, Mieth et al. 2004; Mieth, Schäfer et al. 2004). Although private drivers may have AVL technology, their movements presently are not observable by others. However, that is changing. For example, in the Capital District Advanced Traveler Information System (CD-ATIS) experiment conducted in Spring 2005, 200 drivers were connected to a central server which did record travel characteristics, including the route taken to a destination (Demers, List et al. 2006). Also helpful from a path

standpoint is automatic vehicle identification (AVI) technology which is prevalent in regions with tolled transport facilities (such as roads, bridges, and tunnels) and variable fee storage facilities (such as park-and-ride lots and airport parking). AVI technology enables partial tracking of vehicles with tag transponders by placing sensors at locations throughout a network (tag readers at a toll booth, for instance). Note, the details of a trip are lost between any two sensor locations (links traversed, waiting times at signals, and so forth), but a large-scale picture is captured. Regardless of AVL and AVI technology, tolled facilities can capture OD patterns, total travel times, space mean speeds, and traffic volumes within their networks. Without AVI, AVL, and tolled facilities, the picture goes blank without sensor infrastructure.

Consider finally, little or no OD pattern nor path information is collected on pedestrian trips which are at the start and end of all other trips. However, since these trips are rarely the cause of significant congestion (outside of dense urban areas) and severe incidents, they will not be considered here. Rather, this research is focused on the road network because there is a need to increase data collection for improved network observability.

To summarize, as the flexibility of a transport network is increased (i.e. mobility becomes less constrained) and the fee for service changes from variable to fixed, then our ability to observe the paths taken by people and freight decreases without the aid of external sensors. Hence, determining the level of observability of traveled paths in networks with varying

types and amounts of instrumentation is the focus of this doctoral research because there is a need to improve data collection strategies for increased network observability.

1.1 Framing the Question

To concretely see how network instrumentation can affect an agency's ability to collect path flow data, a small example is presented in Figure 1.1 for a single origin-destination (OD) pair. The network has eight arcs (all one-way) and all paths must cross one of the three bridges. There are three possible paths with some link overlap. Consider three instrumentation options: (1) automatic vehicle location (AVL), (2) automatic vehicle identification (AVI), and (3) loop detectors. The options are arranged according to the amount of information they collect as well as the mobility of the sensor (more to less for both metrics).

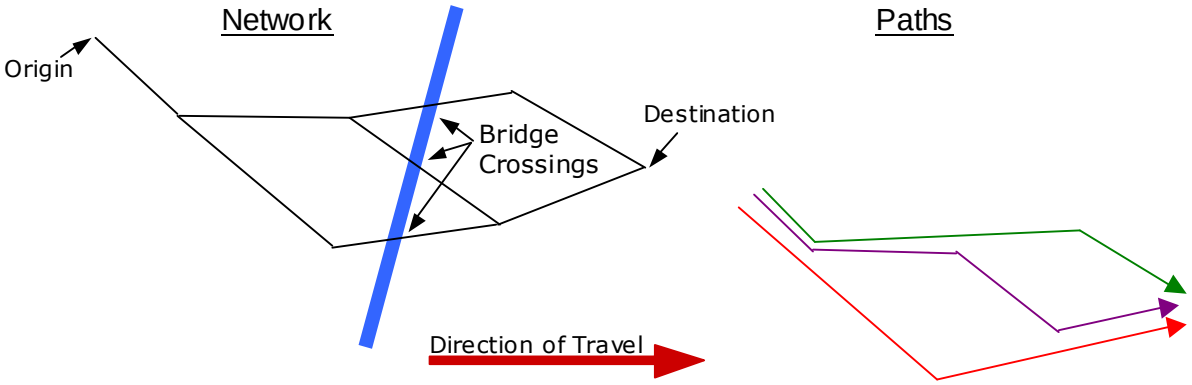
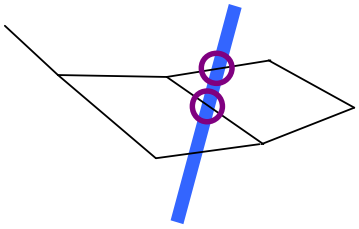


Figure 1.1 Simple Network with One OD Pair

The first sensor type considered is AVL; it is a probe-based technology that can transmit and/or record the details of a trip from door-to-door. Therefore, an AVL-based system enables us to see the *entire path* of a vehicle in both time and space. Hence, there is no need for other sensor types. For the network in Figure 1.1, yielding path flow counts (or other measures like travel time) from such a system would translate to each vehicle traveling between the OD pair being AVL-equipped.

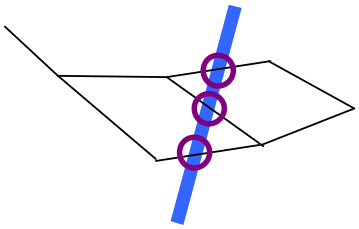
If some trip details and mobility are sacrificed, then the second instrumentation option is encountered, that of AVI. Generally speaking, AVI systems require two pieces, the transponder (or tag) mounted on a vehicle and the tag reader (the instrument providing observability) externally mounted along the road network. The latter is typically fixed, but portable ones are becoming available and being tested as in a current RPI project (Lee 2005). A tag reader captures the time and identity of each AVI-equipped vehicle passing its location. Therefore, if two or more readers are on a single path then AVI captures information for that path segment (or *subpath*). And note, AVI technology is generally focused on high-order facilities such as freeways or facilities that require tolls. Data is gathered at



(a) AVI tag readers + Origins info = all path flows captured

```
 x1 +  x2 +  x3 = 1
Dx1           = v1
      Dx2     = v2
```

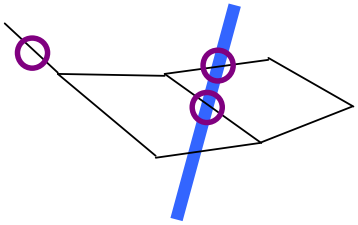
3 equations and 3 unknowns (x1, x2, x3) since D is known. Therefore, the formulation is both necessary and sufficient.



(b) AVI tag readers or volumetric counters capturing all path flows

```
 x1 +  x2 +  x3 = 1
Dx1           = v1
      Dx2     = v2
            Dx3 = v3
```

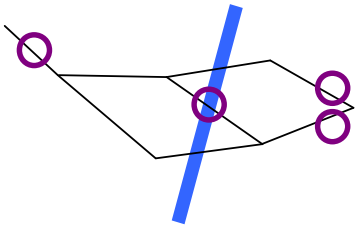
4 equations and 4 unknowns (x1, x2, x3, D). Therefore, the formulation is both necessary and sufficient for capturing path flows.



(c) One alternate configuration for AVI tag readers or volumetric counters capturing all path flows and some subpath travel times

```
 x1 +  x2 +  x3 = 1
Dx1           = v1
      Dx2     = v2
D             = v0
```

4 equations and 4 unknowns (x1, x2, x3, D). Therefore, the formulation is both necessary and sufficient for capturing path flows.



(d) AVI tag readers capturing all path flows and travel times

```
 x1 +  x2 +  x3 = 1
Dx1           = v4
      Dx2     = v2
      Dx2 + Dx3 = v5
```

4 equations and 4 unknowns (x1, x2, x3, D). Therefore, the formulation is both necessary and sufficient for capturing path flows.

Figure 1.2 Different Instrumentations of Network

select locations, missing detailed observations between and beyond collection points. In this example, if a screen line is used connecting the bridge crossings while separating the O and D as in Figure 1.2a, one can measure the path flows and compute the path utilization coefficients if (n-1) or 2 of the bridges are AVI-equipped with tag readers and one knows the number of vehicles either starting at the O or ending at the D. If no OD information is known, then one would require (n) or 3 tag readers, one for each bridge to observe all vehicles (Figure 1.2b). However, only *spatial paths* and not *temporal paths* will be known in these two cases because there is only one time point for each instrumented path. To measure path travel times on this network, two other cases are shown. Figure 1.2c shows a tag reader network that covers part of the whole network, capturing full path flows and two subpath travel times. To fully collect both *spatial paths* and *temporal paths* data, a set-up such as in Figure 1.2d with 4 tag readers would be required. Hence, an AVI system can operate much the same as an AVL system, but with more forethought and hardware required in the planning stages.

Finally, basic loop detectors are the third instrument considered. They capture only volumetric data at select locations, therefore no path information is collected unless you creatively locate the detectors throughout the network – rather impossible with a grid network. In this case, like the AVI case, your best option is to place loops on the screenline for *spatial paths*, and note that you would need two or three detectors depending on the availability of OD data just like in the AVI case. The configurations shown in Figures 1.2c and 1.2d can also capture path flows for volumetric counters but not travel time data without

making assumptions (such as First In, First Out). Therefore, the difference from AVL and AVI is that travel times can never be observed with basic loops because there is no vehicle identification tracking.

Based on this small example, it is evident that path characteristics are difficult to obtain and depend on careful sensor choices and locating. Therefore, a fundamental question that arises is, what data is required to reconstruct a traveler's path? Once this data is known, then appropriate sensors can be selected to instrument a network. And the problem of where to place the sensors in the network becomes the next step. Focusing on the necessary data, a traveled path has several components, both spatial and temporal:

- Start location
- Start time
- Vehicle trajectory between the start and end locations
- Waiting times
- End location
- End time
- Locations where waiting occurs (say, vehicle is in queue at a traffic light)

A summary of sensor attributes and how they relate to reconstructing a traveler's path are listed in Table 1.1. An in-depth discussion of various traffic sensors is being created for a separate document.

Table 1.1 Sensor Attributes Related to Path Reconstruction

			TRAFFIC DATA COLLECTION METHOD											
SENSOR ATTRIBUTES Legend: symbols are from less to more versatile ◇❖◆ zero to full information			**License Plate**	**Survey**	**Floating Car**	**Aerial**	**Loop**	**Smart Loop**	**ATR**	**Video/ Laser**	**Radar Gun**	**TMC**	**AVI (transponder)**	**AVL (GPS)**
General														
◇	❖	◆												
Short-term		Long-term	◇	◇	◇	◇	◆	◆	◇	◆	◇	◇	◆	◆
Fixed	Partially Fixed	Mobile	◇	❖	◆	◆	◇	◇	❖	❖	❖	❖	❖	◆
Manual	Partially Automatic	Automatic	◇	◇	◇	◇	◆	◆	❖	◆	◇	◇	◆	◆
Stand-alone		Integrated	◇	◇	◇	◇	◆	◆	◇	◆	◇	◇	◆	◆
Path-specific														
Trip Origin			❖	◆	◆	◇	◇	❖	◇	◇	◇	◇	❖	◆
Departure Time			❖	◆	◆	◇	◇	❖	◇	◇	◇	◇	❖	◆
Actual Path / Vehicle Trajectory			❖	◇	◆	◇	◇	❖	◇	◇	◇	◇	❖	◆
Trip Destination			❖	◆	◆	◇	◇	❖	◇	◇	◇	◇	❖	◆
Arrival Time			❖	◇	◆	◇	◇	❖	◇	◇	◇	◇	❖	◆
Potential Proxies														
Volume			◇	◇	◇	◆	◆	◆	◆	◆	◇	◆	◇	◇
Individual Vehicle Speed			◇	◇	◆	◆	◇	◆	◇	◆	◆	◇	◆	◆
Direction of travel (heading)			◆	◆	◆	◆	◆	◆	◆	◆	◇	◆	❖	◆
Vehicle Identification			◆	◆	◆	◆	◇	❖	◇	◆	◇	◇	◆	◆
Vehicle Location – facility			◆	◆	◆	◆	◇	❖	◇	◆	◇	◇	◆	◆
Vehicle Location – lane			◆	◆	◆	◆	◇	❖	◇	◆	◇	◇	❖	◆

Note difference between floating car and AVL: floating car here is referring to a controlled field study (often for collecting space mean speed data on particular facilities, not actual trips by the driving population), not in widespread use.

Approximately half of the path components mentioned above are of concern for origin-destination table estimation. Therefore, current OD estimation techniques are a possible starting point for path reconstruction. For example, (Zhou and List 2006) suggest a method to place detectors in a network for OD estimation recognizing at least one detector must be present on each path between an OD pair for an effective count; this is observed in the Figure 1.1 example. However, this work must be extended to differentiate vehicle trajectories between OD pairs (especially where paths overlap) so that path counts instead of OD counts

are captured. Hence, more fixed detection equipment is required and/or further AVI and AVL detection is necessary. For instance, vehicle trajectory information can be collected:

- Directly from AVL devices.
- Directly from AVI devices and loop detectors fitted with inductive signature recognition equipment (here referred to as "smart loops") (Ritchie; Abdulhai and Tabib 2003; Sun, Arr et al. 2004) but with a loss of detail between tag readers, and from the origin to the first tag reader and from the last tag reader to the destination.
- Indirectly from laser-based detection systems that yield vehicle lengths and video-based vehicle detection using image processing technology (Oh and Stephen G. Ritchie 2002).
- Indirectly from fixed sensors such as loop detectors that have limited capabilities to collect more than volume, occupancy, and speed information. Basically, these sensors cannot correlate a vehicle crossing one with the same vehicle crossing another one, although there has been some success with using vehicle length measurements on freeway sections (Coifman 1998) and see (Nichols and Cetin 2007). Therefore, assumptions must be made as to when and where a particular vehicle will cross another fixed sensor.

Also of note, in the event an OD matrix is used to assist in path flow analysis and sensor locating, it may be helpful to refer to (Bierlaire 2002) who created a quality measure for OD matrices estimated with link counts. The measure requires knowledge of a network's topology and the route choice model used to develop the matrix. Besides a measure of

quality, the technique also identifies paths that are missing link count data, suggesting insight into where detectors are required.

1.2 Research Objectives

The research proposed herein is in support of two primary research objectives. First and foremost is the goal of extending the current theoretical frontier of quantifying path flows and their characteristics. This is planned to be accomplished by exploring small networks to start, then creating formulations for increasingly general networks. The second objective is to quantify the tradeoff between direct observation and inference with respect to path flows so that future projects intent on measuring path flows can be guided toward the most beneficial mix of observations and inference based on their available means (for example, current sensors on-hand, available modeling expertise, and budget constraints).

To sum up, here are the objectives in the form of a few guiding questions:

- How can transportation engineers and planners more accurately determine the path flows on a network through instrumentation adjustments?
- How can the tradeoff between direct observation and inference be quantified?
- How can route planning be validated?

1.3 Motivation & Research Value

Development of a credible picture of traffic flows has always been an issue – often overcome by using a heavy dose of inference (as will be shown in Section 2). When determining flows, there is often a balancing act between efficiency (a common measure is cost or budget) and

accuracy; an agency or firm can only instrument so much of a network. Therefore, it is critical that the tradeoff between efficiency and path flow accuracy be quantified for personnel to make appropriate decisions. Three examples are briefly presented to highlight the potential impact of path flow knowledge (or lack thereof).

1. *What if planners assume inaccurate traffic flows for a region's future?*
    - Funds may be allocated to "improving" routes that will not be used – a poor decision incurred by ineffective use of resources to develop the flow estimates (wasted dollars).
    - Insufficient funds may be allocated to routes that will see a marked, unexpected increase in traffic resulting in high v/c ratios and poor levels of service.
2. *What if traffic engineers estimate traffic flows with limited accuracy for timing a signal network?*
    - Drivers on roads with higher estimated flows than actual flows have sufficient green time but (1) side streets drivers are forced to wait through unused main street green times and (2) road capacity is inefficiently used.
    - Drivers on roads with lower estimated flows than actual flows wait in extensive queues at traffic signals with insufficient green times.
3. *What if dispatchers route their pick-up and delivery vehicles on tours based on a logistics specialist's false traffic flow assumptions?*
    - If roads on the tour have higher flows than anticipated, then vehicles will arrive late to one or more destinations, possibly missing the pick-up/delivery time window.

- If roads on the tour have lower flows than anticipated, then vehicles will arrive early to one or more destinations incurring unproductive time while waiting for the pick-up/delivery time window.

Based on these examples, there is a need for further path flow research. This dissertation is put forth to fulfill that need.

1.4 Paper Organization

Section 2 is a review of select literature addressing four components that shape a picture of path flows and some current methods utilized for determining traveled paths followed by a discussion of the tradeoff between inference and observability when quantifying path flows, and wrapped up with thoughts on gaps in the current literature. Section 3 outlines the methodology for determining path flows in an instrumented network with descriptions of the applied model, performance measures, and analysis tools. Next, Section 4 includes the experiment design to test the methodology through the random generation of networks then assessed for their instrumentation's ability to determine the path flows. Section 5 has results of the performance measures for the numerical tests. Finally, concluding remarks and future work are presented in Section 6. Also included are appendices with (a) LINGO mathematical programs, (b) sample input data, and (c) sample output data.

2 LITERATURE REVIEW

2.1 Introduction

If all vehicles are instrumented with AVL, then it is a trivial problem to discern the path flows of a network – count up all the vehicles, tally up what paths they were on. However, most transport systems are not and will not be in such a state in the near future. Therefore, discerning path flows in the near term requires using the data available from other instrumentation configurations. Depending on the type of instrumentation and its network coverage, varying amounts of observability and inference will be required to determine the path flows. One of the goals herein is to quantify the tradeoff between inferring and observing path flows.

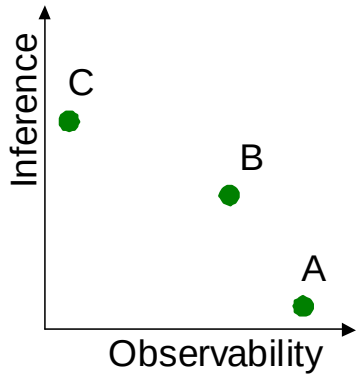


Figure 2.1 Tradeoff between Data and Inference

Conceptually, this tradeoff can be plotted as in Figure 2.1. If condition A is present, then there is almost complete coverage of the network with sensors that can yield path flow information (similar to having a high percentage of AVL-equipped vehicles in the network); hence, there is a need for almost no inference to determine the uncovered paths. Being in condition A therefore means that the quality of path flow discernment should be quite good provided the sensing instruments are reliable. The primary disadvantage of condition A is the high cost of such a

level of instrumentation, whether it is incurred by transportation agencies and/or by consumers. Hopefully, the costs will drop over time as technology advances enable more networks to be highly instrumented. In condition B, budget constraints may have hindered a higher level of sensing so more reliance on inference is required. This inference may come in the form of engineering judgment such as applying conservation of flow equations, it may also include information derived from driver surveys, finally, traffic assignment models may be applied to the available data to fill in the gaps. Here in condition B, there is a strong call for quantifying the tradeoff between observability and inference, likely dependent on the type of each one, so that the greatest number of path flows can be distinguished. For instance, a network with 50 percent of links sensed with loop detectors may be better served by inference in the form of an OD survey with route choice questions rather than conservation of flow equations since the survey data asks about what paths a traveler follows through the network; condition B in the survey case is expected to yield a more accurate picture of the path flows than the conservation of flow case. Finally, condition C is the worst possible one with little or no data observed on which to base an estimate of path flows. In this case, the analyst relies heavily on inferring the correct path flows – quite a challenging task with weak substantiation. In summary, quantifying the relationship between observability and inference to create the best estimate of path flows is a key part of this proposed work.

To drive home this tradeoff concept and highlight the data collection issue, consider the following situation. You are in the world of traffic simulation (using PARAMICS or VISSIM perhaps) with the ability to tag however many vehicles you desire so that you may

track their movements through a network. Further suppose that the path decisions made in the simulation would also be made in the real world (or recognize that this is not the case, but accept the simulated decisions as truth for now). Then the question posed becomes, what output routines must be written so the tagged vehicles' paths become observable? In other words, the simulation model knows the path truth (for all vehicles), but how can it be extracted? Similar to real-world condition A in Figure 2.1, if one writes a routine that tags 100 percent of the vehicles, then all paths are extracted with little work but at a high expense because processing times are slowed as the number of tagged vehicles increases (likewise in the real world it is costly to tag everyone). Now, if someone uses a routine that tags a percentage less than 100, then some paths are extracted but not all – again, this is similar to condition B because it is less costly but also less data-rich (see Figure 2.2).

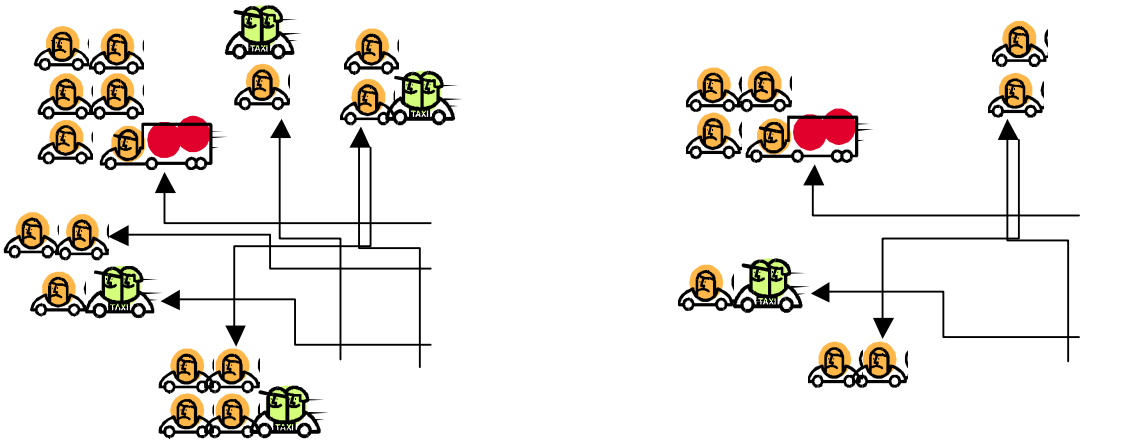


Figure 2.2 Potential Effect on Path Discernment of Partial AVL Coverage

2.2 Examining Relevant Literature

A literature review was conducted to explore how researchers to-date have measured and estimated traffic flows on paths. Discussed below are materials directly related to quantifying path flows.

Think of four possible building blocks to create an estimate of network path flows such as in . The lowest and most important building block is that of *observed data*. Without it, there is no truth. However, as will be discussed later, the available data may not uncover the whole picture of path flows because of sensor limitations. Therefore, other tools are needed; based on the literature reviewed, three tools are commonly used in transportation engineering: *choice behavior, flow estimation,* and *traffic assignment*. As shown in Figure 2.3, these tools can be combined with data in a host of ways to yield path flow estimates. Each building block will be examined in turn and supported by two or more examples from the literature.

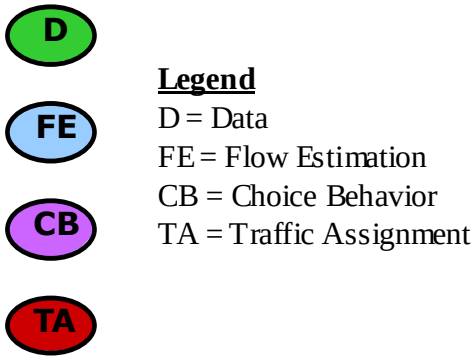


Figure 2.3 Path Flow Building Blocks

2.2.1 Data

As discussed earlier, path flows can be directly obtained through AVL data that captures both spatial and temporal trip information for a particular vehicle – see "Probes as path seekers: a new paradigm" (Demers, List et al. 2006). Data for path flows may also be

collected via video cameras with overlapping views and the images processed with geometric analysis. Two examples of this empirical method are *"Path Detection in Video Surveillance"* (Makris and Ellis 2002) and *"Monitoring pedestrians in a* [sic] *uncontrolled urban environment by matching low-level features"* (Vannoorenberghe, Motamed et al. 1996). Both of these papers rely on motion detection research applied to tracking pedestrian movements. Makris and Ellis developed a method based on overlapping and non-overlapping video images whereas Vannoorenberghe used a single camera with a fixed view in conjunction with a background reference image. From an instrumentation standpoint, these methods require a lot of hardware and generate reams of data for short network segments and therefore are not optimal for large road networks.

However, if instrumentation yielding complete path information (such as AVL devices or video imaging) are unavailable, then data must be obtained from other, less ideal sensors or methods and the paths induced. For example, automatic traffic recorders (ATRs) are sometimes used instead of turning movement counts (TMCs) or outdated data are often used when acquiring new data exceeds the allotted budget. In these situations, volumes crossing particular points are recorded with path information to the next junction (driveway, ramp, intersection, or interchange) but not beyond it. And although the next junction may also be instrumented, vehicles could only be accurately tracked in the simplest of networks such as ones with single lane arcs with first-in, first-out (FIFO) rules enforced, and no on-street parking or driveways. In more complex networks, paths must instead be induced from the collected data. Therefore, data are often combined with one of three other tools to yield

better path flow estimates including choice behavior, flow estimation, and traffic assignment – each tool is now discussed in turn.

2.2.2 Choice Behavior

Extending beyond deriving path flows from empirical data has been accomplished by some analysts through translating decisions made by individual travelers into route choice behaviors. So route choice behavior research focuses almost exclusively on the demand side of transport. And the methods are often drawn from the field of econometrics and the concepts of random utility theory. Commonly collected through survey instruments (for example, see (Khattak and DePalma 1997; Asakura, Hato et al. 2000; Bekhor, Ben-Akiva et al. 2002; Lo and Chan 2003; Doblas and Benitez 2005)), a sample of travelers are asked to share what factors are important to them when choosing a route between an OD pair, or explicitly asked (such as with travel diaries) what routes they generally travel between locations such as home, work, school, shopping, and recreation destinations. Based on the given answers, analysts can develop route choice models that accurately depict the sampled travelers' choices as well as, hopefully, the broader population's route choices. Because these models can create a picture of path flows with less field data than methods discussed earlier and they represent a more timeless measure, they become powerful tools that are often used long after they are conducted. It is suggested here that less field data is necessary when results from a survey instrument are available and that survey instruments are more timeless than field data because people's preferences are more static than traffic flows from one moment to the next, and from one year to the next. For example, if a person prefers to drive on freeways rather than arterials, then even if the network topology changes (say a new

freeway is built), then it is known with high certainty and without field data that this person will likely switch to driving the new freeway instead of arterials connecting relevant OD pairs. Likewise, if a person desires driving the quickest route to a location and it is known how he/she determines that route (such as through radio versus television reports) then researchers can adjust path flow estimates based on the driver's information being available enroute or only pre-trip. To sum up, choice behavior information can be a powerful asset for quantifying path flows.

Two research teams that incorporated choice behavior for traffic flows are Cascetta et al. (Cascetta, Russo et al. 2002) and Bell and Cassir (Bell and Cassir 2002). The former discusses a route perception model for urban road networks. Recognizing that the choice set varies from individual to individual and few people have a choice set encompassing all possible routes, the authors developed a model incorporating perception that could augment standard route choice models in the traffic assignment process. Therefore, when translating OD flows to path flows it is prudent to consider the impact of traveler perception.

The latter work (Bell and Cassir 2002) viewed route choice through the lens of game theory. While holding onto the assumptions of user equilibrium for the traffic assignment process, uncertainty about route costs is explicitly factored into the choice formulation – implicitly accounting for travelers having a "strategy toward risk". So in this model, travelers are expected to examine all outcomes prior to selecting a route; in other

words, they participate in a “mixed-strategy Nash equilibrium of an n-player, non-cooperative game”.

Related to route choice modeling with some travel demand rules possible, but also some supply side rules, is the category of flow estimation – discussed next.

2.2.3 Flow Estimation

In the context of path flows, *flow estimation* is the application of logical rules to the network to restrict solutions to reasonable ones (and they may derive from demand or supply side knowledge). For instance in Figure 1.1, to travel between the origin and destination a traveler had to cross a bridge; therefore, a logical rule could be every path must include one bridge link – a supply-side constraint. For a second example as in Figure 2.4, one can choose to restrict the possible paths to reasonable paths and define reasonable with a circuity index, the more indirect a path, the more unreasonable, so options (a) and (b) might be acceptable while (c) is unacceptable. Another example would be to require the conservation of flow throughout the network, so if 100 vehicles flow into a transshipment node, then 100 vehicles should flow out of that node. A final example set of rules can be drawn from knowledge of the land uses in a region – demand-side constraints; if a host of factories operate near one another, all with three 8-hour work shifts (starting at 8 a.m., 4 p.m., and 12 a.m.), then nearby links would be required to show higher inflows (trips toward the factories) than outflows just before the start of a shift and vice versa just after a shift ends.

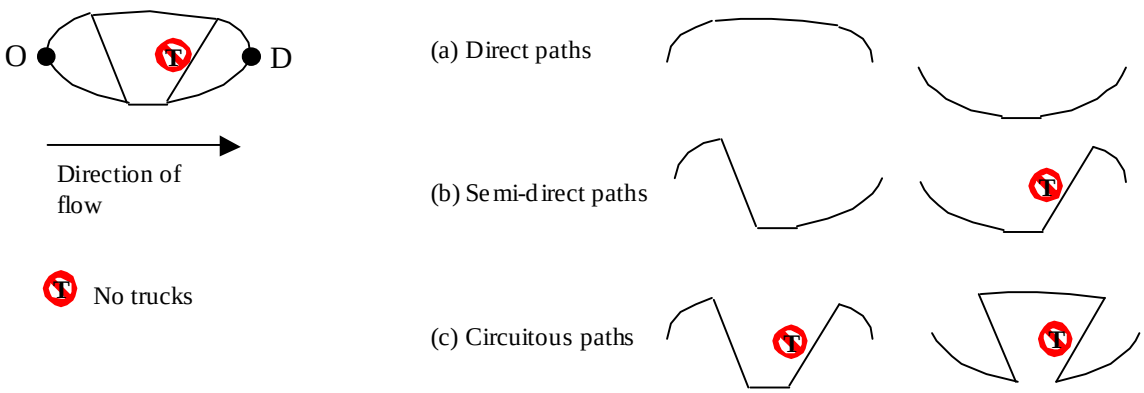


Figure 2.4 Categorizing Paths based on Their Directness

Hence, the difficulty is defining "reasonable" and recognizing that this term will be defined differently when circumstances change. For instance, it is reasonable to assume that commuters travel the fastest route, but unreasonable to assume tourists will do the same – so trip purpose is a key factor in determining what is reasonable. Another set of factors might be driver age and time of day since the elderly might search out well-lit routes at night, foregoing shorter routes. A third factor is vehicle type because trucks are restricted from traveling certain links; in Figure 2.4, this might eliminate 3 paths because one link shows a truck restriction. As mentioned in the examples above, a fourth factor is surrounding land use which can control such factors as when heavy flows occur (factories), times for restricted speeds (schools), and directional flow changes (part-time high occupancy vehicle lanes). So by evaluating potential factors, analysts can develop logical flow estimation rules that when enforced lead to improved path flow estimates or predictions.

Focusing on truck travel further, the authors of a 1994 paper titled *"Estimating truck travel patterns in urban areas"* (List and Turnquist 1994) applied flow estimation techniques to estimate truck travel patterns. They brought in data from multiple data sources, then determined logical paths by using a geographic information system (GIS) and applying conservation of flow rules. Likewise, again in 2002, List teamed up with Eisenman (Eisenman and List 2004) to estimate OD matrices with a similar methodology. The researchers collected data from three sources (probes, link counts, and an old OD matrix) and applied flow logic that included the use of only "reasonable" paths through the network. Based on research such as in the above two articles, insight into the impact of different data sources on the relationship between inference and observability may be possible with the data already collected. In other words, pursuit of such an analysis may quantitatively indicate how much path observability can be obtained from a data type, enabling the filling in of Figure 2.5 with some concrete results.

Another flavor of flow estimation, that of creating a non-assignment model, is illustrated by a pair of authors who developed an OD model for the specific case of estimating time-varying OD distributions (i.e. as in the real world, flows between an O and a D change from one time period to the next, such as hourly) (Chang and Tao 1999). Four data types were input into the model including: link and cordon counts, a potentially unreliable prior OD matrix, and path utility coefficients (PUC – the fraction of an OD flow on a unique path).

Finally, an example of flow estimation applied in conjunction with a traffic assignment model is in (Bell, Shield et al. 1997). The flow estimation component enables links without observed volumes and travel times to have traffic assigned to them based on their capacities and using a penalty (delay) for when a link's demand is greater than its capacity.

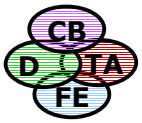
2.2.4 Traffic Assignment

Similar to choice behavior, traffic assignment (TA) is a technique to infer traffic flows when the data available are unable to yield a clear picture on their own. Unlike choice behavior models based on survey data and the logical rules that make up flow estimation, traffic assignment is based on theories of how traffic distributes itself on a network. The primary focus of the technique is on the supply side of traffic with tools including capacity constraints, link impedance functions, and cases such as system optimal and user optimal equilibrium. Briefly discussed here are some examples from the literature.

Dial's Probabilistic Choice Algorithm (Dial 1971). Dial created a "multipath assignment model" guided by five functional specifications to try and overcome the shortcomings of the all-or-nothing method (instability, failure to reflect actual behavior) through assigning traffic based on the likelihood of a path being used. Hence, his model was an attempt to assign traffic to a network using common sense assumptions (referred to as flow estimation rules here) and the use of a two-pass Markov model. It is important to note that Dial's algorithm is not an optimization model like the equilibrium models discussed next.

On the cutting-edge of TA research today is providing TA in real-time situations, called dynamic traffic assignment (DTA). To do so usually means either sacrificing the theory (relaxing assumptions to simplify and speed calculations) and/ or supplying the system with both expensive equipment (such as high-performance computers with parallel processors) or dividing up the decisions (such as with a bi-level mathematical programming model). Three examples from the literature that utilize DTA are now mentioned.

Chui and Mahmassani creatively updated route guidance via an automaton approach with both data and traffic assignment tools (Chiu and Mahmassani 2003). The researchers applied an a priori math program with updated route guidance given to two classes of drivers.



Focusing on both high performance computing and theory relaxation, another pair of researchers explored the evolution of network flows under route choice dynamics over long time periods such as within-day and day-to-day (Srinivasan and Guo 2004). The DYNASMART dynamic TA model was used to simulate the experiments. User equilibrium was the theory of choice that was then relaxed; it proved to be a wise decision since the results showed the network performed significantly different from equilibrium. Besides TA, this project also included choice behavior with a calibrated route choice model as well as flow estimation elements (such as the link capacity constraints and a modified Greenshields model for speed-density relations).

An example of a bi-level programming model that includes a traffic assignment element, specifically stochastic user equilibrium (SUE) is (Xu, Lam et al. 2004). In the lower level, the SUE is part of the "traffic-flow simulator" (TSF) which is Xu and Lam's equivalent to the path flow estimator (PFE) developed by Bell et al. except the latter team's initial PFE was based on UE and then modified to incorporate SUE principles (Bell, Shield et al. 1997). So the lower level assigns traffic to the network and updated the OD matrix while the upper level of the program calibrates various parameters of the network to create an integrated model that has feedback between the two problems.

2.3 Summarizing Prior Efforts, Recognizing Gaps in Current Knowledge

It was found through this literature review that there has been a heavy emphasis on two topics, the area of origin-destination research and the use of traffic assignment models to provide inference into the question of concern. Two key issues were uncovered through the review, both centered on link utilization percentages (or arc percentages). First, most arc percentages are generated, not observed. Second, arc percentages are often implicitly incorporated into OD estimation procedures. However, there was little research into verifying link or path utilization coefficients and almost no path-based work utilizing probe data.

Returning to the idea introduced at the beginning of this literature review, the quality and quantity of path flow data is dependent upon a mix of observations and inferences. Often tempered by budget limitations, an analyst needs to maximize the information gained while minimizing the potential for erroneous results by choosing the best combination of observation instruments and inference tools such as in Figure 2.5. And a mix of observability and inference will probably be required. Just as in economic theory, making this selection is similar to reaching for the highest isobar possible so that an estimate has the best estimate that a person or agency can afford. Examining the more-detailed inference versus observability tradeoff graphs in Figure 2.5 and Figure 2.6 at this time will prove helpful.

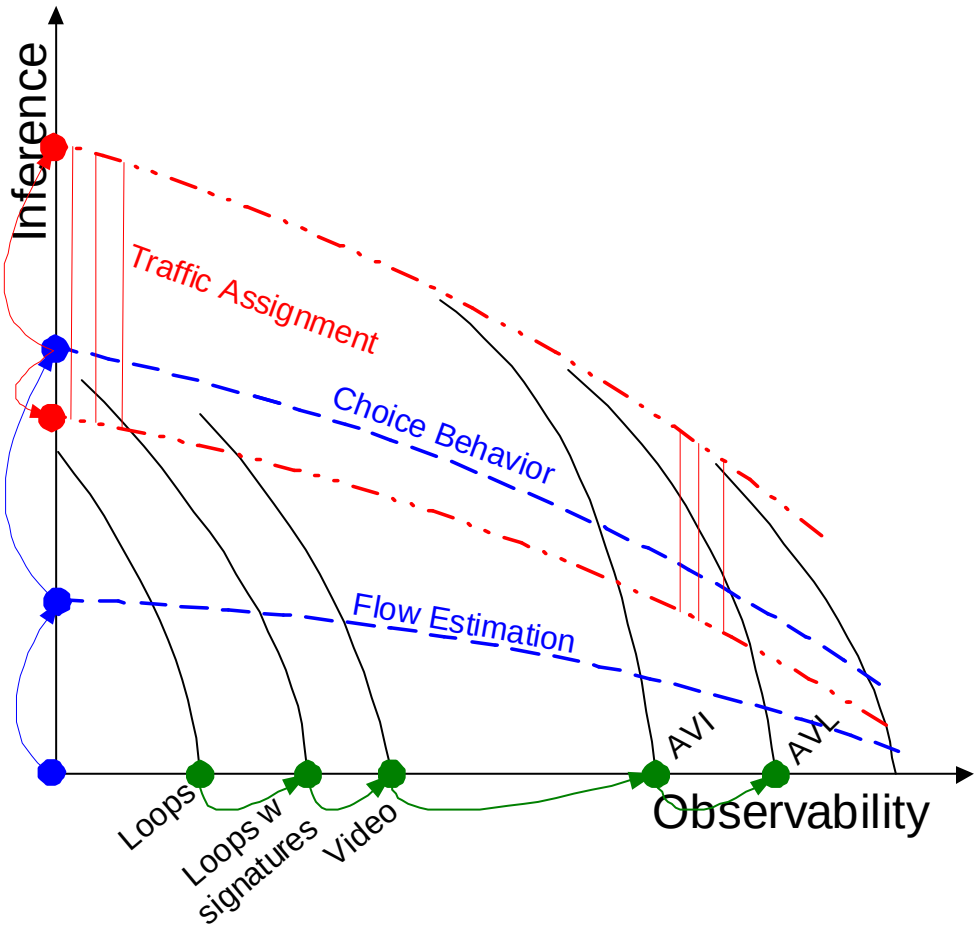


Figure 2.5 The Tradeoff between Inference and Observability

Observability Axis. If the observability axis is comprised of individual sensor types organized from least information gain to most information gain as you move from left to right along the axis and you consider one sensor type at a time, then the quality of your observations improves over this movement. For example, with loop detectors only volumetric data is obtained, but if one steps up to loops that record vehicle signatures then that researcher can potentially match some vehicles through a series of loop detectors because now there is volumetric and identity data. Continuing to swap out better and better

sensor types, one moves to the other end of the spectrum – Automatic Vehicle Identification (tag readers) and Automatic Vehicle Location (GPS).

Examining the observability axis further (see Figure 2.6), it is expected that different sensor types will yield varying amounts of path flow information. Consider two base cases (in other words, both without the use of inference), loops versus AVL probes and assume both have zero errors. If 100 percent of a general network is instrumented with loop detectors, then 100 percent of the link volumes will be known; however, 100 percent of the path flows will not be extractable except in very simple networks where FIFO can be proven to hold and where paths do not overlap because again only volumetric data is available with no identifying information. Therefore, full network coverage does not necessarily mean full information. Moreover, since full information will not be attainable with full network coverage with some sensor types, then inference would be required at all times to make up for the information shortfall – hence the anticipation of a steeper slope for the loop detector curves than the probe curves in Figure 2.6. In contrast, if 100 percent of the vehicles are probes (i.e. AVL-equipped), then we have 100 percent of the path flows barring any GPS errors and data transmission issues; and little or no inference is necessary so flatter curves are shown for high levels of probes.

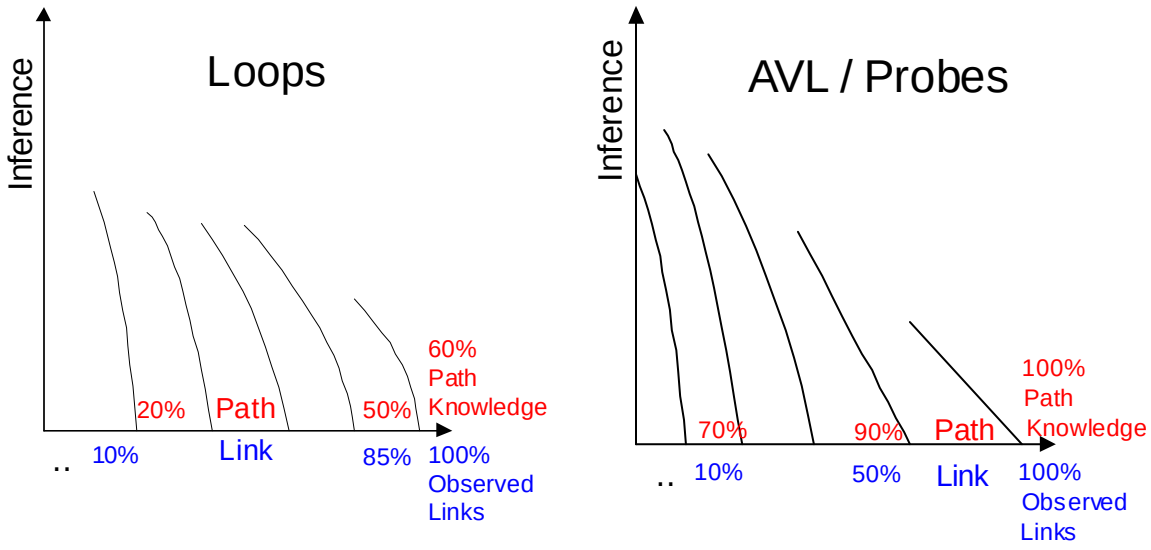


Figure 2.6 Potential Inference vs. Observability Graphs for Different Sensor Types

Inference Axis. Now examine the inference axis, which is ordered from least to most inference used as one moves from bottom to top along this axis. You can make ZERO assumptions and stay on the observability axis, thereby relying wholly on empirical analysis to extract path flow information. Or, you can make a small (marginal) improvement by introducing logical concepts such as with flow estimation – like requiring conservation of flow in a network and excluding "circuitous" or "unreasonable" paths from selection. It is anticipated that one can make the largest marginal improvement if path choice behavior data is introduced (shown as the biggest leap) because without collecting traffic data we gain insights into people's path preferences and prior behavior. Granted a good sampling strategy must be employed, but then it becomes a powerful addition to data alone for determining paths. Finally, a common practice in the world of OD estimation is that of applying a traffic assignment model. Now, traffic assignment models can strengthen *or* weaken path flow

estimation since they depend on assumptions that may or may not apply to the network in question. Therefore, these must be handled with utmost care.

Combining Observability and Inference. The third case suggested in the graph is when a combination of each is applied to a given situation, and it is here that a gap in knowledge exists. The type of sensor or combination of sensors will effect the amount of path information available as will the inference tools employed. Although some curves were suggested in this text, they are not backed up by analytical or empirical data; therefore, the actual shape of each curve is suspect. Hence, by examining the tradeoff between observability and inference for path determination, more clearly defined relationships between different observation instruments and inference tools can be discovered.

2.4 Anticipated Contributions

This dissertation work is to broaden the transportation engineering body of knowledge by quantifying the tradeoff between direct observation and inference of path flows on a road network. The goal is to develop a viable method to determine path flows in a network. It is anticipated that three contributions will be crucial to successfully undertake this research. First, measuring the predictability of path utilization rates and the extent to which that predictability is dependent upon the data available and the quality of that data. Second, creating a methodology to address the predictability of path flow rates which in some ways inverts the more common process, that of origin-destination estimation. Third, an improved understanding of the interplay between observations and inferences in determining the path

utilization coefficients. These contributions are driven by a desire to understand whether particular models are based on observed and/or inferred data and how each one influences the choice of method and path flow rate outcomes. In other words, strived for is an articulation of how much reliance on inference and/or observability is necessary when a certain path utilization estimation method is applied. Following on the heels of this initial research is that of creating models for path flow observability under crisis, incident, and blockage conditions. A potential further contribution would be to use the developed math programs to validate common route planning algorithms.

3 METHODOLOGY

Exploring the question of how to discern path flows from one another across a road network has led this researcher to review literature with the finding that most authors have estimated path flows with loop detector data, an old or estimated OD matrix, and sometimes other data sets. For methods, they relied heavily on using traffic assignment modeling, some choice behavior analysis, and flow estimation techniques. Few authors exploited the wide array of technologies available today for instrumenting a network; two examples that do so are (Gentili and Mirchandani 2005) and (Zhou and List 2006), but only the former focuses on path flows whereas the latter concentrates on OD estimation, adding to a broad area of established and ongoing research. The flip side to discerning path flows, that of defining them, was also discovered to be a large area of active research, such as for routing purposes. But little path flow research has addressed the issues of (a) reliability in the instrumentation, (b) reliability of other input data or models, (c) reliability and confidence level of the path flows solution, (d) the relationship between what is observed and what is inferred, and (e) verifying that defined path flows are those actually occurring in the network (and discerned), which are all directly relevant to the practical application of path flow estimation and to guiding instrumentation research to meet the needs of the evolving world of transportation. Therefore, this dissertation research addresses the key questions of (1) how well can path flows be determined from an existing instrumented network, and (2) how much inference is required to estimate all the path flows.

This dissertation research was guided by the following methodology to address the problem of optimizing the information obtained from sensors given an existing system of detectors on a road network:

1. Develop a mathematical program (MP) to determine path flows.
2. Create or find a road network; preferably with path flow data available for verification.
3. Solve the math program using a set of randomly generated scenarios that involve different levels of stochasticity in the problem inputs.
4. Assess the performance of the math program based on performance measures and comparison to the actual path flows (when available).
5. Repeat this process (steps 1 through 4) – tweaking the math program until it is able to determine the path flows well.
6. Adapt the math program to more complex and realistic network conditions, again by repeating steps (1) through (4) and adjusting the math program to increase its accuracy and usefulness to the broader community of researchers and practitioners. It is recognized that full path enumeration is only sensible for small networks. Beyond this size, methods such as k^{th} shortest path and column generation that obviate full path enumeration were explored for the implementing algorithm.

An initial mathematical program was created during the dissertation proposal process for the problem that incorporated three instrumentation options and it was applied to a 3-node toy

network for exploratory purposes. That model was refined and its predecessor is specified in Section 3.2 and discussed in detail with the implications of the model specification discussed in subsection 3.2.5, plus several important cases mentioned in subsection 3.2.6. And potential performance measures to evaluate the math program's results are described in Section 3.3. Following the methodology is the experiment design (Section 4), then the findings of the analysis conducted so far on 10-node networks (Section 4.1) and concluding remarks (Section 6).

3.1 Problem Functional Specification

Functional specification – the blueprint for the design of a system.[1]

The proposed functional specifications are as follows:

1. The solution method is to include a mathematical program for optimization.
2. The function of the math program is to determine path flows from an instrumented network and/or instrumented vehicles using a network.
3. The model should be independent of time, i.e. static in nature to focus on one instant.
4. Conservation of flow shall be upheld throughout the network.
5. The model should be applicable regardless of the network topology.
6. The model should enumerate only the k shortest paths.

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[1] http://www.techweb.com/encyclopedia/defineterm.jhtml?term=functional+specification
Full citation: Technology information about **functional specification** on both Answers.com and TechEncyclopedia. Computer Desktop Encyclopedia Copyright © 2007 by Computer Language Company Inc.. Published by Computer Language Company Inc.

And borrowing three specifications from Dial's multipath assignment model (Dial 1971):

7. "The model should give all reasonable paths between a given origin and destination a non-zero probability of use, while all unreasonable paths should be given a probability of zero."
8. "When there are two or more reasonable paths of unequal length, the shorter should have the higher probability of use."
9. "The model's user should have some control over the path diversion probabilities."

It is desired that a model of the following form be developed:

$$Min\ z = \gamma_{AVL}(predicted - observed)_{AVL} + \gamma_{AVI}(predicted - observed)_{AVI} + \gamma_{LOOPS}(predicted - observed)_{LOOPS}$$

However, with each sensor bundle yielding one or more pieces of data, this exact form was modified.

3.2 The Model

3.2.1 Notation

D_{od} - vector of origin-destination flows

v_a - flow on arc a

x_p - percent of OD flow on path p (path utilization coefficient)

y_{oda} - percent of OD flow on arc a (link utilization coefficient)

α_{odp} - incidence matrix of OD pairs to paths

β_{odpa} - incidence matrix of odp triplets to arcs

$\gamma_v,\ \gamma_x,\ \gamma_y$ - weighting factors

m = true value of variable m

$\tilde{m}$ = measured value of variable m

$\hat{m}$ = predicted value of variable m

3.2.2 Mathematical Program – First Variation (MP1)

$$\min \sum_a \gamma_v \left| \frac{\hat{v}_a - \tilde{v}_a}{\tilde{v}_a} \right| + \sum_{oda} \gamma_y \left| \frac{\hat{y}_{oda} - \tilde{y}_{oda}}{\tilde{y}_{oda}} \right| + \sum_p \gamma_x \left| \frac{\hat{x}_p - \tilde{x}_p}{\tilde{x}_p} \right| \qquad \textbf{Equation 1}$$

s.t.

$$\sum_{odp} \beta_{odpa} \hat{x}_p \tilde{D}_{od} = \hat{v}_a \quad \forall \text{ arcs a} \qquad \textbf{Equation 2}$$

$$\sum_p \beta_{odpa} \hat{x}_p = \hat{y}_{oda} \quad \forall \text{ oda triplets} \qquad \textbf{Equation 3}$$

$$\sum_p \alpha_{odp} \hat{x}_p = 1 \quad \forall \text{ OD pairs} \qquad \textbf{Equation 4}$$

$$v_a, x_p, y_{oda}, D_{od} \geq 0 \quad x_p, y_{oda} \leq 1 \quad \text{(for true, measured, \& predicted)}$$

3.2.3 General Description

The proposed math program is comprised of one objective function, three constraint equations, and upper and lower variable bounds as needed. It is formulated as a static model so the complexities of time-dependent OD travel are not yet incorporated at this stage of

experimentation. The MP is designed to capture path information from three types of sensor bundles:

1. Fixed-location, volume-only detectors such as loops (point sensors).
2. Fixed-location (at least for a particular model run), vehicle identification detectors such as today's AVI tag readers.
3. Mobile, vehicle identification, location, speed, and heading detectors such as the current AVL-equipped vehicles (probes).

In Figure 3.1 the MP can be examined in context with the input and output information.

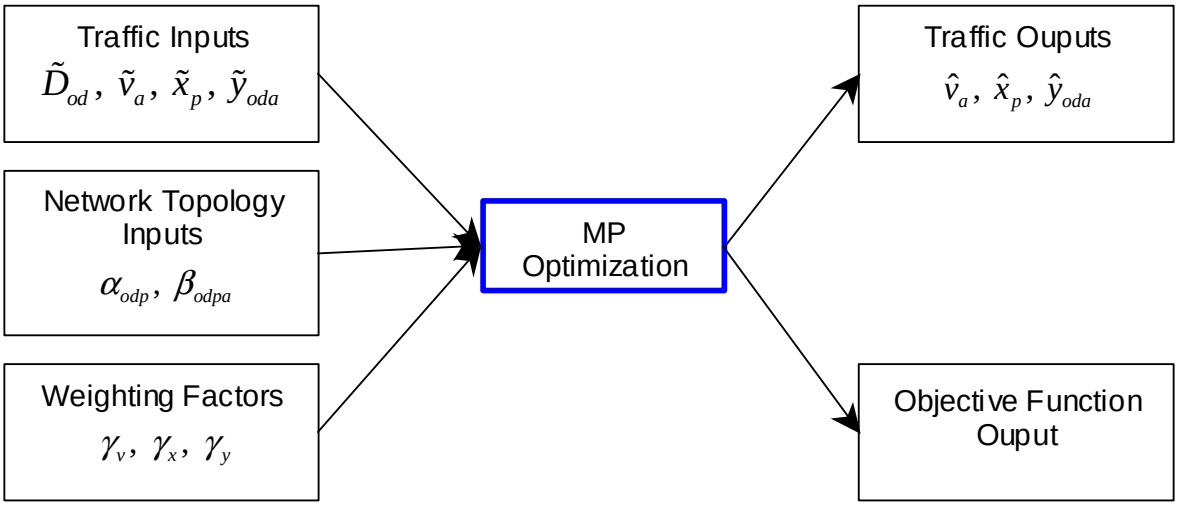

Figure 3.1 Flow of Data in the Problem

The model states that with three key ingredients (link flows plus link utilization coefficients and OD flows from other data sources) path utilization coefficients for the entire network can

be determined. The objective function is a minimization of three sums (Equation 1), each of which is the absolute value of the difference between an estimated value minus a choice variable and this difference is then divided by the choice variable to ensure that the magnitude of the difference is captured and not the sign of it. The first sum focuses on the link flows, the second sum is for link utilization coefficients (LUCs), and the third is for the path utilization coefficients (PUCs). Therefore, the quality of the outcome will depend upon which variables are known (measured) and which are estimated through other means. Moreover, any of the three variables (v_a, y_{oda}, x_p) can be the dependent variable. By minimizing these three variables' differences the math program is designed to create dependent variables that are closely aligned with their measured counterparts. In other words, an assumption is made that the independent ("~") and dependent ("^") variables should not be significantly different, rather one is used to tweak and fill in the gaps of the other. This is a common practice in OD estimation (using a target matrix, see (Sherali, Sivanandan et al. 1994) for one example) but has drawbacks related to the quality of the input OD flows, as will be discussed shortly.

The next three equations constrain the minimization so only reasonable values are allowed. Equation 4 is to ensure that no more and no less than 100 percent (shown in decimal form in the equation) of traffic for a given OD pair is distributed onto the paths used by said pair; in other words, all flows are assigned to a path and the percent of PUCs sum to 100 for each OD pair. The second constraint (Equation 3) ties the path and link utilization coefficients together by requiring that for a given OD pair, all the paths p crossing a particular arc *a* are

accounted for (and the sum of the PUCs equals the LUC for that link). And Equation 2maps the OD flows to the link flows (conservation of flow equation) by relating the PUCs to the link flows with the understanding that on a given link, and for a given OD pair, the link utilization coefficient will necessarily equal the proportion of traffic between the O and D on all paths that cross the link of interest; hence, the use of the β_{odpa} incidence matrix that maps each path flow (PUC) to the links traversed.[2]

Since this model is for a traffic network, both the network's topology (incidence matrices α_{odp} and β_{odpa} showing connectivity) and the traffic volumes v_a must be greater than or equal to zero so non-negativity constraints are included in the formulation. Moreover, two of the variables, x_p and y_{oda}, are proportions having both lower and upper bounds of zero and one, respectively.

As a whole, some key assumptions are implicit in this formulation. First, fixed sensors can be located along any arc in the network. Second, mobile sensors are associated with the arcs they traverse, but an explicit count of them is not possible (the number of sensors is a higher level issue if this were part of a bi-level problem). Third, monitored arcs have enough sensors for all lanes. Finally, the goal of this MP is to organize all the available sensor data to derive values for path flows (or path utilization coefficients), specifically by seeing how close predicted values can be driven toward observed values. So, this is a data-driven process that assumes matching the observed values is a wise objective. However, it is

[2] Paths, like links are numbered consecutively for the entire network. Hence, x_p with p = 1 to P and v_a = 1 to A. LUCs are numbered using both the link of interest and the OD pair of interest since both pieces of information are required to identify them, unlike paths or links.

recognized that at least two error sources may exist, sensor measurement errors and modeling errors. The former depends on the device used and the conditions of the experiment whereas the latter can depend on coding errors, data entry errors, and incorrect theories. Therefore, this process must be explored to validate whether it is applicable when errors of different types and degrees are present.

3.2.4 Objective Function

As mentioned above, the objective function (Equation 1) is minimizing the differences of the observed data with the predicted data for link flows, link utilization coefficients, and path utilization coefficients. So the measure of optimality is to minimize the differences between the traffic flow-related input and output variables for the maximum information gain for path flow determinations.

Notice further that the variables are of distinctly different magnitudes with v_a and D_{od} being in terms of vehicle flows (integer) whereas x_p and y_{oda} are proportions ranging from 0 to 1, therefore the magnitudes are normalized through the division of the predicted minus observed differences by the observed values.

Next observe that a variant of the L1-norm is used, but an L2-norm which is computationally easier could also be used. The Euclidean distance or L2-norm,

$\|m\|_{p=2} \equiv \left(\sum_{i=1}^{n} |m_i|^p \right)^{1/p} \equiv \sqrt{m_1^2 + \cdots + m_n^2}$, is conducive to partials since it is quadratic, but it is complicated once the objective function is normalized (to ensure all components are in the

zero to one range). And, it is important to look at the partial derivatives of the objective function to see how the function will shift with a change in each variable.

Note that the L1-norm, $\|m\|_{p=1} \equiv \left(\sum_{i=1}^{n} |m_i|^p \right)^{1/p}$, will not yield a good partial derivative because the absolute value function is not continuous (non-smooth). On the other hand, the L1-norm will allow one to see that there is an ideal shift for each variable (namely, $\hat{v} = \tilde{v}$, $\hat{y} = \tilde{y}$, and $\hat{x} = \tilde{x}$). So to enable such discovery, a variation of the L1-norm is included in the objective function.

Finally, weightings of each summation in the objective function are provided for two reasons. Firstly, each variable may or may not be incorporated depending on the available data so the summations of variables can be easily multiplied by a weight of zero to remove them from the objective function without altering the entire model. For example, loop data (v_a) is easy to acquire so will often be included whereas link utilization data is harder to come by (it may happen through choice behavior surveys), so the y_{oda} summation may often be multiplied by zero. Secondly, the weights can incorporate penalties/ costs that could signify error or uncertainty in the observed data.

3.2.5 Implications of the Model

The proposed MP design for predicting path flows distinctly characterizes the problem at-hand. First, the impact of individual sensor types will be considered. Second, the effect of

origin-destination data is discussed. And third, constraints that could be added are mentioned.

3.2.5.1 Sensor Type

AVL Sensors. If complete AVL data are available, then all the information needed exists for predicting path flows and the solution is trivial to find; notice that $\hat{x}_p$ shows up in every equation (see MP2 below) so the math program can be driven to a solution with $\tilde{x}_p$ known. Observe that there are few articles that discuss the AVL sensors with regard to path flows (Schäfer, Thiessenhusen et al. 2002; Nanthawichit, Nakatsuji et al. 2003; Kühne, Schäfer et al. 2003-08; Demers, List et al. 2006); rather, most AVL articles include a treatment of travel time estimation.

$$
\begin{aligned}
&\min \sum_p \gamma_x \left| \frac{\hat{x}_p - \tilde{x}_p}{\tilde{x}_p} \right| \\
&\text{s.t.} \sum_{odp} \beta_{odpa} \hat{x}_p \tilde{D}_{od} = \hat{v}_a \qquad \forall \text{ arcs a} \\
&\qquad \sum_p \beta_{odpa} \hat{x}_p = \hat{y}_{oda} \qquad \forall \text{ oda triplets} \\
&\qquad \sum_p \alpha_{odp} \hat{x}_p = 1 \qquad \forall \text{ OD pairs} \\
&\qquad v_a, x_p, y_{oda}, D_{od} \geq 0 \qquad x_p, y_{oda} \leq 1
\end{aligned}
\tag{MP2}
$$

AVI Sensors. With AVI data, recognize that there is no single variable in the MP that represents AVI data, rather, it can be included in the formulation in two different manners depending on the goal – is the researcher trying to improve the estimation of link utilization

coefficients or both link utilization coefficients and path utilization coefficients? Another way to look at this is that AVI data provide a second set of point-to-point flows (potentially some OD flows), based on the sub-network covered by the tag readers, plus they provide trip chain information. Therefore, if the researcher's main focus is on the accuracy of LUCs, there is no added value that the AVI network also provides linked trip information, so the researcher can ignore the path information and only input the sub-network OD flows to provide a lift to the math program thereby improving the quality of the LUCs. However, if the focus is on improving the PUCs, then a second lift can be done by including the linked trip information because these chains are now of immense value. Mathematically, the two variables impacted have additional information from the AVI sub-network that can be shown as follows:

$$\left[\tilde{D}_{od}\right] \Leftarrow \left[\begin{array}{c} \tilde{D}_{od} \\ \hdashline \tilde{D}_{od-subnetwork} \end{array}\right] \qquad \left[\tilde{x}_{p}\right] \Leftarrow \left[\begin{array}{c} \tilde{x}_{p} \\ \hdashline \tilde{x}_{p-subnetwork} \end{array}\right]$$

In the past seven years, AVI research has picked up with a handful of OD estimation articles now published (Asakura, Hato et al. 2000; Dixon and Rilett 2002; Oh, Ritchie et al. 2002; Antoniou, Ben-Akiva et al. 2004; Dixon and Rilett 2005; Zhou and List 2006).

Loop Detectors. Lastly, with only volume sensors (loops), the math program can be reduced to the following form:

$$\min \sum_{p} \gamma_v \left| \frac{\hat{v}_a - \tilde{v}_a}{\tilde{v}_a} \right|$$

$$\text{s.t.} \sum_{odp} \beta_{odpa} \hat{x}_p \tilde{D}_{od} = \hat{v}_a \quad \forall \text{ arcs a} \qquad \text{(MP3)}$$

$$\sum_{p} \alpha_{odp} \hat{x}_p = 1 \quad \forall \text{ OD pairs}$$

$$v_a, x_p, y_{oda}, D_{od} \geq 0 \quad x_p, y_{oda} \leq 1$$

Here, the second constraint of MP1 drops out since there is no direct effect on the link volume variables, although intuitively we know they are connected and once the predicted values of the path utilization coefficients are solved for, then we can use Equation 3 to calculate the predicted link utilization coefficients. Over the years, several researchers have attempted working with link volume data for OD estimation (Cascetta 1984; Bell 1991; Yang, Sasaki et al. 1992; Sherali, Sivanandan et al. 1994; Yang 1995; Camus, Cantarella et al. 1997; Cascetta and Russo 1997; Cascetta and Postorino 2001; Sherali and Park 2001; Timms 2001; Hazelton 2003; Lo and Chan 2003; Zhou, Qin et al. 2003). However, for path flow estimation this leads to an underspecified problem. Not only is one constraint dropped from the formulation, but two summation terms from the objective function are unnecessary and drop out leaving the (MP3) formulation. Yet this MP is not particularly helpful. For example, if you have a situation with 10 nodes in a network, then there are 90 OD pairs excluding the 10 *i* to *i* pairs. Further, the spanning tree is 9 links or 18 one-way arcs and the maximum network density is approximately 44 arcs for an average of 31 arcs. This translates into 1 objective function equation, 31 equations for the first constraint – one for each arc flow, and 90 equations for the second constraint – one for each viable OD pair, for a total of (1 + 31 + 90 = 122) 122 equations. And the number of unknowns is simply the total number

of arc flows plus the total number of PUCs which equates to (31 + 360 = 391) 391 unknowns. So the problem can be set up with approximately 120 equations and 400 unknowns – clearly underspecified.

As is evident based on the above discussion, it is unlikely with current sensor attribute bundles that only the link utilization coefficients (y_{oda}) will be measured and that the only term in the objective function would be for the y_{oda} variables. However, LUCs are commonly included in OD estimation models along with other data (Lam and Huang 1996; Liu and Fricker 1996; Lo, Zhang et al. 1996; Hjorth 1999; Hazelton 2000; Hjorth 2002; List, Konieczny et al. 2002; Lo and Chan 2003).

3.2.5.2 Origin-Destination Data

Addressing the issue of OD-flow data quality is crucial because of the interaction these flows have with link and path flows. Hence, the $\tilde{D}_{od}$ vector[3] causes flow shifts in v_a and proportional changes to x_p and y_{oda}. Looking at the big picture for OD flows, what if the standard deviation is left alone, but the means for each OD pair are not measured well – now what affects the answer? In other words, the means in the $\tilde{D}_{od}$ vector are shifted uniformly high or low as in Figure 3.2. For example, if given observed link flows and an OD matrix: if an OD matrix flow decreases, then it forces less traffic to generate more volume, therefore more circuitous paths happen so the same traffic covers more links (see Figure 3.3).

[3] The math program formulation in this dissertation specifically uses a vector instead of a matrix for the origin-destination flows to simplify the mathematics.

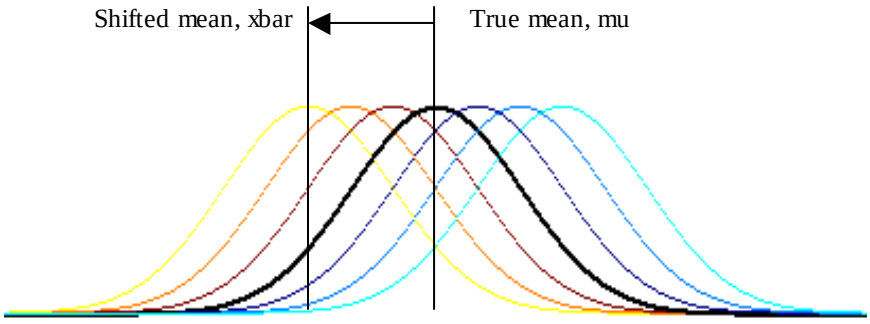

Figure 3.2 Shifted means of Dod matrix
Source (accessed 2/2007): https://www.covariable.com/continuous.html with the following settings: mu=0, sigma=0.4, x=[-3 to +3]

To say it another way, if OD flows are decreased by 10 percent but measured link volumes are left alone, then because of how the optimization is set up, it will shift flows around to the most painful links (sabotage high value links) unless the objective function is normalized (as done in MP1) to account for the link volumes being orders of magnitude larger than the 0 to 1 range of the PUCs and LUCs. The predicted link volumes will be matched with those links with observed volumes by shifting around unobserved link and path flows.

Also it should be asked, when might such a shift in OD flows happen all at once? It could happen that the entire D_{od} vector is shifted high or low if there was (a) an OD survey that over- or underestimated the flows, or (b) a calibration error occurred with a screen line flow counter. The latter sensor system is now mentioned.

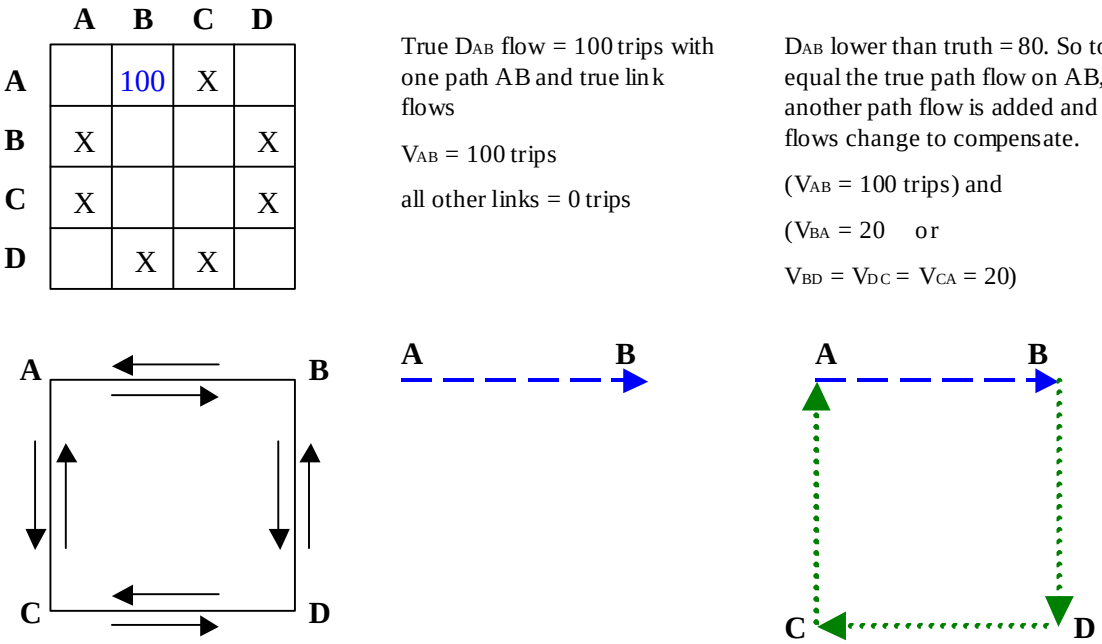

Figure 3.3 Potential Impact of an Inaccurate OD Matrix on Link Flows

Now, a similar situation can occur when screen lines are placed in the network. For instance, Figure 3.4 illustrates the need for careful selection of screen lines because if poorly chosen then a messy (or inaccurate) OD matrix can lead to circuitous paths whose flows are double-counted. See (Wu and Chang 1996) for a good treatment of this issue.

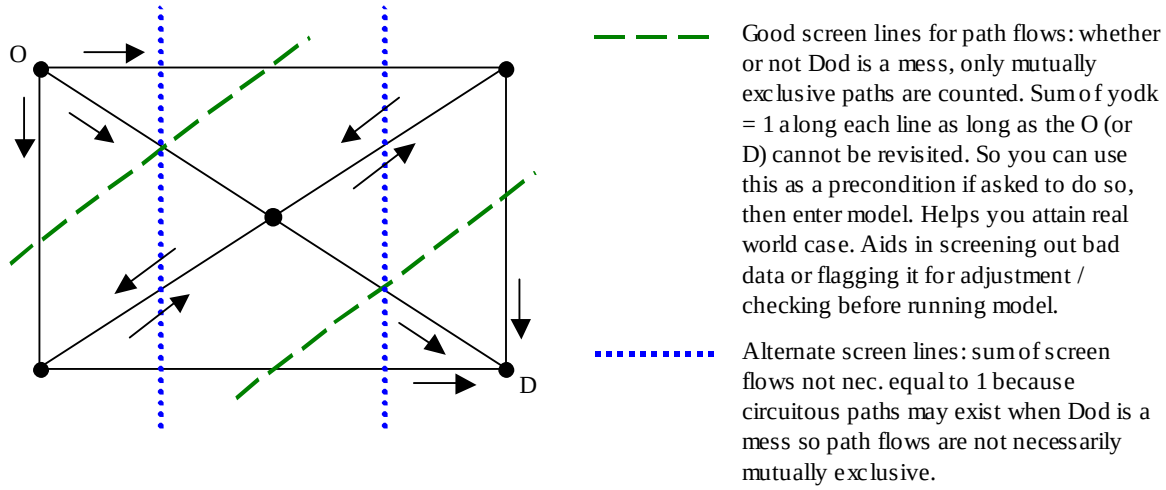

Figure 3.4 The Effect of Screen Line Choice on Counting Path Flows

Furthermore, for any OD pair there is a countably finite number of screen lines that require the y_{oda}'s to sum to 1 (see Figure 3.5 showing isobars of solution correctness). And if the wrong screen lines are chosen, then the sum of the y_{oda}'s for each OD pair would be greater than 1 so the MP constraints would be affected by this choice. Specifically, Equation 2 would be upset by y_{oda} values adding to more than 1 for a given OD pair (i,j) because this implies the OD pair uses arc a for more than 100 percent of the trips that pass between i and j and traverse that link – this is only possible if some vehicles cross arc a more than once during the same trip. So, if screen line data are a desired input, then a precondition of running the MP must be that the sum of y_{oda}'s equal 1 is strictly satisfied for each OD pair.

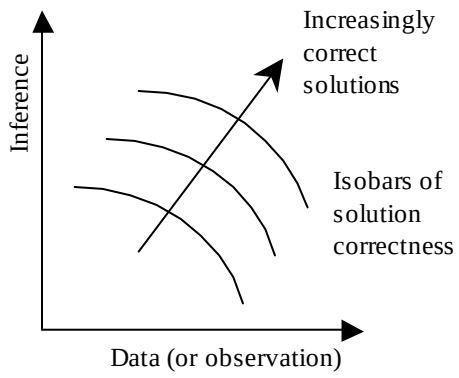

Figure 3.5 Screen lines and Isobars

Now, if we refer back to the inference versus observability diagrams, then using screen lines for traffic counting may be comparable (on the same isobar) as 100 percent loop detection because although screen lines would yield less than 100 percent volume data, there would now be greater than zero percent OD information so we would have partial volume data (some v_a's) and partial OD data (some $\tilde{D}_{od}$ information). Now, some logic is required to determine the paths taken.

Next, recognize that $\tilde{D}_{od}$ and v_a are volumes so we can make a clear argument on why they would go lower or higher individually or globally (as in the Figure 3.3 example). For instance, poor data collection, sensor type, and wrongly calibrated sensors could account for such volume shifts. Additionally, recognize that x_p and y_{oda} are more difficult to change globally up or down because they are percentages for local conditions.

Another concern is how can less emphasis be placed on the OD inputs if they are old or estimated? Two possible actions are: (1) change the constraint from $\sum_{odp} \beta_{odpa} \hat{x}_p \tilde{D}_{od} = \hat{v}_a$ to an inequality, and/or (2) remove $\tilde{D}_{od}$ outright so there is no constraint, but then this complicates how to calculate path flows from the PUCs because this would completely

change the model specification. A good source here is (Van Aerde, Rakha et al. 2003); the authors compare synthetic estimation to trip distribution estimation of OD matrices. And for validating OD data from surveys or synthetic sources using loop detectors, see (Stathopoulos and Tsekeris 2005); with (Gan, Yang et al. 2005) and (Chootinan, Chen et al. 2005) offering insight into the relationship between OD flow error bounds and locating traffic counters.

Lastly, examine the relationship between y_{oda} and v_a when the y_{oda} values are correct, but the v_a's are noisy. When y_{oda} is complete and correct and v_a is low, then this is a contradiction because these are strongly related. For example, if there is 100 percent AVL data available so the y_{oda}'s were observed (via Thruway data) but the DOT is using loops for the v_a's and the data sets have not been reconciled, then one should notice the v_a's are low or high and the y_{oda}'s seem close to being exactly correct. This causes upset in the math program. The x_p's must be adjusted to meet the y_{oda}'s and compensate for the v_a errors.

3.2.5.3 Constraints Yet To Come

The proposed math program is a starting point for further research and the building block for more complex programs. Specifically of interest for adding to the math program are four items: link capacities, penalty functions, integer flows, and path restrictions. Currently, the links are uncapacitated, allowing for an infinite amount of flow as might occur with an all-or-nothing assignment process. This is probably the most unrealistic condition and should be removed first. Penalty functions would add further realism to the program by incorporating the issue of delay and possibly congestion pricing. Although flows are currently not required

to be integer, such a constraint may not be added until near the end of the analysis process because integer programs are oftentimes difficult to solve for an optimal solution in a reasonable amount of time. And finally, path restrictions (such as hazmat routes) can be instituted to again add realism.

With the above model implications in mind, it is now helpful to see the potential cases and discuss a small selection of them in more detail.

3.2.6 Important Cases & Their Implications

The table and figure below represent the 27 possible cases (3 dependent variables $\times$ 3 conditions). The first case has the most input data (Case 1: the 3 variables *x*, *y*, and *v* are measured for the entire network) while the last case has no input data measured but rather it is all estimated (Case 27: 3 variables, all estimated from other sources). The remaining cases have some amount of data measured and some estimated (or inferred) for model input. If the cases are plotted on a $1 \times 1 \times 1$ cube as in Figure 3.6, then a simple pattern is discovered based on the amount of data measured which can be equated to the sum of the *x*, *y*, and *v* values for each case; note that the values of 0, ½, and 1 are shown although the ½ can be replaced by any fraction between 0 and 1. The resulting pattern includes 7 slices through the cube with each slice having more or less measured data per case than its neighbors. Of special interest are the *v*-axis (Case 27 to Case 20) which represents the loop detector sensor bundle and the diagonal of the cube from Case 27 to Case 1 (like a skewer through the center of all the slices) which represents the AVL sensor bundle with an increasing amount of network coverage. Therefore, by simply knowing the case (or its position in the cube, an

initial idea can be formed of what errors need to be considered (measurement vs. estimation errors) and how strongly they might affect the solution (for example, more estimation error may incur more overall error as compared to more measurement error). With this initial background, some select cases are now explored.

Case	x	y	v	Sum	Percent Measured
1	1	1	1	3	100%
2	½	1	1	2.5	84%
3	1	½	1	2.5	
4	1	1	½	2.5	
5	½	½	1	2	67%
6	½	1	½	2	
7	1	½	½	2	
8	0	1	1	2	
9	1	0	1	2	
10	1	1	0	2	
11	½	½	½	1.5	50%
12	0	½	1	1.5	
13	½	0	1	1.5	
14	½	1	0	1.5	
15	0	1	½	1.5	
16	1	½	0	1.5	
17	1	0	½	1.5	
18	1	0	0	1	33%
19	0	1	0	1	
20	0	0	1	1	
21	½	½	0	1	
22	½	0	½	1	
23	0	½	½	1	
24	½	0	0	.5	17%
25	0	½	0	.5	
26	0	0	½	.5	
27	0	0	0	0	0%

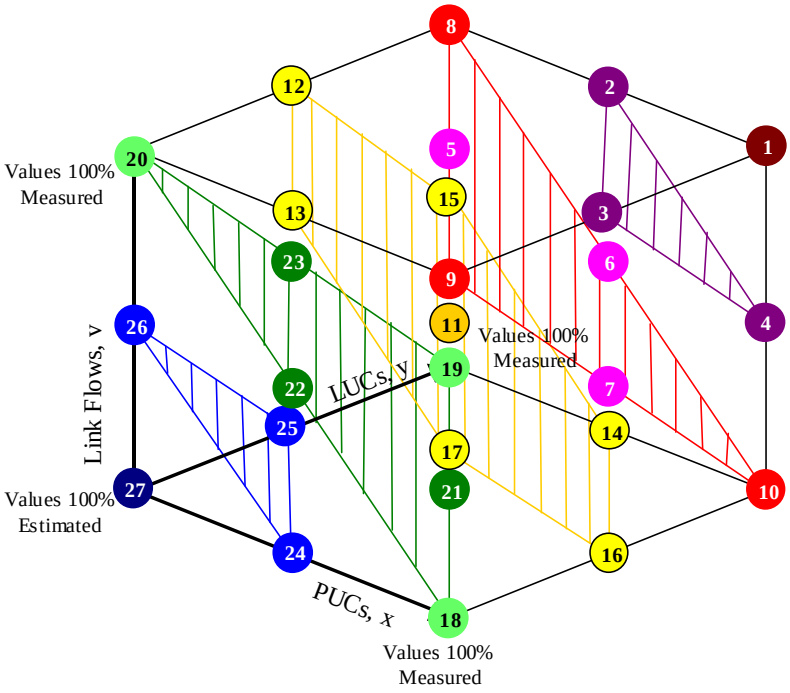

Figure 3.6 Inference and Observability Combinations for Three Variables

Case 1: Full AVL Data. Say all three variables were measured: link flows, LUCs, and PUCs throughout the network because all vehicles had a built-in GPS receiver that

transmitted data regularly with the vehicle's identity to a traffic management center server. Then the errors incurred in the given math model are purely based on measurement and not on estimation or inference. Full AVL data would fit here.

Full AVL data $\Rightarrow$[4] $\tilde{D}_{od}$ known $\forall$ *od* pairs,

$\Rightarrow$ x_p known $\forall$ paths $p \in P$ $\forall$ *od* pairs,

$\Rightarrow$ $\tilde{v}_a$ known $\forall$ $a \in A$, and

$\Rightarrow$ $\tilde{y}_{oda}$ known $\forall$ arcs $a \in A$ $\forall$ *od* pairs.

Now, if complete data exists (whether measured or estimated), but the given sum of the path utilization coefficients is 0.8, then a precondition should be added to the model to force the sum to equal 1.0.

Case 11: Partial AVL data. If you are strapped for dollars and reduce the data analysis task to only look at a small percent of the passenger trips, then you enter into the partial data world. This leads to a rich set of data that sparsely covers the network. The difficulty here is that no knowledge is available about missing links and missing OD pairs so inference would strongly impact that subset's predicted values. Another point is that the missing x_p's can be anything because they drop out of the objective function (since there is no measured value to compare to the predicted value).

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[4] In mathematical terms, this symbol means "implies".

Helpful in this case would be requiring certain fleets such as public busses and/or taxicabs to use AVL equipment so that a minimum level of network coverage could be regularly attained with a known chance of path overlap or probe clustering (such as transit routes overlapping or taxis all waiting at the local airport). In other words, the predictable routes of busses afford the model with a base, unchanging network of information whereas the taxis yield broad coverage of a region, although the paths are unpredictable.

Case 18 or 24: Full AVI data. Depending on whether the defined network includes only facilities with tag readers (such as a freeway network) or a mix of facilities with and without tag readers Cases 18 and 24 are the resulting cases, respectively. As mentioned in the previous section, data from AVI-type sensors translates into $\tilde{D}_{od}$ being known for a subset of network locations (some of which may be OD pairs, some may be intermediate points) and observed x_p data coming from the trip chain data when a vehicle passes multiple tag readers.

As an aside, it should be noted that data from loops with inductance signatures for all links are similar to AVI data, except that a higher error is associated with all measurements (such loop detectors may inaccurately match vehicles identities from one loop to the next in high flow situations (since two vehicles of the same make and model probably have quite close signatures)).

Cases 20 & 26: Loop data for all or some links.

Loop data for all links $\Rightarrow$ $\tilde{v}_a$ known $\forall\, a \in A$.

When all links have known flows but no other data, then the MP3 model results with the x_p's and y_{oda}'s dropping out of the objective function. Traffic counts for a part of the network is far from ideal with only a small percent of the possible information being collected based on Figure 3.6 (this example shows 17 percent). And as discussed in the previous section, there has been quite a bit of research to create OD matrices from link volume data, but there is little research into determining path flows without assuming a traffic assignment model; the following papers assumed a TA: (Bell, Shield et al. 1997; Lam and Xu 1999; Chen, Chootinan et al. 2004; Nie, Zhang et al. 2005).

3.3 Potential Performance Measures

With the math program described and its potential implications discussed, it is now useful to talk about evaluating the MP's performance. Remember that this math program is designed to match predicted values to given values. Thus, the question being asked is how close can the predicted values be driven toward the observed values? So, it is a data-driven process.

To assess the quality of the predicted variables, five types of performance measures are seen as potentially useful.

1. Coefficient of Variation (CV) for v_a, y_{oda}, and x_p
2. Sum of Absolute Errors (SAE)
    - of observed to true values for v_a, y_{oda}, and x_p

- of predicted to observed values for v_a, y_{oda}, and x_p

3. Prediction accuracy of path utilization coefficients
4. Root Mean Square Errors (RMSE) of path and link utilization coefficients with respect to each sensor type
5. Data Envelopment Analysis (DEA)

3.3.1 Coefficient of Variation (CV)

The coefficient of variation is an input parameter for both the origin-destination data and the traffic data that can be ranged so the sensitivity of the model to a sensor type or the OD data can be assessed.

3.3.2 Sum of Absolute Errors

Two common measures of error are the sum of absolute errors (or differences), SAE, and the sum of squared errors (or differences), SSE; a comparison is listed in Table 3.1.

Table 3.1 Comparison of SAE and SSE

Measure	**Math Formulation**	**Penalty**	**Least Absolute Differences Solution**
Sum of Absolute Errors	$\sum_{\forall \tilde{x} \in X} \left\| \hat{x} - \tilde{x} \right\|$	Same for all guesses – distance	$\min \sum$: when $\hat{x} = \tilde{x}_{median}$
Sum of Squared Errors	$\sum_{\forall \tilde{x} \in X} \left(\hat{x} - \tilde{x} \right)^2$	Severe for poor guesses since squared	$\min \sum$: when $\hat{x} = \tilde{x}_{mean}$

Both measures can assist the analyst in quantifying the quality of values estimated through an optimization process. There are two distinctions between the measures. First, the SSE

applies a much higher penalty to poorer quality data than the SAE since the former squares the errors. Second, the Least Absolute Differences (LAD) solutions (minimum values) of the two measures are based on differing central tendency quantities, the median for the SAE and the mean for the SSE. Hence, the SAE is more forgiving of a skewed distribution or one with outliers for estimated values, whereas the SSE is less robust (more sensitive to such deviations). Lastly, the SAE reduces to a linear programming formulation whose optimality can be proven. LAD regression, for example, through the Barrodale-Roberts simplex formulation.[5]

When calculating SAEs, the first quantities naturally under examination are the differences of (a) the observed to predicted values of a variable and (b) the true to predicted values of a variable (when available). For example, consider for the former the traffic volumes on each link in the network. Link traffic volumes are probably the most used variables in OD estimation since traffic counts are a common input and easy to validate. The potential metric is simply:

$$\hat{v}_a - \tilde{v}_a \qquad \textbf{Equation 5}$$

In Figure 3.7, there is a plot of the link flow difference ($\hat{v}_a - \tilde{v}_a$) versus the sample number for a single link (arc 1) for a test network. Evident in this example is that many runs had a

[5] Retrieved from "http://en.wikipedia.org/wiki/Least_absolute_deviations" Category: Optimization . Retrieved on 8/22/2007.

slight underestimation (see all the negative values) of the predicted value of link traffic flows but when flows were overestimated the differences were quite large.

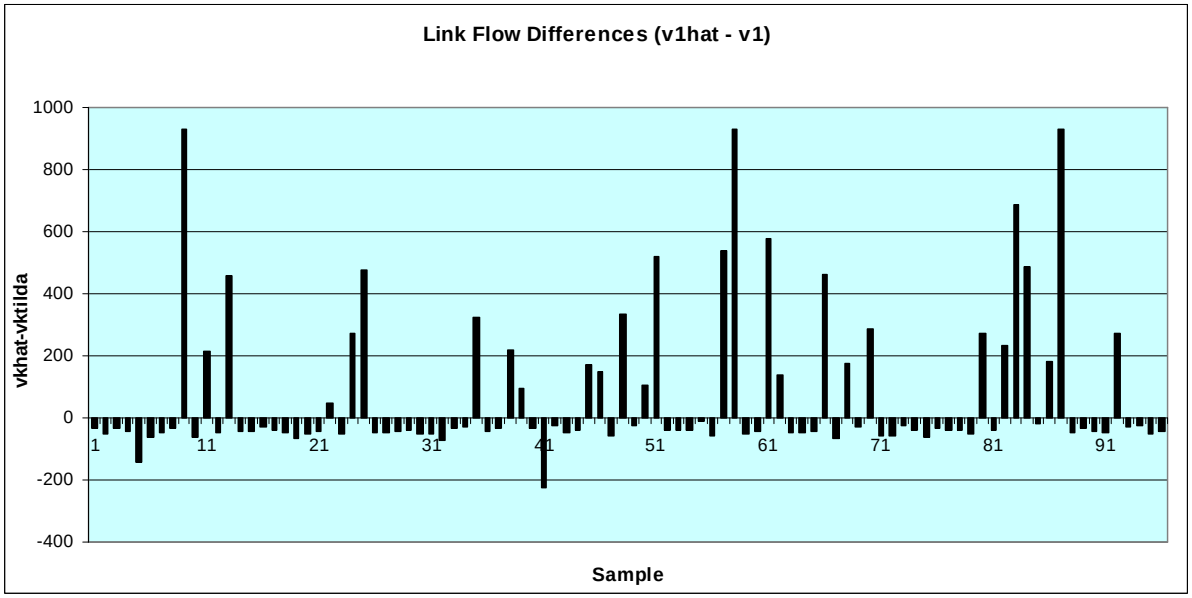


Figure 3.7 Flow Differences on Arc 1 for an Example Case

And in Figure 3.8, the link flow differences are plotted on a radar plot for all links. This format can make it easy to identify outliers and typical behavior for each link.

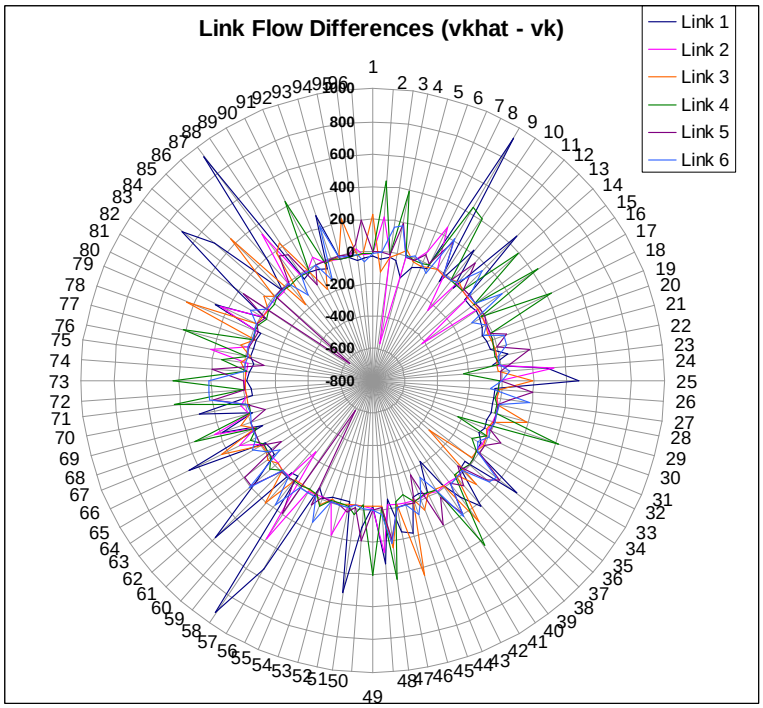


Figure 3.8 Flow Differences on All Links for All Simulation Runs of a Set

For the latter case between the true values and the observed or estimated values, a sample of the data fit of link utilization coefficients is shown in Figure 3.9 and the formula is here:

$$\hat{y}_{oda} - y_{oda}$$ **Equation 6**

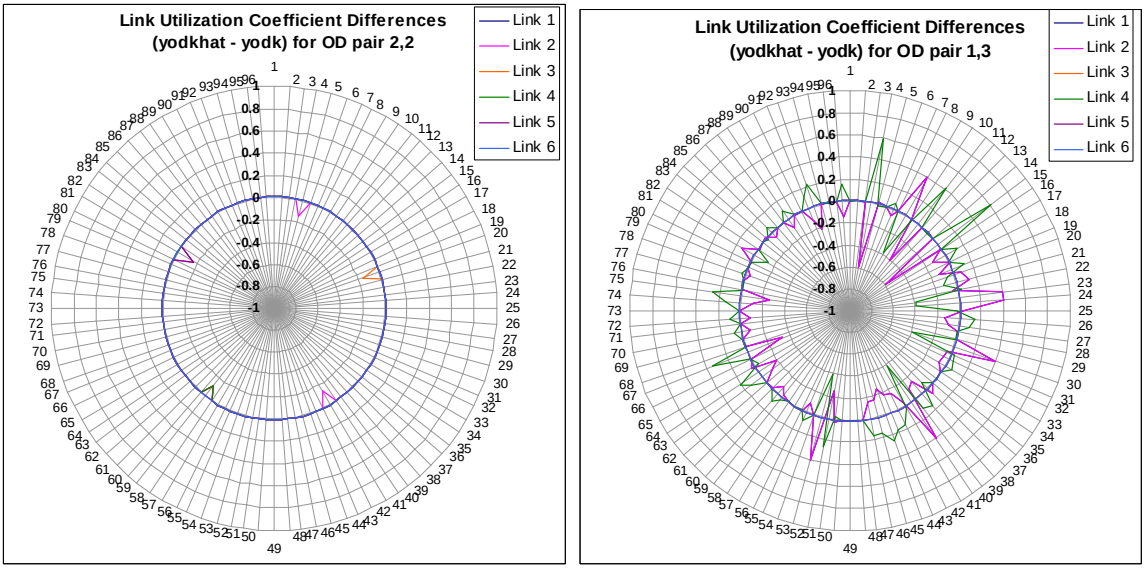


Figure 3.9 Link Utilization Coefficients for an Example Case

The two examples in Figure 3.9 illustrate the fit between the predicted and true values with the left radar plot generally having an excellent fit for all LUCs on all links whereas the right radar plot is noisier but shows an interesting trend between a pair of links (links 4 and 5).

With the differences themselves explored, the sum of differences can then be examined if the analyst wants a sense of whether flows were generally over- or underestimated as shown in Equation 7. Or the analyst can directly examine the SAEs.

$$\sum\left(\hat{x}_p - \tilde{x}_p\right) = \begin{cases} > 0 & \text{path flows are overestimated} \\ = 0 & \text{estimated \& observed flows match} \\ < 0 & \text{path flows are underestimated} \end{cases} \qquad \textbf{Equation 7}$$

3.3.3 Prediction Accuracy of Path Utilization Coefficients

3.3.3.1 Unweighted Prediction Accuracy of PUCs

This measure is suggested so the path utilization coefficients can be more closely scrutinized. As shown in the equation below, it is a ratio of the number of PUCs that are within 20 percent of the true (or observed in most cases) PUC with the total number of paths employed. It indicates a goodness of fit to the target data based on the size of the network (number of possible paths).

$$\frac{\text{\# of non-zero PUCs within 20\% of true PUC}}{\text{\# of paths employed}}$$

Equation 8

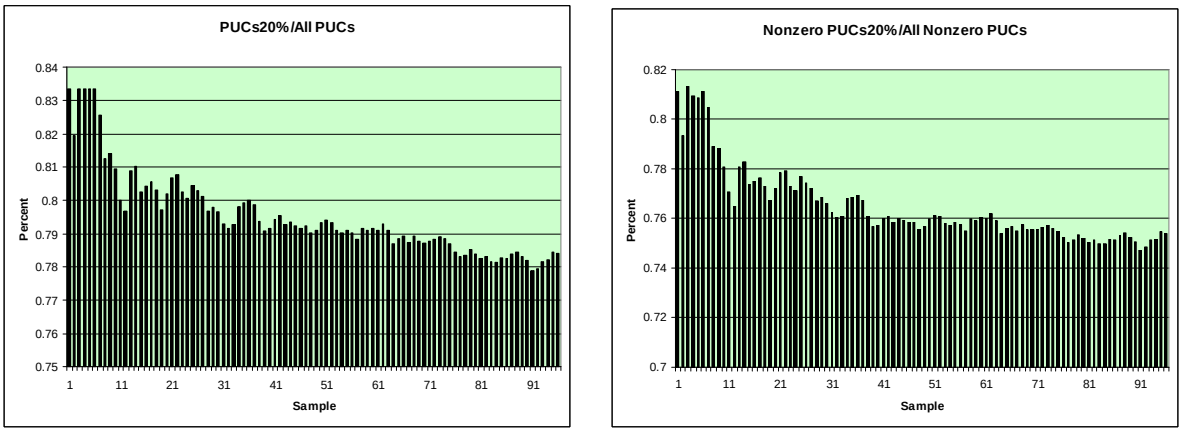


Figure 3.10 Unweighted PUC Prediction Accuracy – 2 Variations

3.3.3.2 Weighted Prediction Accuracy of PUCs

The last PUC metric (shown below) is related to the previous one, except that the PUCs are now weighted by the total traffic in the network instead of the network topology.

$$\frac{\text{Total trips on paths whose utilization is within 20\% of the true utilization value}}{\text{Total trips passing through the network}}$$ **Equation 9**

Figure 3.11 shows this metric to examine the model's performance. Note that when the percentage is high, this means that the majority of traffic is flowing on paths that correctly approximate the measured PUCs. So the path flows should be considered more reliable than if the opposite case were true (a low percentage for this metric means most flow was modeled on paths that are not well-approximated in terms of path utilization coefficients).

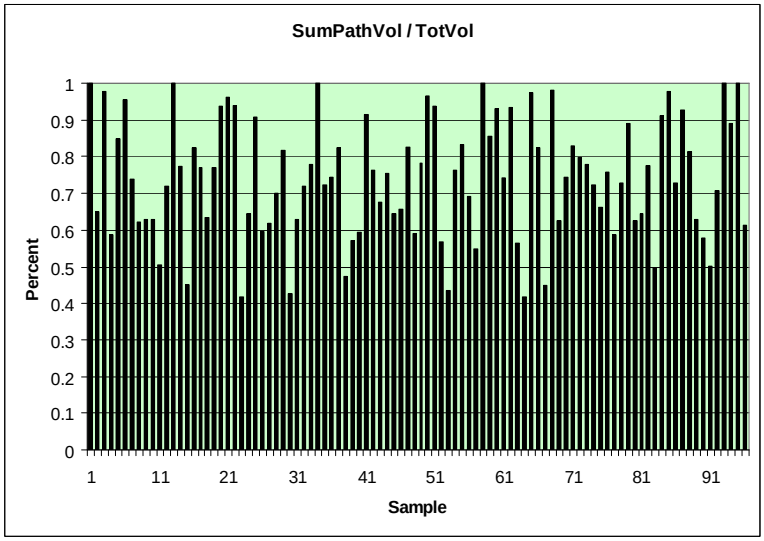


Figure 3.11 Weighted PUC Prediction Accuracy

3.3.3.3 Path Overlap Issues

Considering the metric *(% of PUCs within 20% of the true PUC)* there is an issue of how good or bad the PUCs fit the target data. One can reason that an effect will be seen (an increase in the standard deviation) because the OD pattern is slightly shifting and the model

gets into trouble with the link flows and LUCs because of the noise. Now, if the metric is found to be insensitive to these changes, then a pathological case has been found – the OD flows are separate (no path overlaps – mutually exclusive as in Figure 3.12 (a) and (b)) and one can move D_{od} anywhere but the correct answers (for LUCs and PUCs) will be obtained. Here, even though one may have inaccurate OD flows, because the paths do not share links the PUCs and LUCs can still be estimated correctly. Alternatively, some path overlap implies link flows and LUCs can change to accommodate the discrepancies such as for Figure 3.12 (c).

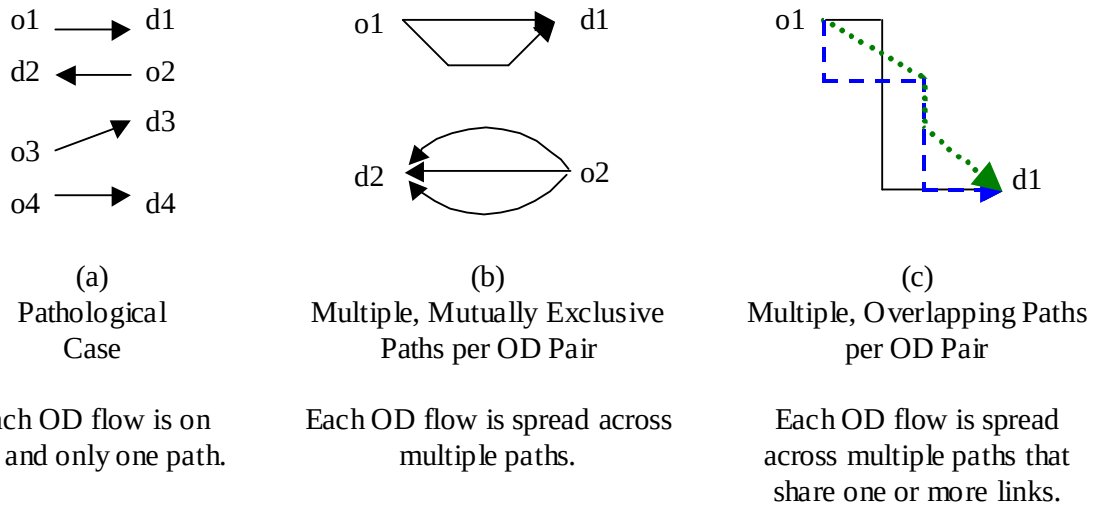


Figure 3.12 Examining the Implications of Path Overlap

The more path overlap that occurs means the path flows can become confounded. Think of a Manhattan metric problem (see Figure 3.13), if you increase the number of avenues, what happens? More and more paths overlap. Therefore, you run into extreme difficulties of

relating link flows to path flows because the number of paths increases significantly while the number of fixed sensors only increases by the number of links.

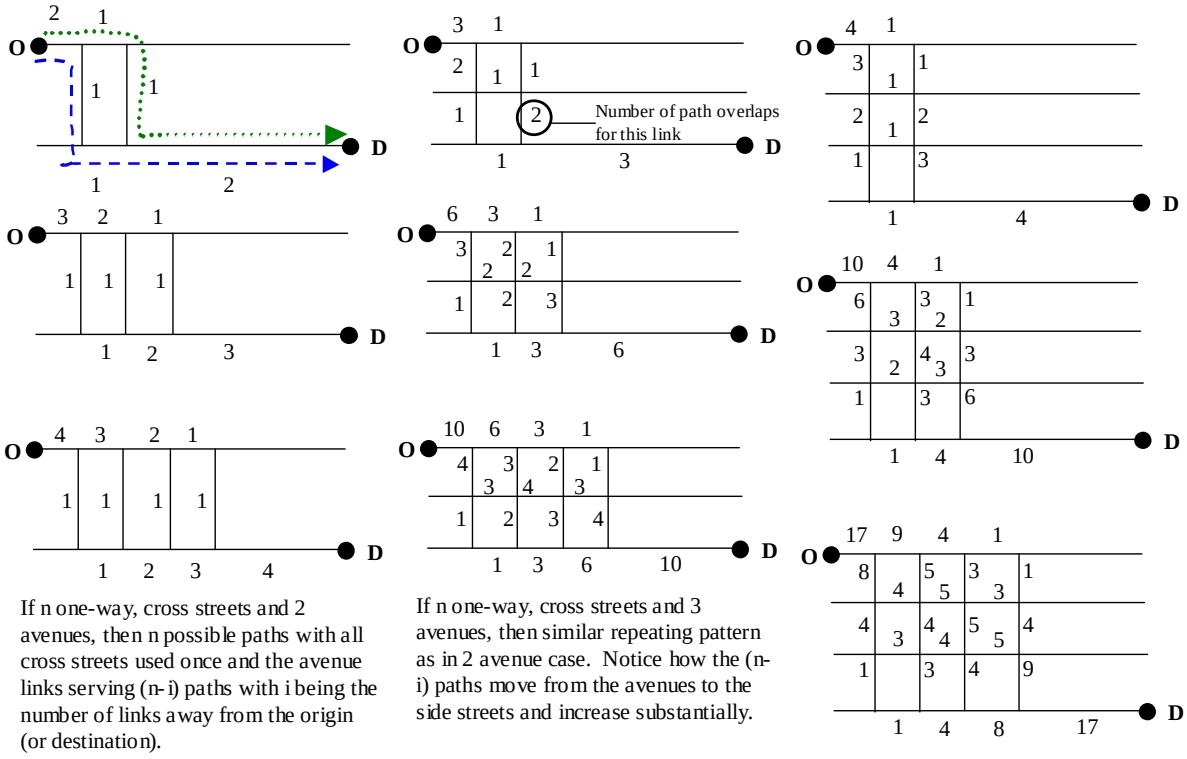


Figure 3.13 Examining Path Implications for a One-way Manhattan Metric

One team of researchers (Van der Zijpp and Catalano 2005) addressed the path overlap issue in an algorithm they developed for finding the k-shortest paths in a network. Their algorithm enables the incorporation of several types of constraints including a "detour constraint" to ignore paths that are too long as compared to the shortest path and an "overlap constraint" to

ignore paths that share too many of the same links. These ideas were incorporated into this research.

3.3.4 Root Mean Square Error

$RMSE_{LUC}$. The fourth potential performance measure category includes examination of root mean square errors for link utilization coefficients. The RMSE can be examined for each sensor type to see if there is a quantifiable relationship between the error, the sensor type, and the number of sensors employed.

- *$RMSE_{LUC}$ vs. Number of Loops.* It is expected that as the number of loops in a network increases, that the $RMSE_{LUC}$ will decrease to a minimum lower bound. It is also anticipated that if the detectors are clustered in only a section of the network that the same number of loops evenly dispersed would yield a lower $RMSE_{LUC}$.
- *$RMSE_{LUC}$ vs. Percent of Vehicle Fleet Equipped with AVL*
- *$RMSE_{LUC}$ vs. Number of AVI Tag Readers.* Unlike loops where every vehicle in the system is detectable if it passes a sensor, an AVI system can only detect vehicles with a tag transponder. And unlike AVL where the concern is only what percent of vehicles are appropriately equipped, an AVI system needs to take into account both the percent of vehicles equipped with tags and the number and location of tag readers throughout the network. Therefore, in the AVI case it is necessary to examine a family of curves.

It is suggested that the RMSE's be plotted against the number of sensors as in Figure 3.14.

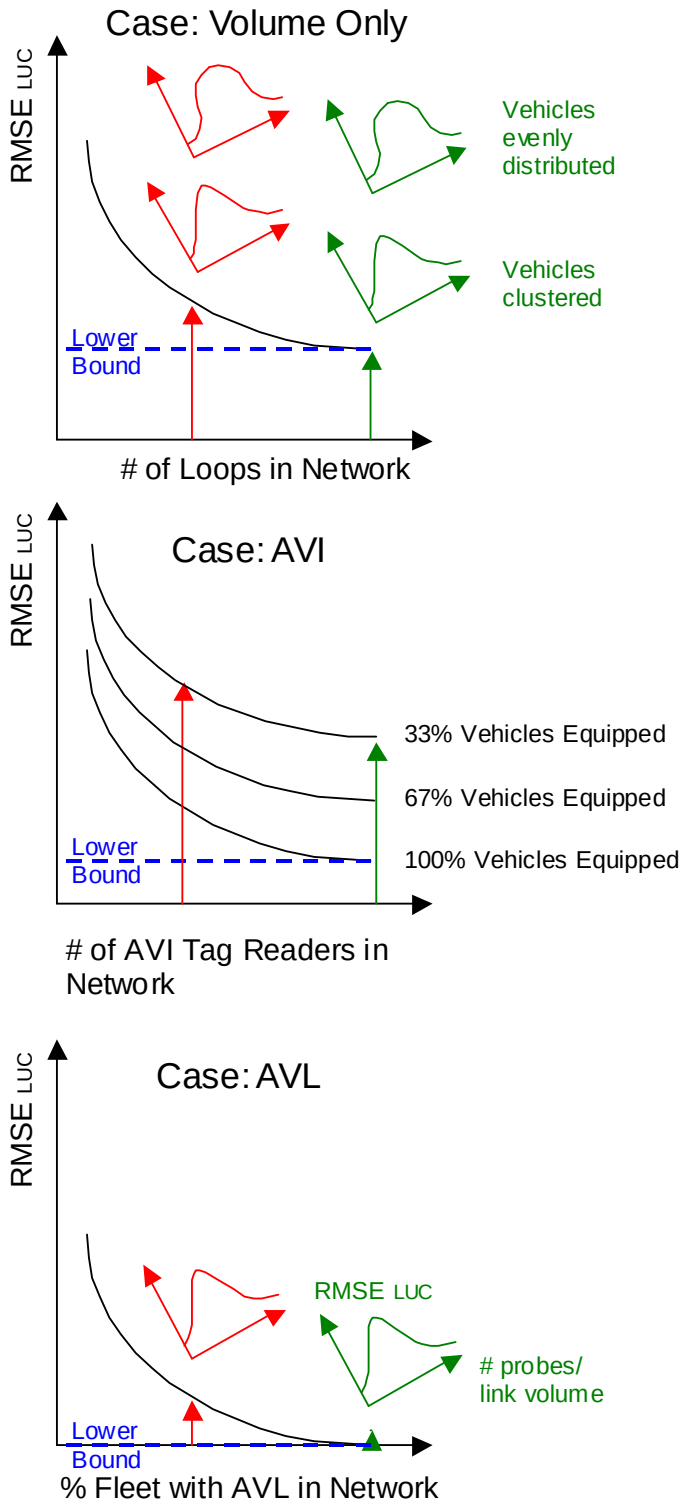


Figure 3.14 $RMSE_{LUC}$ vs. Quantity of Instrumentation – 3 Cases

3.3.5 Data Envelopment Analysis

Data envelopment analysis (DEA) is a useful tool when the relationships between the input and output variables are unclear, but what is desired is an efficiency rating of the applied process based on benchmarks determined solely by the available data. Therefore, this is a potential fifth performance measure.

DEA could assist in the adjusting of the optimization program because it is able to distinguish which variables are improving or worsening the efficiency.

- Distances from the efficiency frontier indicate whether there is a technical inefficiency or a mix inefficiency (distance to a vertex of the frontier, radial distance to the frontier)
- Technical inefficiency – all of the inputs in their current proportions need to be either increased or decreased by some percentage to improve the efficiency of the process
- Mix inefficiency – there is too much or too little of one or more of the inputs so the proportions of the mix need to be changed to improve the efficiency of the process

One caveat regarding this process is that it requires there to be the same number of elements for each type of input and output which is unlikely to occur in a network. For example, it is unlikely that there will be 10 arc flows observed yielding 10 PUC estimates so that 10 (input / ouput) ratios can be calculated.

3.4 Analytic Tools

The analysis conducted as a part of this dissertation was performed with the aid of Microsoft Excel and Hyper LINGO Release 10.0 by LINDO Systems, Inc. (see Appendix A for the math program written as LINGO code). The two tools are linked via VBA code written especially for this dissertation work (a summary of it is in Appendix B and further questions can be directed to the author). The VBA code reads in all the data, organizes it into a fashion readable by LINGO, calls up the LINGO software, then accepts the LINGO output data and post-processes it to automatically calculate the various performance measures and fill in the graph templates. Within Excel, the data is placed on a variety of worksheets, organized as follows:

- True data, if known (or if created for hypothetical networks)
- Raw observed data
- Estimated data
- All data from the previous sheets arranged for reading by the VBA code
- LINGO model for reading by the VBA code
- D_{od} vector data, as read and processed by LINGO for each simulation
- Results sheets for placing the results of the optimization back into Excel with graph templates already set up

The LINGO optimization software has a variety of solvers that are possible to enable. Currently, the analysis has been performed using the following solvers:

- The General Solver is decided upon by the LINGO software and the default has been left in place for LINGO to decide on the method whether it is a cold or warm start.
- The Linear Solvers include the primal simplex, dual simplex, and barrier method. Each method is available for use when necessary. The linear solvers were invoked.
- The Nonlinear Solver can follow one of five strategies (Crash Initial Solution, Quadratic Recognition, Selective Constraint Evaluation, SLP Directions, Steepest Edge). The default strategy is SLP Directions. This solver is not invoked.
- The Global Solver has not currently been invoked because of the extensive time it takes to solve 250 simulations per case and its tendency to crash the computer. However, it is recognized that without the global solver solutions may actually be local optima instead of global ones so the values of the objective function and dependent variables could be significantly affected.

4 EXPERIMENT DESIGN

There are several ways in which one can study the determination of path flows from sensor data. Key decisions include: the choice of a physical network, the measurement or generation of traffic – how and by what means, the development of a method to estimate the path flows (or a proxy for them), and an analysis methodology. For instance, in terms of choosing networks, actual transport networks could be used. They could be found locally or from around the world. In contrast, virtual traffic networks could be created. In either case, the networks could be large or small, homogeneous or heterogeneous, freeways only or freeways and arterials, and so on. In this section, the key aspects of the experimental process for this research are described and the logic presented.

An overview of the experimental process is illustrated in Figure 4.1. The figure serves as a guide to the discussions that follow. In brief, the experimental process comprises three basic steps. Step 1 generates the problem scenarios. These scenarios comprise three pieces: a network, an OD matrix, and an information revelation vector. Each of these sub-steps is shown in the figure. Step 2 applies the math program to estimate the path flows. Step 3 analyzes the method's results. Feedback loops pass intermediate results back to earlier steps so the results can be refined. This is especially true for Step 2. The result is an assessment of the methodology's ability to accurately estimate path flows through a network.

The remaining sections of this chapter fully describe the design.

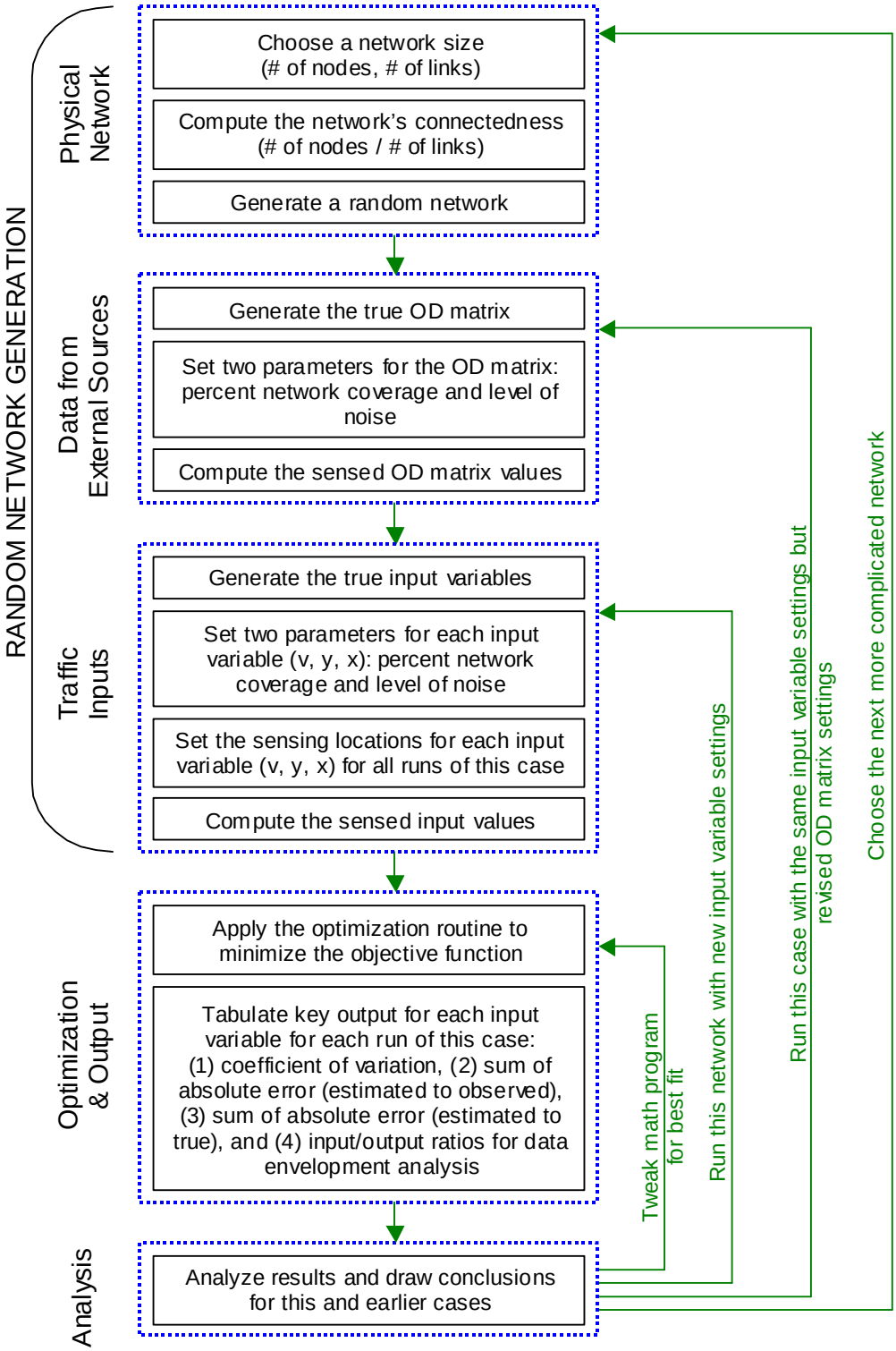


Figure 4.1 Experiment Design

4.1 Random Problem Generation

Step 1 generates a random problem scenario. A physical network is generated, an OD matrix is created, and link flows are developed.

4.1.1 Physical Network

Small, simple networks are examined that have a limited number of nodes and links; without loss of generality however, nothing in the formulation or code is restricting the use of larger networks. Each of these is described in quantitative terms. The graphical measures are listed in Table 4.1.

Table 4.1 Graph Theoretic Transport Network Descriptors

Descriptor	Formula	Definition
Measures of Completeness		
Circuit Rank	$m = e - v + c$	Minimum number of edges (m) to remove from a graph to create a cycle-free graph
Cyclomatic Number	$\mu = m - v + p$	Maximum number of independent cycles
Alpha Index	$\alpha = 2\mu / (v-1)(v-2)$	
Beta Index	$\beta = e / v$	$< 1 \Rightarrow$ trees, simple networks $= 1 \Rightarrow$ network has one cycle $> 1 \Rightarrow$ a complex network with many cycles
Gamma Index	$\gamma = 2e / v(v-1)$	Similar to β but normalized for the number of vertices. Ranges from 0 to 1 with 0 being for trees ($2/v \Rightarrow 0$ as $v \Rightarrow \infty$) and 1 being for fully connected networks.
Other Measures		
Circuity Index	$\Sigma d_{ij} / \Sigma a_{ij}$	Measure of accessibility = network distance / Euclidean distance
Chi Index of Concentration		Measure of a network's concentration (i.e. is all traffic on one road)

Source: Author's notes from Hani S. Mahmassani's Systems II course at UT-Austin, 10/13/94
Variables: a_{ij} = distance from i to j via a straight line, c = # of connected components, d_{ij} = distance from i to j via the network edges, e = # of edges (links), v = # of vertices (nodes), p = # of subgraphs.

Each network is defined by four inter-related characteristics:

- Size 1, N: Total number of nodes (intersections and/or roadway endpoints).
- Size 2, L: Total number of links connecting the various nodes (these may be one-way arcs or two-way links, but for now these are assumed to be two-way links).
- Beta Index, β: ratio of total links to total nodes (L/N). Generally, $\beta < 1$ signifies trees and simple networks, $\beta = 1$ signifies a network with a single cycle, and $\beta > 1$ denotes a multi-cycle, complex network. This ratio will range from a maximum of *(N-1)/2* for a fully-connected network (each node connected by a single link to each other node) to a minimum of *(N-1)/N* for a sparsely connected network (such as a linear or star graph). Although it is rare that a transportation network will match a single graph type, the beta index is a good indicator of the closest graph, how many cycles exist, and how the network may look.
- Gamma Index, γ: ratio that is a normalized version of the Beta Index. $\gamma = 2L / N(N-1)$. It simply ranges from 0 to 1 with 0 being for trees and 1 representing fully-connected networks. Because of the 0 to 1 range, it has excellent potential as a parameter for this study.[6]

To generate random physical networks, an extension of the methodology developed by Malandraki and Daskin (1992) and Melkote and Daskin (2001) is employed. (Malandraki

[6] Other graph theory measures and indices were explored, but were not found to adequately characterize the network succinctly.

and Daskin 1992; Melkote and Daskin 2001) [7] The program is based on a pseudocode called GENRAND2 and employs the following process:

1. Generate nodes
    - Choose the number of nodes, N
    - Generate coordinates (x, y) for each node based on a probability distribution
2. Generate links (with a bias towards shorter links)
    - Choose the number of links, L
    - Generate a spanning tree
    - Generate the remaining links
    - Calculate the length of each link
3. Set the capacity of the network
    - Generate capacities for the nodes
    - Generate capacities for the links

4.1.1.1 Philosophy of Generating the Networks

A Visual Basic routine inside Microsoft Excel (see Appendix B) was employed to generate the networks.

[7] The original GENRAND2 program was not used because Turbo Pascal is no longer a viable programming language and to-date this research has been conducted using VBA code.

Network Nodes. The number of nodes was fixed at 10 so that the networks could remain small and yet have between 9 and 45 links (or 18 to 90 one-way arcs).[8] Following Melkote and Daskin (2001), nodes are assigned x and y integer coordinates within a 100 ×100 unit square based on a probability distribution – Uniform(0,100) by sampling without replacement to ensure no two nodes share the same location.

Network Links. The number of links is also randomly selected from a uniform distribution. Generating how the links would connect the network is again drawn from Daskin's GENRAND2 work because it is necessary to have all nodes connected to the network by at least one link, then further links are allowed as long as certain criteria are met. Generating a spanning tree is simple. Note that a minimum spanning tree is not required as part of this study; the decision to not require such a tree was based on (a) keeping the code as elegant as possible, and (b) recognizing that few roads outside of urban grids are straight and therefore of minimum distance. This step required creativity. First, a spanning tree is created through the following steps:

---

[8] Two questions that might arise based on the process as described so far are addressed below.

Why not look at all combinations of the number of nodes and arcs? Surface network sizes are randomly sampled (with the number of nodes fixed at 10 and the number of links between a spanning tree to a maximum of 3 times the number of nodes, without loss of generality) to see if patterns could be discovered at this level of detail. Nuances may be found by exploring more (nodes, arcs) combinations in future research.

Why not look at a (nodes, arcs, topology) triplet instead of just a (nodes, arcs) pair? Because the geometry or topology of the network is not the focus here, rather the network size is the focus. And how that size affects the quality of the PUCs for a given mix of sensors at a particular penetration rate (percent of network coverage). Therefore, whether the network looks like (6,7)  or (6,7)  , is expected to be of less impact on the question of instrumentation affecting determination of path flows.

- Step 1. Select a node at random. Select another node to create the first link.
- Step 2. Search through the nodes to find one that has been touched before. Find another node that has not been touched and create the next link.
- Step 3. Stopping criteria: repeat step 2 until no more nodes are left untouched.

Second, additional links are added until one of two criteria is met, (1) the total number of links has been reached, or (2) no more links can be added without violating the *maximum number of links crossing over one another* condition (think tunnel, bridge, or overpass here, not intersection or interchange).

Network Paths. Network paths are created based on a k-shortest paths algorithm. The rationale for this rests in (a) the difficulty of enumerating all paths in large networks (Dial 1971), and (b) a recognition that drivers may not always choose the absolute shortest path (Jeihani 2005) but are unlikely to choose exceedingly long or circuitous paths for most travel needs. The decision was made to focus on the k-shortest paths between each node pair since this could be conducted once. Therefore, the five shortest paths between each OD pair are generated for each physical network. A multi-path implementation of Dijkstra's routine finds the k-shortest paths that do not exceed a circuity limit.[9] In other words for this study, if the shortest path between O and D is 7 units, and the other paths are 8, 12, 13, 15, and 23, then if the circuity limit is set to 2.0 (no more than twice the shortest path length), only the

[9] Therefore, for this study, two flow estimation rules are being imposed that add some inference, (a) maximum of k paths per OD pair, and (b) circuity limit on paths. Hence, if we revisit the inference versus observability graph, then the cases under consideration are slightly above the observability axis.

paths of 7, 8, 12, and 13 would be saved since 15 and 23 exceed $7 \times 2 = 14$ even though there is a fifth path that can be saved.

Cost of Traversing the Network. To be similar to real-world conditions, costs for arcs are assigned a fixed cost and also a variable cost based on the number of vehicles traversing the arc as well as the arc's length. For simplicity the following formulae are employed:

$$cst = cv(1 + \mu_1 dva + \mu_2 adist) \qquad \textbf{Equation 10}$$

$$dva = \max(0, va - \mu_3 cap) \qquad \textbf{Equation 11}$$

where

$cst =$ total user cost of traversing an arc
$cv =$ user cost
$dva =$ arc volume exceeding reserve capacity
$adist =$ length of arc
$va =$ volume on arc
$cap =$ capacity of arc
$\mu_i =$ scaling factor ($\mu_1 = \mu_2 = 0.01, \mu_3 = 0.70$)

4.1.2 Traffic on the Network.

A 10-step process develops the volumes for the network.[10] The process ensures that the OD flows created are consistent with four key inputs of each network (n_N, n_A, va_a, and y_{oda}).

[10] An infinite number of OD matrices, paths chosen, and arc volumes are possible for any given network. The only stipulation is that the arc volumes need to be consistent with the OD matrix and the path utilizations. An

1. manually develop initial arc volumes (va_a)
2. calculate the loaded arc costs (cst_a)
3. generate the k-shortest paths for each OD pair (see earlier text)
4. calculate path costs (c_p)
5. synthesize the path utilization coefficients (x_p) with a logit function
6. generate the path-arc incidence map
7. generate the OD-arc incidence map
8. calculate the link utilization coefficients (y_{oda})
9. generate an OD matrix (D_{od}) that is a best fit for (va_a, $y_{oda,}$ $d_{i,j}$)
10. accept as being truth all x_p's, y_{oda}'s, ve_a's, and $de_{i,j}$'s (creates $\tilde{D}_{od}$ vector).

In step 1, volumes are manually allocated to each arc in a network assuming that volumes should range from under-saturated to saturated levels (oversaturated conditions can be explored in future work).[11] With the arc volumes (va_a) from step 1, loaded arc costs (cst_a) are calculated in step 2 via a link cost function ($cst_a = cv_a\,[1 + 0.01(dv_a - adist_a)]$ with $dv_a = \max(0, va_a - 0.7cap_a)$) that has a base cost of cv_a and incrementally increasing costs based on arc length ($adist_a$) and for when the volume exceeds a percentage of an arc's capacity (here, 70 percent is assumed) whereupon it is assumed the level of service of the arc begins to degrade. Then in step 3, the k-shortest paths for each OD pair are generated using the arc

---

"optimal" way to generate such information is not of significant interest here. This 11-step process quickly bootstraps its way to a consistent set of OD flows, path utilizations, link utilizations, and arc volumes.

[11] The arc volumes are picked ensuring $va_a < cap_a$ so one would expect that no arc would violate its implicit capacity constraint.

costs information to derive select paths, avoiding costly path enumeration. In step 4, path costs (c_p) are calculated simply as the sum of the arc costs for each path. Path utilization coefficients (x_p) are next synthesized in step 5 by applying a multinomial logit function.[12] Two incidence mappings are then generated in steps 6 and 7, the path-arc incidence map and the OD-arc incidence map, respectively. Note that Steps 5, 6, and 7 obviate the need to run a traffic assignment optimization to yield link utilization coefficients. Instead, with the information amassed so far, the link utilization coefficients (y_{oda}) can be directly calculated in step 8. In step 9 an OD synthesis optimization is run to generate an OD matrix (D_{od}) that is a best fit for the input data. This final OD matrix for each network is what is called the "true" OD matrix (D_{od}) during the experiment.[13]

[12] PUC logit function applied: $x_p = \frac{e^{-\lambda c_p}}{\sum e^{-\lambda c_p}}$ with c_p = user cost to traverse a path and $\lambda = 0.01$. A multinomial logit model consistent with Dial (1971) so that the classic sense of Wardrop's first principle would be achieved for the path volumes. Implicitly, this asserts that the assignment is at equilibrium.

[13] Technically, the resulting x_p's, y_{oda}'s, ve_a's, and D_{od}'s are not consistent with the original va_a's and cst_a's. But this is irrelevant because it is always possible, without loss of generality, to revise the arc cost functions, since they are hypothetical anyhow, so that the ve_a's produce cst_a's that, in turn, produce x_p's that are consistent with the multinomial logit function results.

4.1.2.1 OD Synthesis Formulation

Notation:

n_A = total number of arcs

va_a = initial volume on arc a (input)

ve_a = final volume on arc a (output)

$d_{i,j}$ = target demand from i to j

$de_{i,j}$ = final demand from i to j

z = objective function value

$dedev$ = sum of squared errors for OD demands

$vadev$ = sum of squared errors for arc flows

n_N = total number of nodes

n_{ODA} = total number of OD-arc incidences

o_n = origin node associated with OD-arc incidence vector index n.

d_n = destination node associated with OD-arc incidence vector index n.

a_n = arc associated with OD-arc incidence vector index n.

y_n = arc utilization coefficient associated with OD-arc incidence vector index n.

OD Synthesis Model:

$$\min z = dedev + vadev \qquad \textbf{Equation 12}$$

$$dedev = \sum_{j=1}^{n_N}\sum_{i=1}^{n_N}(de_{ij} - d_{ij})^2 \qquad \textbf{Equation 13}$$

$$vadev = \sum_{a=1}^{n_A}(ve_a - va_a)^2 \qquad \textbf{Equation 14}$$

s.t.

$$ve_a = \sum_{n=1}^{n_{ODA}} y_n de(o_n, d_n) \qquad \forall\ arc_a \text{ when } a_n = a \qquad \textbf{Equation 15}$$

This model is a variant on (List, Konieczny et al. 2002) in which the only model inputs are the link volumes and the model is quadratic instead of piecewise linear. The above model takes three inputs – initial arc flows, LUCs, and a target OD matrix[14] – and yields two outputs – final "true" arc and OD flows. The model is constrained by the LUCs; the final arc flow across arc *a* must equal the sum of all final OD flows that traverse arc *a*. The objective function driving the model includes two components, both of which are sums of squares. The first component minimizes the squared difference between the final and target OD flows. The second one minimizes the same between the final and initial arc flows. The sum of squares strongly penalize larger deviations from the inputs; this has the effect that ve_a approaches va_a.

4.1.3 Instrumentation & Traffic Realizations

The *Traffic on the Network* section was a description of how consistent vehicle flows are generated for each network; these are considered the "truth", the actual flows on a network as if it were fully observable. From the true data, realizations are sought based on what is observed in a particular case, for example a case with 20 percent of the network's arcs instrumented with volume counters and a 2-year old OD matrix from the local planning agency is one such realization. Three traffic variables are sought, link volumes, link utilization coefficients, and path utilization coefficients. Three sensor bundles that cover a

[14] The target OD matrix is simply a matrix with all OD flows equal to zero.

wide-array of data collection possibilities and technology offerings are considered in this endeavor to measure such traffic information:

- Arc volume sensors that are at fixed locations
- AVI sensors with fixed tag readers
- AVL sensors which are fully mobile since drivers with an AVL system will be choosing their routes so the AVL sensors will be located according to their decisions.

For each sensor bundle, there are two parameters that can and are varied, (1) network coverage, and (2) information quality. Figure 4.2 has an illustration of instrumentation choice. The sensing locations for each input variable (v, x, y) are held constant during the time period being explored, like a snapshot of the system. Moreover, the sensing locations are to be held constant for the 25 realizations of the OD pattern for each physical network.

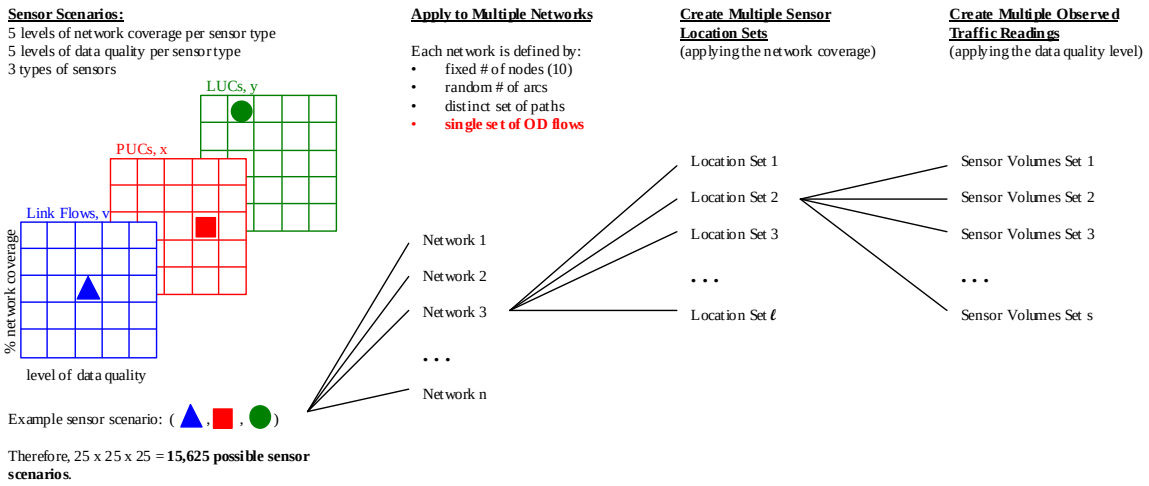


Figure 4.2 Possible Sensor Instrumentation Scenarios

Traffic data can be collected along any arc or link in the network on a regular basis or sporadically, based in part on the sensor type. Hence, a network's coverage may vary from time period to time period in terms of the number of sensors on the network and the clustering of said sensors. Focusing on a single time period, a range of network coverage from zero sensors on the network (0% coverage) to sensors on every link (100% coverage) are tested to determine the impact of percent coverage. Regarding clustering, it seems like a distance measure such as the average distance between sensors might be reasonable; this needs to be explored further, but is not addressed in this work.

In addition to network coverage, a very real issue is the measurement error of a sensor. And this primarily depends on the sensor type used. Therefore, a range of quality levels are associated with each sensor type for the fictional network's traffic inputs. Generation of a sensor scenario is shown in Figure 4.2

Similar to the traffic input parameters, the OD matrix realizations are based on applying two parameters to the true OD flows (percent network coverage and percent quality of data).

4.1.4 Example Realization

As an example, consider a network with 10 nodes and 20 one-way arcs (A through T). The network has 90 OD pairs and say it has 360 paths (or an average of 4 paths per OD pair, numbered 1 through 360). Next, we are told that 60 percent of the arcs have volume sensors, 10 percent have AVI sensors, and 20 percent of the paths have AVL probes on them. Further, with the instruments used, it is known that the sensor quality for the loops, tag

readers, and AVL devices are 75, 85, and 98 percent, respectively. And an OD matrix is obtained that is expected to have 90 percent of the network covered (there has been new construction since it was collected) and a 30 percent error rate (70 percent quality). Then for a 20-arc network with these conditions, the following vectors would be defined as in Table 4.2.

Table 4.2 Example Realization of a Network

Data Type	Variable(percent network coverage, percent quality)	Number of Locations	One Realization of Locations
Loops	$ve_a(60, 75)$ ∀ links a ∈ A	12 arcs	A, C, D, G, I, K, M, N, O, R, S, T
AVI	$y_{oda}(10, 85)$ ∀ links a ∈ A	2 arcs	G, P
AVL	$x_p(20, 98)$ ∀ paths p ∈ P	62 paths	2, 3, 5, 6, 8, 10, 11, 12, 34, 37, 52, 56, 57, 61, 69, 82, 83, 88, 93, 107, 111, 113, 115, 122, 126, 129, 130, 134, 154, 166, 170, 171, 192, 195, 202, 208, 210, 227, 232, 236, 241, 274, 278, 289, 295, 299, 301, 302, 303, 308, 312, 317, 320, 324, 325, 331, 333, 338, 343, 347, 357, 359
OD	$D_{od}(90, 70)$ ∀ OD pairs od ∈ D	81 OD pairs (324 paths)	

o / *d*	1	2	3	4	5	6	7	8	9	10
1	–	*x*	*x*	*o*	*x*	*x*	*x*	*x*	*x*	*x*
2	*x*	–	*x*	*x*	*x*	*x*	*x*	*x*	*o*	*x*
3	*x*	*x*	–	*o*	*x*	*x*	*x*	*x*	*x*	*x*
4	*o*	*x*	*x*	–	*x*	*x*	*o*	*x*	*x*	*x*
5	*x*	*x*	*x*	*x*	–	*o*	*x*	*x*	*x*	*x*
6	*x*	*x*	*x*	*x*	*x*	–	*o*	*x*	*x*	*x*
7	*x*	*x*	*x*	*x*	*x*	*x*	–	*x*	*x*	*x*
8	*x*	*x*	*x*	*x*	*x*	*x*	*x*	–	*x*	*x*
9	*x*	*x*	*o*	*x*	*x*	*x*	*x*	*x*	–	*x*
10	*x*	*x*	*x*	*x*	*o*	*x*	*x*	*x*	*x*	–

Based on the network description and the factor levels given for both coverage and quality, a realization is randomly generated as shown in the fourth column of the preceding table. Many other realizations are possible with these same settings.

4.2 Optimization & Output

As discussed in the methodology chapter, a math program has been developed for the optimization step (it is not repeated here for brevity). Ten instrumented, physical networks of 10 nodes and varying numbers of links are created along with the true traffic levels. Test cases of sensor realizations and 25 OD pattern realizations are then applied to each physical network. Then each randomly generated network is run through the optimization algorithm and the results compiled in that network's spreadsheet. Input and output information is then prepared for analysis.

4.3 Analysis

The main goal of this dissertation is to develop a method to determine the path flows and PUCs in a network based on the sensors available. So the preferred course of action to obtain the true path flows and PUCs is for all vehicles in a network to have perfect AVL devices collecting and transmitting such data all the time. However, at this time this is an irresolvable problem because path flows and PUCs cannot be seen with current instrumentation. Applying a mathematical program to the available known sensor data is therefore explored for its ability to estimate path flows in fictitious networks where true path flows can be given and the estimates compared to the truth.

Looking at this another way, one challenge in this problem is that, while the best objective function would involve comparing the estimated values with the true values, providing the true values in the math programming formulation makes the problem circular. For certain, in

such a formulation, the optimal solution would be found. It is also unrealistic since the likelihood that the true values would be known is very low except in an AVL situation with 100 percent penetration and high quality devices. Consequently, although the value of the objective function is a useful indication of the math program's ability to find the best answer, it is not performance measure of primary interest or the only one worthy of exploration. A combination of methods is therefore used to extract insight.

For instance, notice in Table 4.3 that there are two avenues of sensitivity research that could be explored. Shown horizontally, for a given set of traffic inputs (*v*, *x*, *y*) a variety of OD estimates varying quality and network coverage could be tested to see how sensitive the accuracy of path flow estimates are to different OD inputs; this could be quite useful for practitioners that acquire OD patterns of unknown quality from other analysts, giving them an idea of how much path flows may be affected by OD data. Similarly, for a given OD pattern (shown vertically), a host of traffic input combinations can be tested. This sensitivity analysis would benefit planners and researchers because those are the decision-makers that can guide a community in the best sensing strategy for reasonable path estimates.

Table 4.3 Sample Scenarios

Network 1

	OD Set 1	OD Set 2	…	OD Set n
(v,y,x) Set 1 (v,y,x) Set 2 … (v,y,x) Set m				

Further explorations are described fully in the next chapter along with their results.

5 NUMERICAL TESTS

In preparation for simulation and analysis, networks were fixed to a size of 10 nodes (100 OD pairs) such as those shown in Figure 5.1 and random numbers of arcs were generated for each network with a maximum number of arc overlaps (bridges, overpasses, and tunnels). Associated with each network was a true OD matrix from which 25 sensed OD matrices were created based on a factorial design with two factors (% coverage, % error) each with five levels so the sensitivity of the estimated PUCs to the available OD flows could be assessed. The percent of OD flows revealed (coverage) ranged from 20 percent to 100 percent (complete) while the percent error ranged from 0 percent (clean data) to 80 percent. Finally, the model's objective function was further simplified to lessen run time. Instead of normalizing every difference by dividing by the measured parameter, the weighting factors were adjusted until the terms ranged approximately between 0 and 1. Therefore, the resulting objective function and full math programming formulation (MP4) is:

$$\min \sum_a \gamma_v \left|\hat{v}_a - \tilde{v}_a\right| + \sum_{oda} \gamma_y \left|\hat{y}_{oda} - \tilde{y}_{oda}\right| + \sum_p \gamma_x \left|\hat{x}_p - \tilde{x}_p\right| \qquad \textbf{Equation 16}$$

$$\text{s.t.} \sum_{odp} \beta_{odpa} \hat{x}_p \tilde{D}_{od} = \hat{v}_a \quad \forall \text{ arcs a}$$

$$\sum_p \beta_{odpa} \hat{x}_p = \hat{y}_{oda} \quad \forall \text{ oda triplets}$$

$$\sum_p \alpha_{odp} \hat{x}_p = 1 \quad \forall \text{ OD pairs}$$

$$v_a, x_p, y_{oda}, D_{od} \geq 0 \quad x_p, y_{oda} \leq 1 \quad \text{(for true, measured, \& predicted)}$$

And in the (MP4) model, γ_v was set to 0.005 to approximately normalize the minimization's first term to between 0 and 1, and γ_y and γ_x were set to 1.0 since PUCs and LUCs already range from 0 to 1.

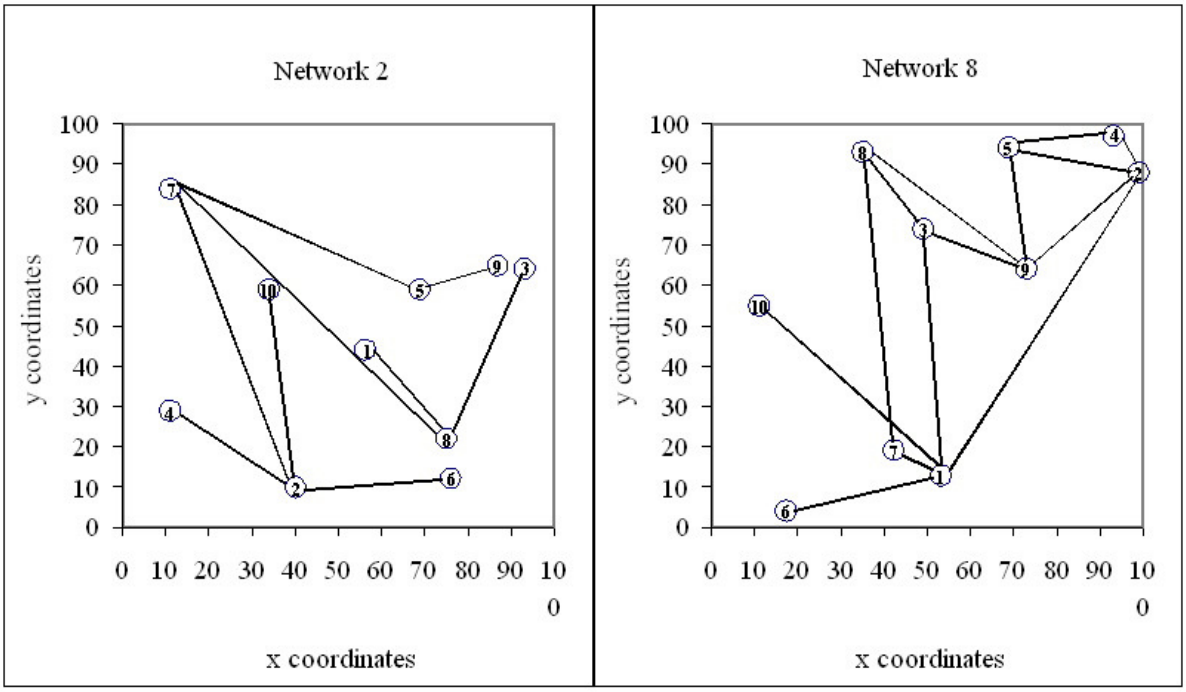


Figure 5.1 Sample Networks

5.1 Testing the Model Specification

Since the model specification is uncommon[15], it is necessary to verify that it performs as expected in known situations prior to relying on it as an exploratory tool. For example, if the

[15] Recall from the literature review, most models associated with traffic flows are defined to estimate OD flows and not path flows or PUCs. Here, OD flows are an input, not an output. Furthermore, such works typically incorporated OD flows and loop detector data as opposed to a broader range of sensors.

model is given complete and perfectly sensed data (Case 1 as shown in Figure 14 of Chapter 3 and listed in Table 5.1 below) with a complete and perfect OD matrix, then it is expected that the estimated parameters are perfect. In other words, the *v*, *x*, and *y* outputs should always match their input counterparts yielding an objective function value of zero and correlations between observed and estimated parameters of 1.0. Likewise, when AVL sensors are in the field and an OD matrix is available for use in the model, it is expected that perfect estimates are derived for path utilization coefficients (see Section 3.2.5.1). Four base cases as shown in Table 5.1 were tested; prior to testing, an expected outcome was assigned given the math program's structure and each sensor bundle's capabilities. Results of the tests are summarized in Table 5.2 and Figure 5.2; they show agreement with the earlier expectations.

Table 5.1 Expectations of Some Base Cases

INPUT	**OUTPUT**	
Case	**Expected**	**Actual**
1. D100Q100, V100Q100, X100Q100, Y100Q100	Perfect V's, X's, and Y's.	√
2. D100Q100, X100Q100	Perfect V's, X's, and Y's.	√
3. D100Q100, Y100Q100	Perfect V's, X's, and Y's.	√
4. D100Q100, V100Q100	Perfect V's only	√

Note: $M\#_1Q\#_2 = \#_1$ percent of variable M sensors exist in the network, each with $\#_2$ percent quality.

Table 5.2 Summary Statistics of the Base Cases

BEST OD FLOWS D51 (D100Q100)	OBJECTIVE FUNCTION VALUE			PEARSON CORRELATIONS (mean +/- 95% C.I.)		
Case	**Max**	**Min**	**Avg**	$\rho(x_p, \hat{x}_p)$	$\rho(v_a, \hat{v}_a)$	$\rho(y_{oda}, \hat{y}_{oda})$
1. VXY100Q100	0.004	0.001	0.003	0.994 +/- 0.001	0.97 +/- 0.007	0.997 +/- 0.000
2. X100Q100	0.000	0.000	0.000	0.994 +/- 0.001	0.97 +/- 0.007	0.997 +/- 0.000
3. Y100Q100	0.000	0.000	0.000	0.987 +/- 0.011	0.97 +/- 0.007	0.997 +/- 0.000
4. V100Q100	0.004	0.001	0.002	0.610 +/- 0.022	0.97 +/- 0.007	0.54 +/- 0.021

Notes: $M\#_1Q\#_2 = \#_1$ percent of variable M sensors exist in the network, each with $\#_2$ percent quality.
$\rho(a,b)$ = the pearson correlation between variables a and b; $-1 \leq \rho \leq +1$. Each case was run on a small sample of 10 independent networks.

In case 1, when the OD matrix is perfect and the observed PUCs are complete and error-free, notice the objective function is basically zero while the correlations of all parameters are at or near 1.0 (see Figure 5.2, top right). Hence, there is a strong match between the observed and estimated parameters output from the model when the data are complete and without error. Therefore, the model specification performs as expected under this condition. In cases 2 and 3, one type of sensor collected field data – either a sensor bundle that could measure PUCs or one measuring LUCs. In both cases, it was expected that the model specification would still enable finding the correct[16] solution. In the case of AVL data (PUCs), the correct solution is expected and trivial to obtain since at 100 percent coverage this sensor bundle is recording the space-time path of every vehicle in the network so three parameters (PUCs, LUCs, and arc volumes) are known (see Figure 5.3(b) which has plots of true versus

[16] Correctness being defined here as the estimated parameters equaling the true parameter values ($\rho = 1.0$).

estimated parameters for 3 sample cases). In the case of AVI data, LUCs are collected and the correct solution for each parameter is expected since a direct mapping of LUCs to PUCs is at the core of the model's second constraint. However, case 4 is an exception to the above cases. In case 4 only link volume sensors are implemented so the model specification does not adequately associate the link volumes to LUCs and PUCs since a variety of combinations could yield a working, albeit incorrect, solution. The model is underspecified. Therefore, in this case the expectation and actual output were congruent with only the link volumes correctly matched whereas approximately half of the LUCs and PUCs were correctly estimated. So overall, the model specification behaved as expected so it was next used for exploratory purposes.

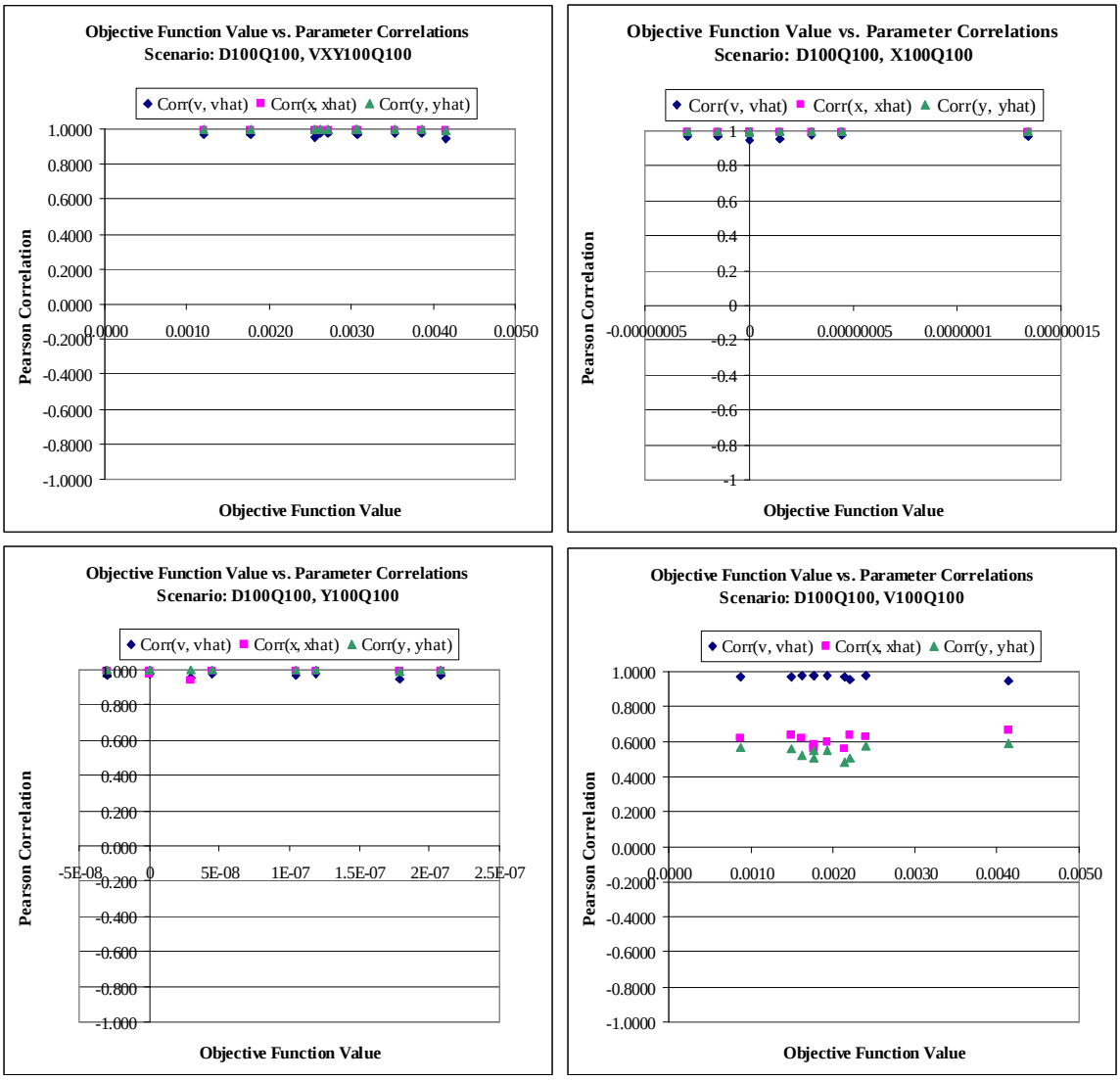
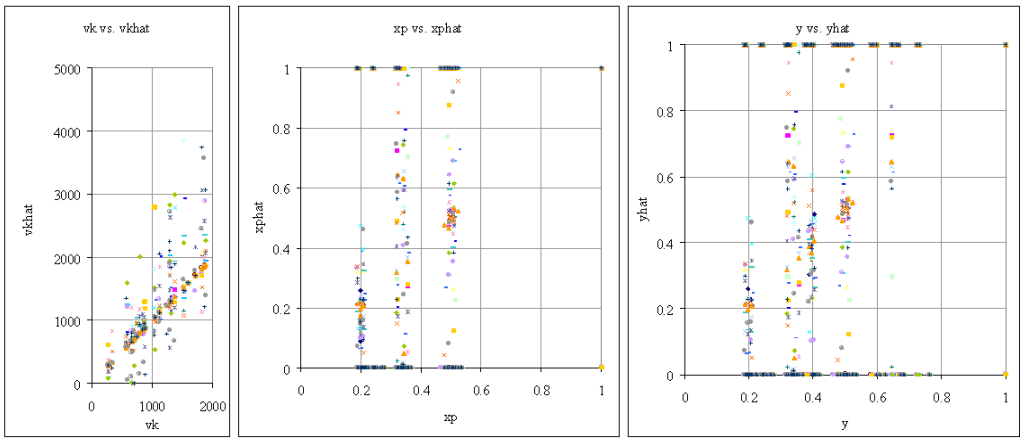
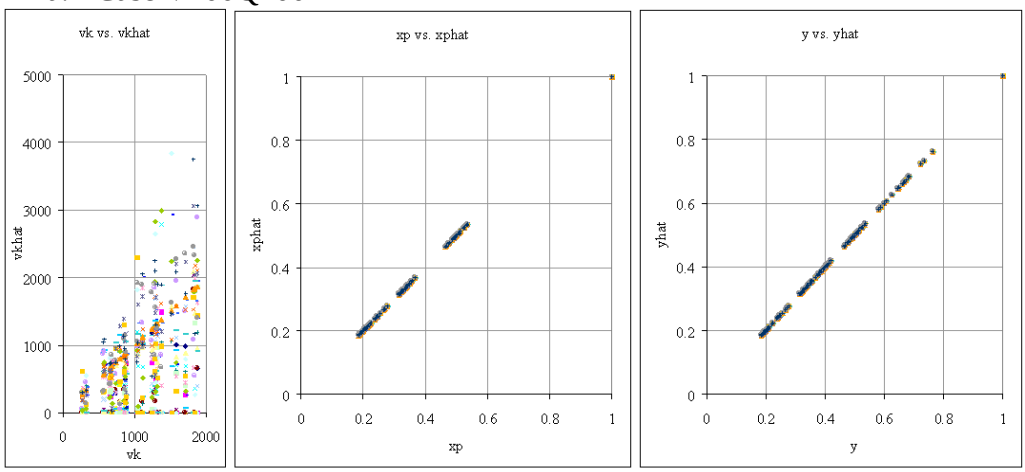


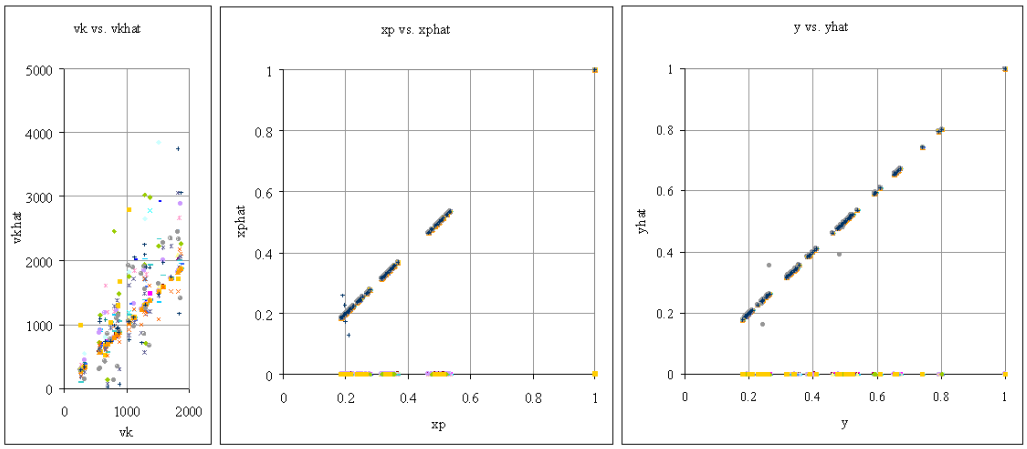
Figure 5.2 Objective Function Values versus Correlations for Base Cases



a. Case V100Q100



b. Case X100Q100



c. CaseVY100Q100

Figure 5.3 Sample Results for a Representative Network (Network 10 with 25 OD flow realizations)

5.2 Exploring the Results

To guide results analysis, three avenues of inquiry were pursued to explore the nature of the relationship between the physical network and how travel across it is sensed and then path utilization coefficients estimated. Along the first avenue, the impacts of sensor coverage, quality, and type are examined. Next, the effect of the available OD matrix's quality and coverage on parameter estimation is explored. Finally, the effect of physical network characteristics are determined.

At the start of this discussion, detailed graphs of results are presented to offer the reader a flavor of the overall analysis process. Following investigation of PUC sensor bundles, results are condensed into summary graphs.

5.2.1 Zero Sensor Case

Before searching for good solutions, the worst case scenario is assessed to highlight how awful parameter estimation with the model can be without additional data collection via sensors or by adding inference. This step yields bounds on the correlations for all other inquiries. Results are listed in Table 5.3 for when the model has complete and perfect OD flows (D100Q100) and when it has a small bit of poor quality OD flows (D20Q20).

Table 5.3 Summary Statistics for Zero Sensor Case

NO V,X,Y CASE (VXY0Q0)	**OBJECTIVE FUNCTION VALUE**			**PEARSON CORRELATIONS (mean +/- 95% C.I.)**		
Case	**Max**	**Min**	**Avg**	$\rho(x_p, \hat{x}_p)$	$\rho(v_a, \hat{v}_a)$	$\rho(y_{oda}, \hat{y}_{oda})$
D20Q20	0.000	0.000	0.000	0.195 +/- 0.053	0.165 +/- 0.118	0.143 +/- 0.050
D100Q100	0.000	0.000	0.000	0.564 +/- 0.027	0.523 +/- 0.090	0.485 +/- 0.027

Note: M#$_1$Q#$_2$ = #$_1$ percent of variable M sensors exist in the network, each with #$_2$ percent quality.

For analysis, the objective function value is not a good indicator of the model's ability to find the correct solution. Instead, it simply means a solution was found, but many others are possible since (a) this math program (MP4) is a linear program and (b) only OD flows were entered into the model. Reviewing the correlations (see Table 5.3 and the top left plot in Figure 5.6 and Figure 5.14), $\rho(v_a, \hat{v}_a)$ has the widest range no matter the condition of the OD flows, -0.219 to 0.558 for D20Q20 to an improved (more correlated) 0.223 to 0.776 for D100Q100. This means that arc volumes are more likely than not estimated poorly from only OD flows; solution correctness will vary considerably depending on the chosen network with these results being for the 10 independent, random networks studied. Both $\rho(x_p, \hat{x}_p)$ and $\rho(y_{oda}, \hat{y}_{oda})$ have narrower ranges than $\rho(v_a, \hat{v}_a)$. When the OD flows are bad, so are the $\hat{x}_p$ and $\hat{y}_{oda}$ vectors with the highest attained correlation of either parameter being less than 0.4 and the averages being 0.195 and 0.143, respectively. However, with a clean and complete OD matrix, the correlations for both improve to a lower bound of approximately 0.4 and an upper bound of approximately 0.6. This suggests that higher quality OD flows can be a good starting point for a practitioner, but poor OD flows will require implementing a sensing system that significantly raises the correlations. In sum, if you are in a zero sensor situation, then no field data is collected, but a cloudy picture is still possible with high quality OD data known for all or most of the region. With this knowledge in hand, the use of sensors in networks is next explored.

5.2.2 Effect of Sensor Coverage, Quality, and Type

Common sense dictates that more sensors are better than fewer, high quality sensors are an improvement over low quality ones, and sensor bundles that capture the most information (AVLs) are better than those collecting the least information (loop detectors). Although proving that these three beliefs are true is necessary, it is not sufficient from a quantitative perspective, nor wholly useful. Rather, discovering what number (or percentage) of sensors begins to yield acceptable parameter estimates is an example of a desired insight. In other words, do breakpoints (changes in slope) in plots of performance measures exist beyond which parameter estimates significantly mirror the true parameters? Finding such breakpoints enables a researcher to direct practitioners to instrument their networks to achieve a desired level of accuracy. So this inquiry is to determine the relations between sensor characteristics and model performance.

5.2.2.1 A Note on Sensor Notation

The next three subsections are focused on sensor quality and network coverage by sensors for data capture. Both measures require some clarification so the reader understands how they are used and how results are interpreted.

A macro-scale investigation is conducted with both quality and network coverage defined in terms of percentages for each sensor type.[17] In general, the percent network coverage

[17] Consider the following plausible situation a researcher or practioner may encounter. Entity A is a bandwidth and GPS data service provider. Entity B is a municipality hoping to quantify route usage within its boundaries to guide future infrastructure planning decisions. Entity A has the path flow information that Entity B desires, but it is proprietary data – so why should B give A all the data? And if only a sample of A's data is revealed to B, then how does B know how it was actually sampled unless B is in charge of the sampling process? For

indicates how much of the network, as properly instrumented by a given sensor type, is observable. Thus, for the three specific sensor types examined:

- V20 means 20 percent of the network's arcs are instrumented with point sensors collecting volume data.
- X30 indicates 30 percent of the network's path utilization coefficients are revealed (not the percent of vehicles). So there is at least one probe vehicle on each of the 30 percent of paths observed generating PUC data.
- Y40 suggests 40 percent of the arcs associated with OD flows are instrumented with AVI tag readers capturing LUC data.

To complete the sensing picture, a quality percentage is applied to account for noise that typically occurs in a real world system. Similar calculations are performed for all three sensor types. [18] Moreover, the percent quality indicates the following for each:

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example, A might want to be clever and not let B know where all the traveled paths are but only give B 30 percent of the traveled paths. So A does not fully reveal the behavior of its customers. Such a situation leaves B without full knowledge. Hence, although B hopes the X100Q100 case has been achieved, this should not be assumed; B may only have an X30Q100 case. Therefore, scenarios have been examined where only some paths are known – B might have good data, just low coverage or vice versa. At the low percent coverage end it is an interesting intellectual exercise.

[18] In the simulation, the measured volume counts are generated by applying a random normal distribution to each true volume count that is revealed. For instance, when V20Q85 is desired the following calculation is performed for a network: (1) 20 percent of all the arcs are randomly selected and their associated true volumes are tagged so they will be revealed (measured). (2) For each arc, the sensor quality is converted to a decimal (85% →0.85) and then multiplied by the true volume count (defined as the mean) to create the standard deviation. (3) The revealed arc flow is then generated from a random normal distribution using the mean and standard deviation as inputs.

- Q85 for a point sensor means that the point sensor is, on average, 85 percent accurate. So all of the point sensors have a 15 percent error rate.
- Q90 for an AVI or AVL sensor has two plausible interpretations. First, similar to point sensors the quality level is an indication of the measurement error associated with the devices used to collect the data. Second and more interesting, the quality rate suggests the penetration level of vehicles instrumented with the necessary AVI or AVL technology on the associated network segment – links associated with OD flows or paths, respectively. In other words, the quality value indicates the clarity of observing the true LUCs or PUCs which is directly related to the penetration rates; so clarity is poor when penetration rates are low.[19]

5.2.2.2 Path Utilization Coefficient Sensors

Consider the situation of a wide-open rural area with no traffic lights but a host of tech-savvy resident-drivers – this is the world of a small network instrumented by only AVL devices. To determine path flows in such a network, OD and PUC data are the available inputs for the model. Now, the percent coverage may vary depending on how many residents have their AVL system on and how many unequipped non-residents are traversing the network. Several potential levels of PUC coverage ranging from zero to 100 percent are plotted against the objective function value in Figure 5.4 (top) and the objective function plus $\rho(x_p, \hat{x}_p)$ in Figure 5.6. In both figures, (1) sensor quality is held at 100 percent and (2) OD flows are held constant at 100 percent for both coverage and quality; results are also listed in Table 5.5.

[19] This method of defining the sensor types in a network enables the researcher to treat the problem simply as a math exercise of revealing variables and observing the effect it has on estimating the true variables.

Gleaning from the former figure that a solution satisfying all constraints was found for each case tested (since all values are defined and essentially zero), it is the latter figure that provides insight. Focus on the y-axis of the Figure 5.6 plots, which measures degree of correlation between the estimated and true parameter values. Not until PUC sensor coverage achieves 60 percent (bottom left plot) do the majority of networks obtain a large positive shift in correlation values for all three parameters (v, x, and y); prior to this percent PUC coverage, $\rho(x_p, \hat{x}_p)$ and $\rho(y_{oda}, \hat{y}_{oda})$ hovered about 0.6 while $\rho(v_a, \hat{v}_a)$ typically was between 0.2 and 0.9. So, a high percentage of paths in the network must be measured (PUCs sensed) if PUCs, LUCs, and arc flows are to be estimated with reasonable accuracy (say, $\rho \geq 0.8$) so about 80 percent of the estimates match their associated true values.

But what about the quality of the sensors? What if not all residents could afford a top-notch AVL device? For this analysis, the percent PUC coverage is held constant at 100 percent while the PUC quality is ranged from 100 percent (a zero error rate) down to 5 percent (a 95 percent error rate); OD flow coverage and quality is maintained at 100 percent. Here, Figure 5.4 (bottom) and Figure 5.7 are the focus; results are also listed in Table 5.5. Right from the start, these graphs look different from those for PUC coverage. First, from inspection, the tabular correlation data with PUC quality varied (X100Q?) are much higher than those for PUC coverage varied (X?Q100). Second, a distinctly different objective function plot is revealed by the PUC quality cases; instead of values centered tightly on zero as before, they are found to peak at approximately 45 when PUC quality is 10 percent and drop slowly to zero as the quality improves to 100 percent. As expected, as PUC quality is decreased, both

the objective function values and correlations worsen as shown in Figure 5.7. Although, the correlations generally remain above 0.6 even when the PUC quality is at 5 percent. This is in contrast to the correlations not exceeding 0.6 until 60 percent PUC coverage is obtained as shown in Figure 5.6.

Recognizing that PUC sensor quality is less important that PUC coverage for estimating x_p, is one step of insight. Another step is determining where the breakpoints are and whether they remain constant as model inputs or network characteristics are changed. Based on the results plotted in Figure 5.5, and using $\rho \geq 0.8$ as a respectable goal, clear breakpoints are visible. A single PUC coverage breakpoint exists at X20Q100 beyond which the 0.8 barrier is exceeded (at about X40Q100). Whereas two breakpoints are perceptible for PUC quality, one at 5 percent (at X100Q5 $\rho(x_p, \hat{x}_p)$ achieves 0.8) and one at 20 percent ($\rho(x_p, \hat{x}_p)$ surpasses 0.8 for most networks). Thus as expected, the picture degrades when either the quality of PUC sensors or the percent of PUC sensors in the field is decreased, with the model being more sensitive to the latter.

To verify the above assertion that observability is of greater import than PUC sensor quality, statistical tests such as analysis of variance (ANOVA) can be conducted. As an example, a two-way ANOVA is conducted to test whether PUC estimates are more effected by PUC sensor quality or network coverage.

Ten observations of each treatment (coverage, quality combination) are examined in this two-way ANOVA. Each factor has three levels.

Factor Q = PUC sensor quality, 3 levels (20%, 60%, 100%)

Factor C = PUC sensor coverage, 3 levels (20%, 60%, 100%)

Response variable = $\rho(x_p, \hat{x}_p)$

Hypotheses to test:

Ho_{QC}: $\gamma_{ij} = 0$ for all i, j	versus	Ha_{QC}: at least one $\gamma_{ij} \neq 0$
Ho_{Q}: $\alpha_1 = \alpha_2 = \alpha_3 = 0$	versus	Ha_{Q}: at least one $\alpha_i \neq 0$
Ho_{C}: $\beta_1 = \beta_2 = \beta_3 = 0$	versus	Ha_{C}: at least one $\beta_j \neq 0$

With:

Ho = null hypothesis

Ha = alternative hypothesis

γ_{ij} = interaction parameter

α_i = main effects for factor Q (PUC sensor quality)

β_j = main effects for factor C (PUC sensor coverage)

Table 5.4 Two-way ANOVA Table of $\rho(x_p, \hat{x}_p)$ for the X?Q?, D100Q100 Set of Cases

Source of Variation	SS	df	MS	F	P-value	F crit
Differences between PUC Quality	0.132169	2	0.066085	65.56125	1.17E-17	3.109307
Differences between PUC Coverage	1.123132	2	0.561566	557.1176	4.54E-48	3.109307
Interaction	0.047157	4	0.011789	11.69593	1.52E-07	2.484441
Within	0.081647	81	0.001008			
Total	1.384106	89				

Notes: SS = Sum of Squares, df = degrees of freedom, MS = Mean Square = SS/df, F = F-distribution statistic, F crit = critical F-statistic below which the null hypothesis cannot be rejected.

Based on the ANOVA results, all three null hypotheses are rejected at the 0.05 level or smaller levels. In other words, interaction effects do exist and are significant, and both PUC quality and PUC coverage effect PUC estimates – more being better in both cases. It can also be concluded that the differences between coverage levels are more important than the differences between quality levels since the mean square for PUC coverage is much greater than that for PUC sensor quality. This finding reinforces the earlier observation based only on the graphs in Figure 5.5 and Figure 5.6 that PUC coverage is more important than PUC quality for obtaining correct PUC estimates. Therefore, it is evident that level of observability more strongly effects PUC estimates than does sensor quality. In sum, AVLs are quite useful for estimating path flows in a network, so there is every reason to push this technology forward recognizing that agencies can gain a decent picture of the path flows by encouraging the sensing of a high percentage of the paths with less regard for PUC sensor quality.

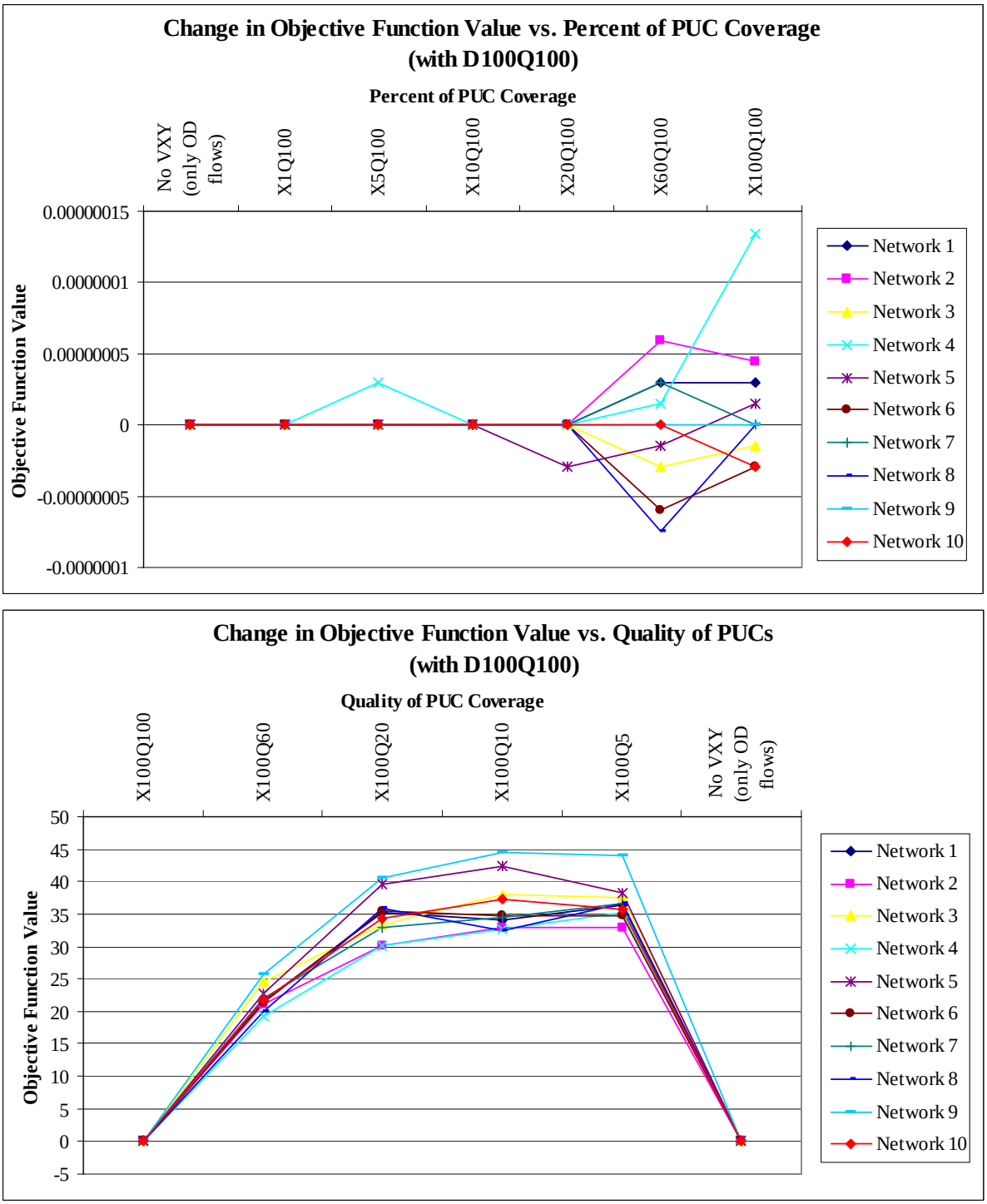


Figure 5.4 Objective Function Values for the X?Q100 (top) and X100Q? (bottom) Cases (both with D100Q100)

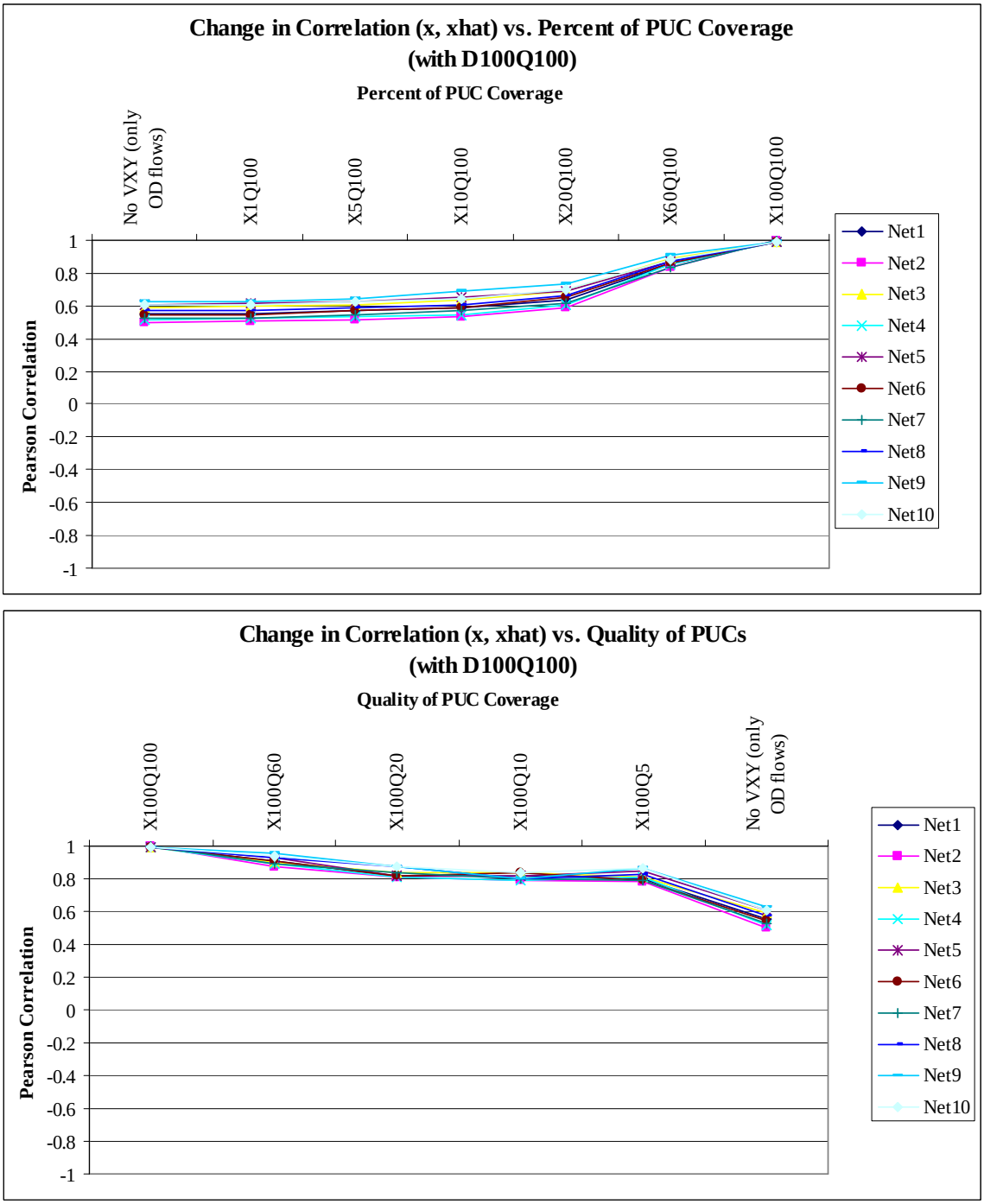


Figure 5.5 Pearson Correlation Values for the X?Q100 (top) and X100Q? (bottom) Cases (both with D100Q100)

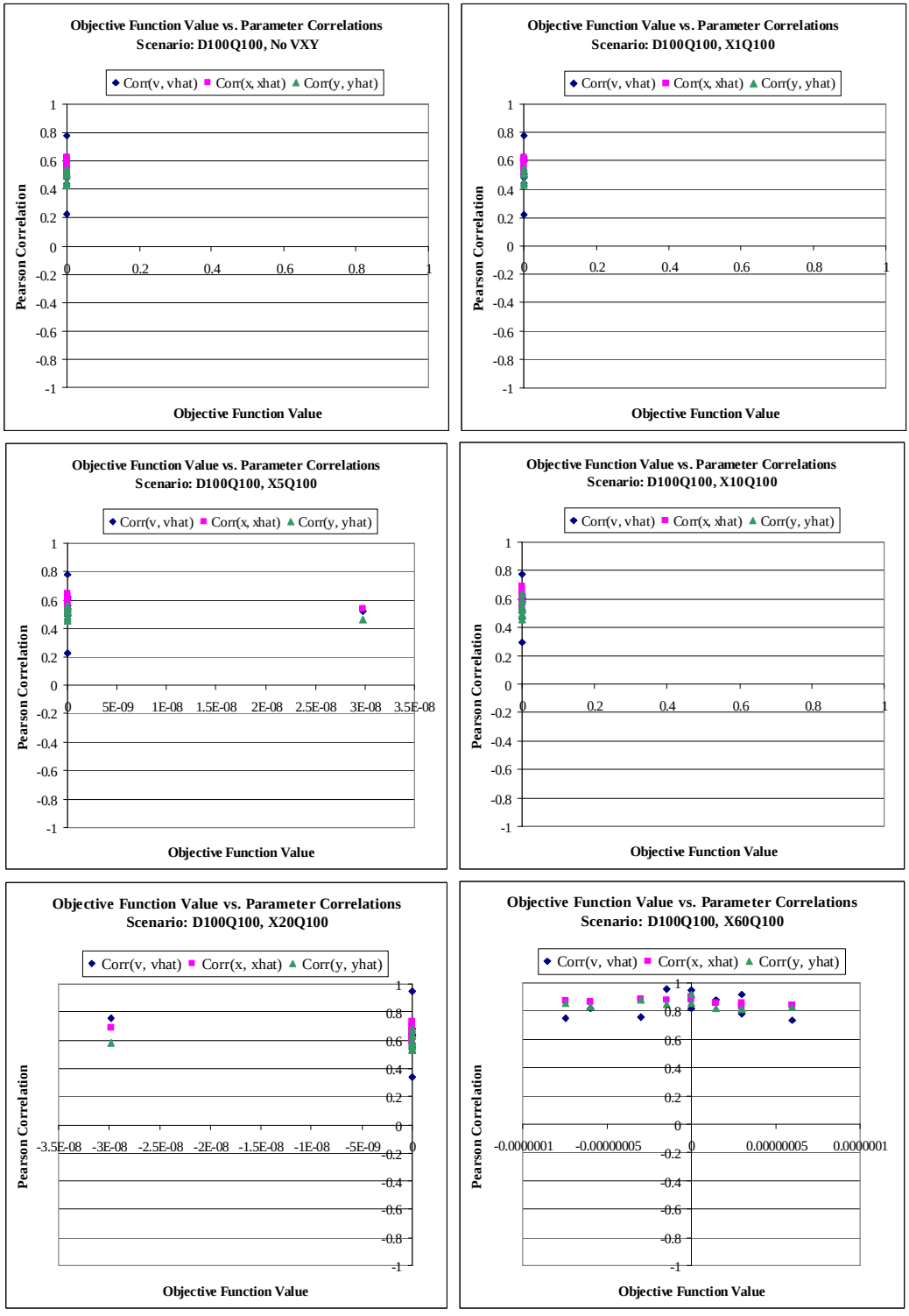


Figure 5.6 Relationships between Objective Function and Correlations as Path Coverage Increases (D100Q100 for all cases)

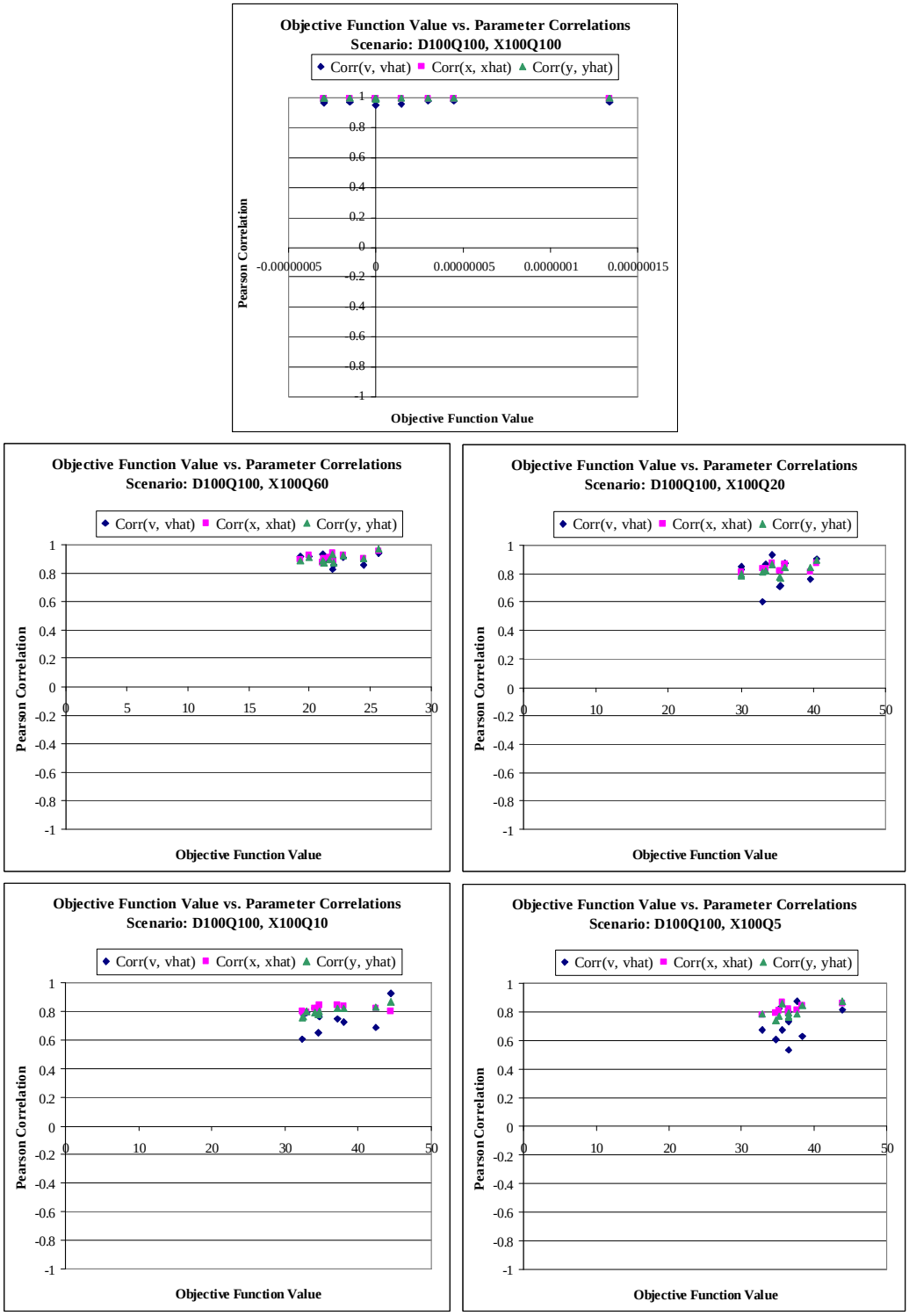


Figure 5.7 Relationships between Objective Function and Correlations as PUC Quality Decreases (D100Q100 for all cases)

Table 5.5 Results Summary with D100Q100

Case	Objective Function for all Networks	Pearson Correlations (mean +/- 95% C.I.) $\rho(x_p, \hat{x}_p)$	$\rho(v_a, \hat{v}_a)$	$\rho(y_{oda}, \hat{y}_{oda})$
No VXY (only OD flows)	0.000 +/- 0.000	0.564 +/- 0.027	0.523 +/- 0.090	0.485 +/- 0.027
X1Q100	0.000 +/- 0.000	0.567 +/- 0.027	0.525 +/- 0.090	0.489 +/- 0.026
X5Q100	0.000 +/- 0.000	0.583 +/- 0.026	0.550 +/- 0.087	0.510 +/- 0.025
X10Q100	0.000 +/- 0.000	0.606 +/- 0.030	0.566 +/- 0.077	0.539 +/- 0.033
X20Q100	0.000 +/- 0.000	0.657 +/- 0.028	0.628 +/- 0.098	0.593 +/- 0.030
X60Q100	0.000 +/- 0.000	0.867 +/- 0.014	0.836 +/- 0.052	0.846 +/- 0.019
X100Q100 (Full AVL data)	0.000 +/- 0.000	0.994 +/- 0.001	0.970 +/- 0.007	0.997 +/- 0.000
X100Q60	22.015 +/- 1.205	0.912 +/- 0.015	0.893 +/- 0.023	0.906 +/- 0.018
X100Q20	34.786 +/- 2.131	0.836 +/- 0.016	0.804 +/- 0.064	0.821 +/- 0.026
X100Q10	0.000 +/- 2.596	0.000 +/- 0.012	0.000 +/- 0.056	0.000 +/- 0.020
X100Q5	0.000 +/- 1.826	0.000 +/- 0.018	0.000 +/- 0.069	0.000 +/- 0.027
V20Q100	0.000 +/- 0.000	0.581 +/- 0.026	0.161 +/- 0.095	0.511 +/- 0.028
V60Q100	0.000 +/- 0.000	0.605 +/- 0.023	0.488 +/- 0.075	0.535 +/- 0.021
V100Q100 (Full loop data)	0.002 +/- 0.001	0.610 +/- 0.022	0.970 +/- 0.007	0.540 +/- 0.021
V100Q60	3.412 +/- 0.708	0.599 +/- 0.024	0.893 +/- 0.028	0.529 +/- 0.023
V100Q20	5.334 +/- 0.849	0.595 +/- 0.024	0.784 +/- 0.053	0.530 +/- 0.025
Y20Q100	0.000 +/- 0.000	0.734 +/- 0.030	0.709 +/- 0.091	0.222 +/- 0.058
Y60Q100	0.000 +/- 0.000	0.957 +/- 0.015	0.932 +/- 0.026	0.490 +/- 0.056
Y100Q100 (Full AVI data)	0.000 +/- 0.000	0.987 +/- 0.011	0.970 +/- 0.007	0.997 +/- 0.000
Y100Q60	51.653 +/- 7.288	0.938 +/- 0.010	0.897 +/- 0.018	0.942 +/- 0.005
Y100Q20	80.72 +/- 10.821	0.889 +/- 0.013	0.870 +/- 0.024	0.877 +/- 0.016
V100Q100, X20Q100	0.002 +/- 0.001	0.691 +/- 0.020	0.970 +/- 0.007	0.627 +/- 0.020
V100Q100, X60Q100	0.003 +/- 0.001	0.889 +/- 0.009	0.970 +/- 0.007	0.866 +/- 0.014
V100Q100, X100Q100	0.003 +/- 0.001	0.994 +/- 0.001	0.970 +/- 0.007	0.997 +/- 0.000
V100Q100, X100Q60	23.174 +/- 1.067	0.919 +/- 0.009	0.964 +/- 0.005	0.910 +/- 0.008
V100Q100, X100Q20	36.582 +/- 1.733	0.855 +/- 0.017	0.953 +/- 0.01	0.839 +/- 0.020
V100Q100, Y20Q100	0.002 +/- 0.001	0.785 +/- 0.025	0.970 +/- 0.007	0.201 +/- 0.050
V100Q100, Y60Q100	0.003 +/- 0.001	0.965 +/- 0.009	0.970 +/- 0.007	0.487 +/- 0.079
V100Q100, Y100Q100	0.003 +/- 0.001	0.987 +/- 0.011	0.970 +/- 0.007	0.997 +/- 0.000
V100Q100, Y100Q60	52.464 +/- 6.172	0.950 +/- 0.010	0.963 +/- 0.007	0.948 +/- 0.010
V100Q100, Y100Q20	0.002 +/- 0.000	0.779 +/- 0.027	0.970 +/- 0.007	0.200 +/- 0.052
VXY100Q100	0.003 +/- 0.001	0.994 +/- 0.001	0.97 +/- 0.007	0.997 +/- 0.000

Notes:

1. The above cases were run for ten 10-node networks with 1 OD flow realization each for a total of 10 runs per case. In the model, $\gamma_1 = 0.005$ to approximately normalize the minimization's first term to between 0 and 1, and $\gamma_2 = \gamma_3 = 1.0$.
2. M#$_1$Q#$_2$ = #$_1$ percent of variable M sensors exist in the network, each with #$_2$ percent quality.

5.2.2.3 Arc Flow Sensors

Acknowledging that few regions have AVLs and the technology is just becoming available (Demers, List et al. 2006; Furchgott 2007), the point sensor cases are explored next (V?Q?). For example, think of an urban arterial network with a host of traffic signals – some fully-actuated and some semi-actuated – thereby requiring point detection (loops) to trigger phase changes. Here, point sensors are predominant and AVLs are not, especially if there is a high density of tall buildings in the vicinity creating an urban canyon where GPS signals are unreliable. In such cases, we must infer the PUCs to estimate the arc flows. With only arc flows and OD flows observed, a murky path flow picture develops. Because an arc may be used by multiple paths and paths are associated with a collection of OD pairs, it is challenging to distinguish what percent of arc flows are associated with each path. Recall from Section 3.2.5.1 that this condition simplifies to (MP3) which is drastically underspecified. This challenge is evident in the weak correlation between x_p and $\hat{x}_p$ which, unlike the AVL cases, fails to increase beyond 0.669 even when there are 100 percent of clean arc flow data observed (see V100Q100 case in Figure 5.3a and Table 5.5). Therefore, it is clear that predicting PUCs from this model based exclusively on available arc and OD flows is likely to yield inaccurate PUC estimates. Hence, today's current infrastructure of loop detectors (arc flow or point sensors) is inadequate for PUC estimates and should not be solely relied upon, but may be useful in combination with AVL or AVI sensors or with additional inference.

5.2.2.4 AVI Sensors

Consider the vast network of North Carolina highways with less than 100 weigh-in-motion (WIM) stations to track truck freight flows (Ramachandran 2007). This is a network instrumented with AVI sensors since each WIM station records vehicle identification information along with the weight of the vehicle and various other pieces of information (often including the origin, destination, and commodity hauled). Such a system would have an extremely low percentage of LUC coverage. But now consider a tolled roadway such as Interstate 90 in the Northeast U.S. which would have a high percentage of LUC sensors because every exit includes AVI sensors reading EZ-Pass and FastLane tags. So networks with a high percentage of LUC sensors do exist.

Nowadays, there are places, such as freeways, where toll transponders (AVI technology) are more prevalent than point sensors. So, again we can examine the impact of a particular technology on our ability to predict PUCs. AVIs offer two pieces of information, both LUCs and a second OD matrix (for example, in the freeway case, each toll facility is a network node). Considering the former in the MP in addition to available OD flows, cases 8 through 10 offer insight into the power of AVI devices in this endeavor. Unlike the other sensor bundles considered, AVI devices are shown to be significantly impacted by their quality for estimating PUCs (e.g. case 9 versus 10), but the opposite is true for estimating LUCs and arc flows with AVI data. Thus, if one solely desires estimated PUCs, then high-quality tag readers are necessary (case 8) for reasonable accuracy. But, if one wants an accurate full network picture (PUCs, LUCs, arc flows), it is unattainable with only LUC sensors and OD

flows; this motivates the need for the inclusion of other sensor types in the data collection effort.

5.2.2.5 Comparing Parameter Estimation Across Sensor Types

With technologies in transportation engineering evolving swiftly, networks with a variety of sensor bundles will be found. Therefore, it is helpful to compare the performance of different groups of sensors (e.g. *x* only, *v* only, *v* and *y*, *v* and *x*, …). To enable such comparisons, a series of plots were created (Figure 5.8 through Figure 5.11 and summarized in Table 5.5) that show the cases tested on the x-axis and the performance measure (objective function and/or correlations) on the y-axis. Plotted in each graph for each case is a vertical line showing the minimum, average, and maximum value of the performance measure. In each figure, there are two summary plots per statistic: D51 is the best OD flow case (100% coverage, 0% error rate or D100Q100); D15 is the worst OD flow case (20% coverage, 80% error rate or D20Q20).

Concentrating on the top plot in each figure which is the D51 (shorthand for D100Q100) scenario, the correlation results are good, and as expected. The curves do not seem to have sharp breakpoints but rather trends. Generally, more quality yields higher correlations and vice versa. Based on the correlations, coverage proves more important than quality to yield better estimates of the truth for *x*, *v*, and *y*.

So far, the sensor discussion has been centered about estimating PUC estimates, so this inquiry begins there. Specifically, with regard to Figure 5.9, estimating the PUCs well is difficult when only arc flows are observed, as evident from a maximum $\rho(x_p, \hat{x}_p)$ = 0.669 for perfect OD flows. So arc flows should not be relied upon for a clear picture of the PUCs in a network. Better PUC estimates can be obtained by relying on PUC or LUC observations. Combining two data types, such as arc flows and PUCs, further improves the correlation between actual and estimated PUCs.

What to convey:

- A broad range of DX sensing options are available to yield good estimates of *x* and *y*, with less ability to estimate *v*'s. V's are only strong for the X100Q100 and X100Q60 cases.
- If relying on DV sensing options, good *x* and *y* estimates will never be obtained (highest correlation is 0.669), but good *v* estimates are possible with high coverage and medium to high quality arc flow sensors. Notice that the *x* and *y* correlations are basically the same between DV sensing options while there is a large change in the *v* correlations; therefore, if only *x* estimates are being searched for, then a lower level of arc flow sensor coverage is acceptable.
- DY cases offered the same range of sensing options for good *x* estimates as the DX cases, but a broader range of good estimates of arc flows. Therefore, DY seems to be the superior sensor type of the three to use alone if all three parameter estimates are required.

- The broadest range of sensing options occurs when DVX cases are offered, especially if all parameter estimates are desired. However, if only *x* or *y* is desired, then these combinations do not offer much gain for the expense incurred to instrument the network with multiple sensor types.
- The DVY cases yield a definite improvement over the DV cases, but there is a decrease in the number of quality estimates seen here, especially for estimating *y*.

Finally, if estimating arc flows is the goal (see Figure 5.11), then LUC sensors are the best to install throughout a network since all tested cases except Y20Q100 yielded $\rho(v_a, \hat{v}_a) > 0.8$ even for the minimum value. If either PUC or arc flow sensors are solely used, then performance is more varied and less likely to yield $\rho(v_a, \hat{v}_a) > 0.8$. Combining a dense network of arc flow sensors (V100Q100) with either PUC or LUC sensors maintains highly correlated arc flow estimates.

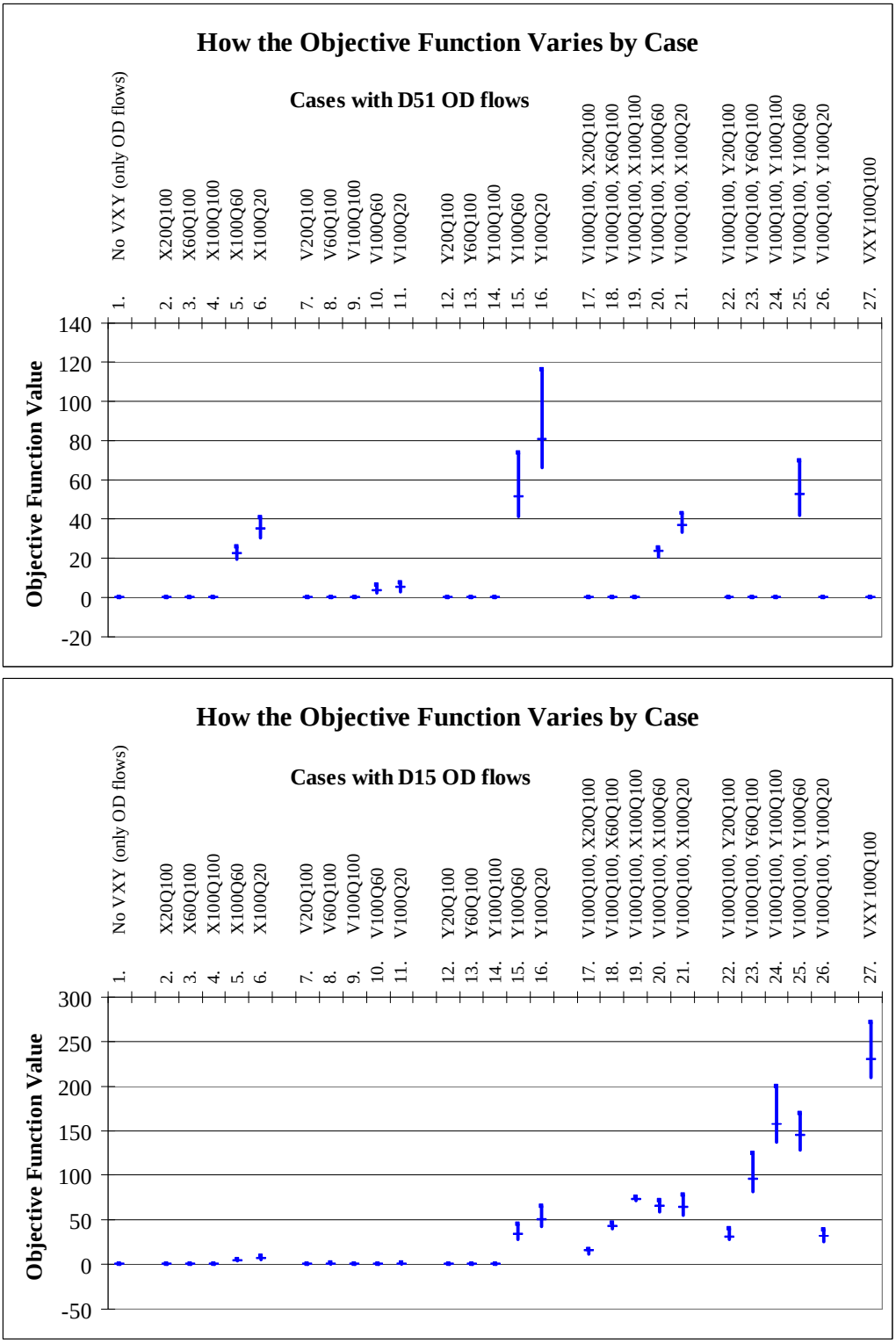


Figure 5.8 Objective Function Value versus Cases

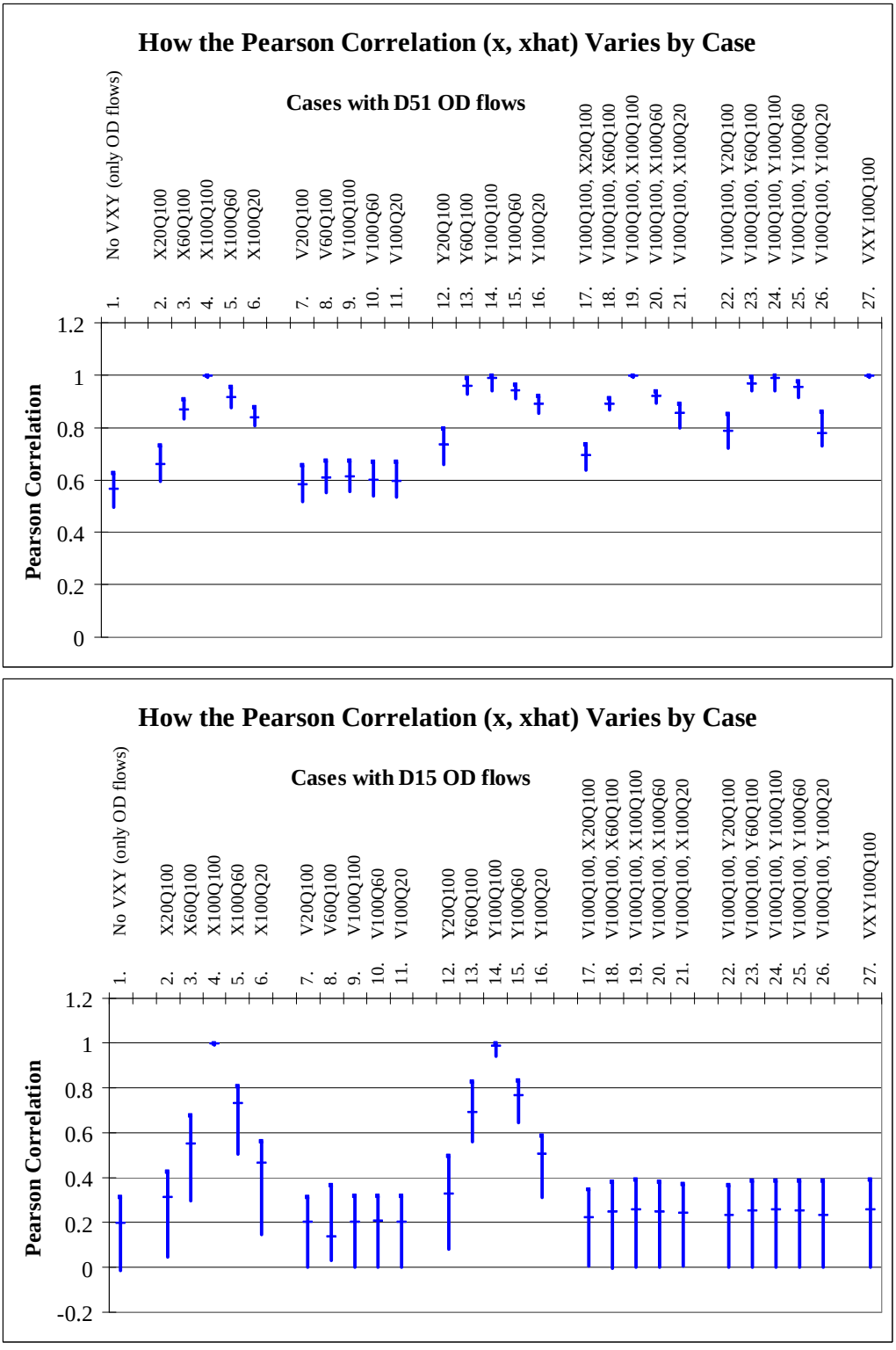


Figure 5.9 Correlation (x, xhat) versus Cases

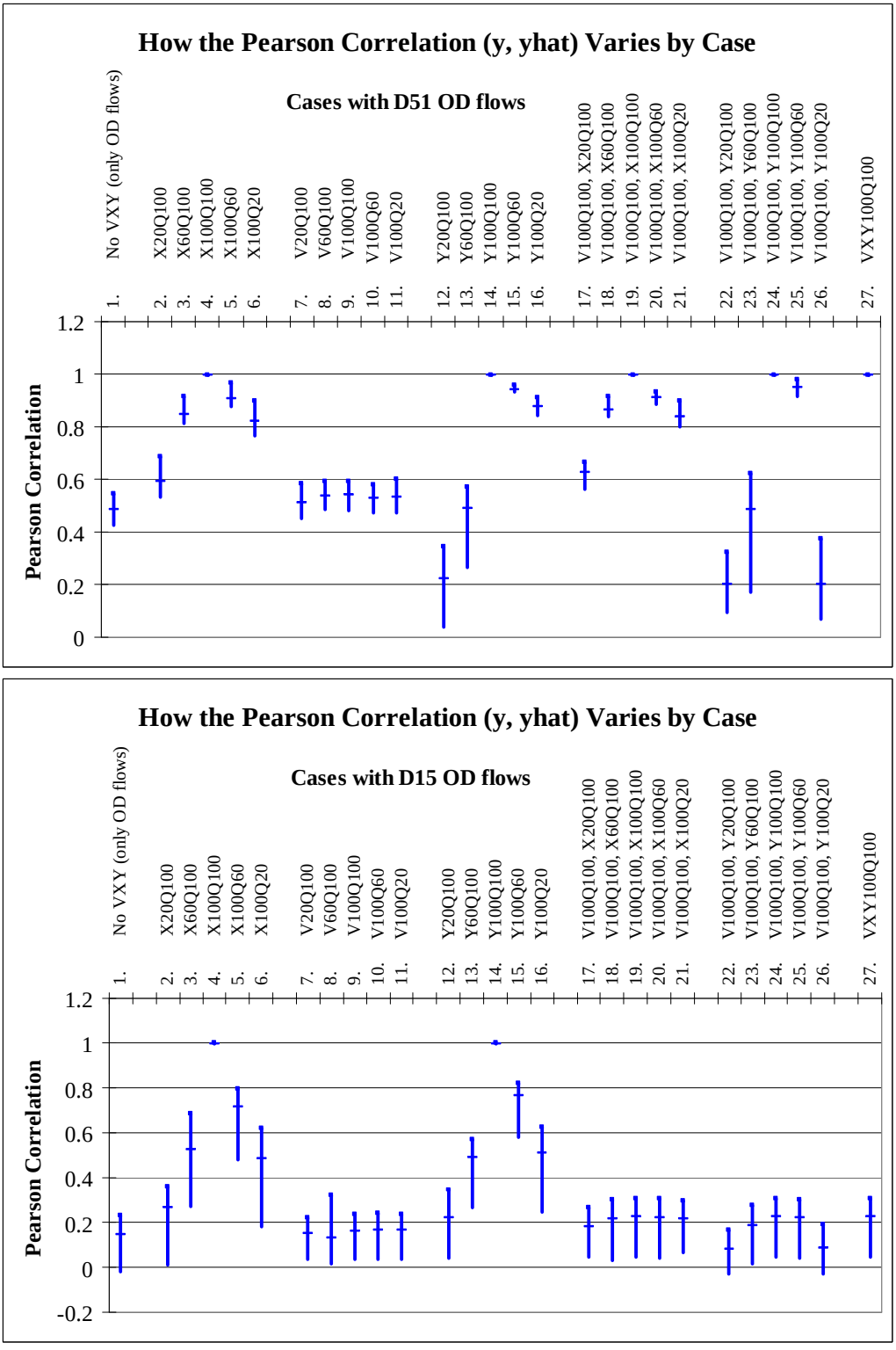


Figure 5.10 Correlation (y, yhat) versus Cases

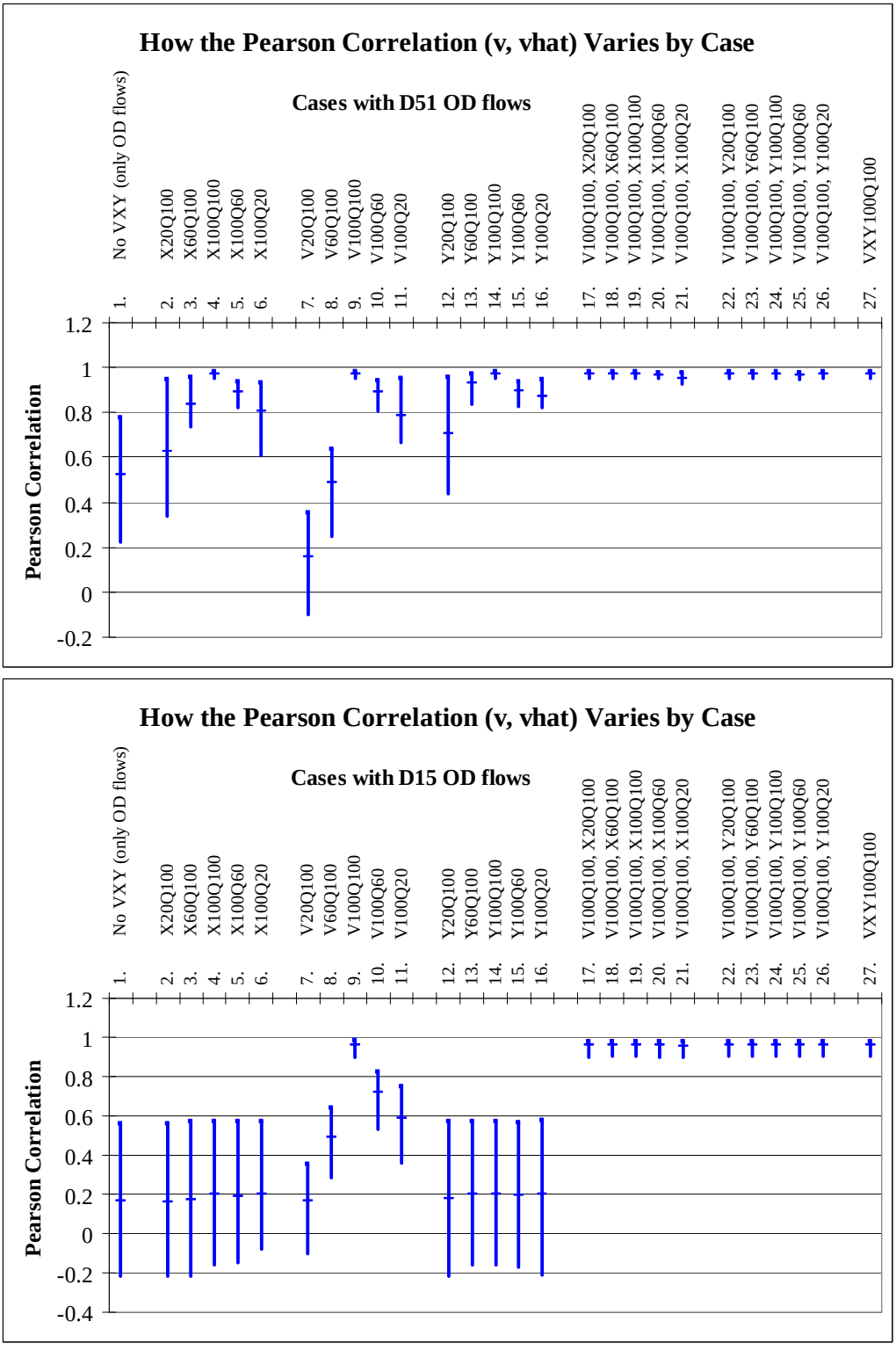


Figure 5.11 Correlation (v, vhat) versus Cases

5.2.3 Impact of the Origin-Destination Matrix

In the previous sections of this chapter, the OD matrix was held constant at 100 percent coverage and quality so sensor type distinctions could be made with respect to parameter estimation. However, complete and perfect OD matrices are only available in carefully controlled experiments or via simulation. The question, then, naturally arises as to how much an OD matrix that is incomplete and/or imperfect effects parameter estimation. To address this question, two lines of inquiry are made. First, parameter estimation is compared when the two extremes of possible OD matrices are available, complete, perfect data (D100Q100) and sparse, poor data (D20Q20). It is mentioned in general and then discussed with respect to the X?Q? cases. Second, the complete block design of OD coverage and OD quality (each factor with five levels) is examined in the context of when (a) PUC data are collected (D?Q?, X?Q?), and (b) arc flows are collected (D?Q?, V100Q100).

5.2.3.1 General Effects of Extreme OD Matrices

Complete, perfect OD matrices are difficult and costly to obtain outside of a simulated experiment, but are they needed? Or rather, how good of an OD matrix is needed when estimating traffic parameters such as $\hat{x}_p$, $\hat{v}_a$, and $\hat{y}_{oda}$? To explore the first question, cases were tested with a good and a bad OD matrix across all ten networks. Results for the D100Q100 scenario are tabulated in Table 5.5 and displayed in the top graphs of Figure 5.8 to Figure 5.11. Likewise, D20Q20 scenario results are listed in Table 5.6 and the bottom graphs of Figure 5.8 to Figure 5.11. Each performance measure is now considered in turn.

Table 5.6 Results Summary with D20Q20

Case	Objective Function for all Networks	Pearson Correlations (mean +/- 95% C.I.) $\rho(x_p, \hat{x}_p)$	$\rho(v_a, \hat{v}_a)$	$\rho(y_{oda}, \hat{y}_{oda})$
No VXY (only OD flows)	0.000 +/- 0.000	0.195 +/- 0.053	0.165 +/- 0.118	0.143 +/- 0.050
X1Q100	0.000 +/- 0.000	0.208 +/- 0.053	0.165 +/- 0.118	0.156 +/- 0.051
X5Q100	0.000 +/- 0.000	0.237 +/- 0.053	0.166 +/- 0.119	0.184 +/- 0.042
X10Q100	0.000 +/- 0.000	0.275 +/- 0.063	0.166 +/- 0.125	0.223 +/- 0.055
X20Q100	0.000 +/- 0.000	0.309 +/- 0.066	0.162 +/- 0.124	0.263 +/- 0.068
X60Q100	0.000 +/- 0.000	0.551 +/- 0.065	0.169 +/- 0.125	0.525 +/- 0.076
X100Q100 (Full AVL data)	0.000 +/- 0.000	0.994 +/- 0.001	0.200 +/- 0.127	0.997 +/- 0.000
X100Q60	4.207 +/- 0.303	0.729 +/- 0.053	0.189 +/- 0.129	0.717 +/- 0.064
X100Q20	6.798 +/- 0.870	0.467 +/- 0.080	0.198 +/- 0.121	0.486 +/- 0.084
X100Q10	6.898 +/- 0.607	0.464 +/- 0.071	0.186 +/- 0.122	0.489 +/- 0.078
X100Q5	6.967 +/- 0.851	0.415 +/- 0.097	0.168 +/- 0.114	0.450 +/- 0.101
V20Q100	0.031 +/- 0.061	0.198 +/- 0.051	0.164 +/- 0.091	0.149 +/- 0.042
V60Q100	0.239 +/- 0.239	0.136 +/- 0.062	0.491 +/- 0.070	0.129 +/- 0.054
V100Q100 (Full loop data)	0.157 +/- 0.157	0.202 +/- 0.052	0.958 +/- 0.015	0.161 +/- 0.039
V100Q60	0.218 +/- 0.145	0.203 +/- 0.052	0.720 +/- 0.059	0.164 +/- 0.039
V100Q20	0.546 +/- 0.299	0.202 +/- 0.052	0.590 +/- 0.070	0.163 +/- 0.039
Y20Q100	0.000 +/- 0.000	0.324 +/- 0.069	0.176 +/- 0.132	0.222 +/- 0.058
Y60Q100	0.000 +/- 0.000	0.692 +/- 0.052	0.200 +/- 0.127	0.490 +/- 0.056
Y100Q100 (Full AVI data)	0.000 +/- 0.000	0.987 +/- 0.011	0.200 +/- 0.127	0.997 +/- 0.000
Y100Q60	34.414 +/- 3.602	0.765 +/- 0.032	0.193 +/- 0.127	0.767 +/- 0.044
Y100Q20	50.774 +/- 4.124	0.503 +/- 0.050	0.200 +/- 0.140	0.512 +/- 0.068
V100Q100, X20Q100	14.658 +/- 1.067	0.219 +/- 0.056	0.957 +/- 0.015	0.182 +/- 0.043
V100Q100, X60Q100	43.444 +/- 1.447	0.247 +/- 0.063	0.957 +/- 0.015	0.213 +/- 0.052
V100Q100, X100Q100	72.767 +/- 0.843	0.255 +/- 0.064	0.958 +/- 0.014	0.223 +/- 0.052
V100Q100, X100Q60	65.669 +/- 2.026	0.247 +/- 0.063	0.958 +/- 0.015	0.218 +/- 0.051
V100Q100, X100Q20	63.929 +/- 3.745	0.240 +/- 0.060	0.956 +/- 0.015	0.213 +/- 0.046
V100Q100, Y20Q100	30.279 +/- 2.237	0.230 +/- 0.058	0.957 +/- 0.015	0.079 +/- 0.039
V100Q100, Y60Q100	95.235 +/- 8.758	0.251 +/- 0.064	0.957 +/- 0.015	0.186 +/- 0.047
V100Q100, Y100Q100	156.906 +/- 13.741	0.254 +/- 0.064	0.957 +/- 0.015	0.223 +/- 0.052
V100Q100, Y100Q60	144.437 +/- 8.492	0.250 +/- 0.064	0.957 +/- 0.015	0.218 +/- 0.053
V100Q100, Y100Q20	31.176 +/- 2.734	0.229 +/- 0.062	0.957 +/- 0.015	0.084 +/- 0.041
VXY100Q100	229.484 +/- 13.717	0.255 +/- 0.064	0.957 +/- 0.015	0.223 +/- 0.052

Notes:

1. The above cases were run for ten 10-node networks with 1 OD flow realization each for a total of 10 runs per case. In the model, $\gamma_v = 0.005$ to approximately normalize the minimization's first term to between 0 and 1, and $\gamma_y = \gamma_x = 1.0$.
2. M#$_1$Q#$_2$ = #$_1$ percent of variable M sensors exist in the network, each with #$_2$ percent quality.

Objective Function Value. The objective function gives an indication of how hard it was for the model to find a solution meeting the constraints. Generally, with the good OD matrix the objective function value only deviates from zero when sensor quality is sacrificed so incorrect, albeit complete, inputs yield poor objective function values, more so than incomplete, correct inputs since there is a chance that the correct missing values can be determined in the latter situation. The other obvious difference is for cases supplied with two or more sensor types. Here, the objective function soars toward 100 for the V100Q100, X?Q? cases, up to 200 for some V100Q100, Y?Q? cases, and above 200 for the VXY100Q100 case shown. Hence, the objective function values clearly show for models with two or more variables that messier and sparser OD matrices worsen model results. Again, the model seems to be having difficulty finding a solution that matches most of the input data. Consider that an objective function value of 200 could mean that 200 $\hat{x}_p$ or $\hat{y}_{oda}$ terms in the objective function could be completely uncorrelated with the truth. And recall the earlier discussion about the under-specification of the simpler V100Q100 case which also plays into these results.

PUC Estimates. Attempting to estimate PUCs with a good OD matrix is possible as long as arc flows are not the sole input (Figure 5.9 top). If PUCs, LUCs, or any combination of two or more parameters (as shown) are input, then reasonable PUC estimates are possible. However, replacing the D100Q100 OD matrix with the D20Q20 scenario (Figure 5.9 bottom), such as the one that might be developed if only ADT data are available for a network, decreases $\rho(x_p, \hat{x}_p)$ severely to below 0.4 for four groups of cases: DV, DVX,

DVY, and DVXY. Furthermore, when a poor OD matrix is present, then two or more variables in the model seem to confound the results and weakens $\rho(x_p, \hat{x}_p)$. Reasonable PUC estimates ($\rho(x_p, \hat{x}_p) > 0.8$) are only possible when almost complete and perfect PUC sensor data are collected or when the same is done for LUC sensor data. Hence, OD matrix coverage and quality strongly effect the ability to acquire reasonable PUC estimates.

Specifically, with regard to Figure 5.9, estimating the PUCs well is difficult when only arc flows are observed, as evident from a maximum $\rho(x_p, \hat{x}_p) = 0.669$ for near perfect OD flows and 0.315 for a poor OD matrix.

LUC Estimates. Similar trends to $\rho(x_p, \hat{x}_p)$ cases but with more pronounced trends and lows are seen in Figure 5.10 for $\rho(y_{oda}, \hat{y}_{oda})$. Again, coverage is shown to hurt the correlation more than the same percentage change in quality. Broader ranges are seen in the bottom chart with a compromised OD matrix so model estimates deteriorate with poor quality OD matrices and estimates become more uncertain.

Examining the combined sensor cases of DVX and DVY, both are good for v but poor for x and y even when X100Q100 or Y100Q100 is used in conjunction with V100Q100. Moreover, x and y are defined directly by OD incidence matrices, so if OD flows are wrongly assigned, these transfer to wrong x and y assignments and levels.

Arc Flow Estimates. Expected trends are observed in Figure 5.11. Coverage is more crucial than quality for all 3 variables alone as seen in the steeper slopes connecting the 20, 60, and 100 percent coverage and flatter slope of the line connecting 20, 60, and 100 percent quality. Notice also that arc flows are poorly correlated when only arc flows are collected as opposed to observing PUCs or LUCs. For cases 17 to 27 in Figure 5.11, there is an excellent match with slightly higher spreads caused by the poor OD matrix. When a poor OD matrix is used, a model with arc flows collected generally yields better estimates of the true arc flows as compared to models with only PUCs or LUCs collected.

To summarize, the results in Table 5.6 clearly point to what the input data are and the relations of the constraints to one another. In other words, correlations are highest for the sensed parameter in each case. And it is evident that a bad OD matrix strongly inhibits good parameter estimation.

The effects of OD matrix coverage and quality on the X?Q? cases are now explored in detail, allowing for the expansion of the PUC sensors discussion in Section 5.2.2.1.

5.2.3.2 Specific Effects of Extreme OD Matrices – X?Q? Cases

Objective Function Values. Little difference is seen in the objective function values between the D100Q100 and D20Q20 scenarios as PUC coverage is varied, both are centered on zero (see Figure 5.12). The general curve shape is the same whether D100Q100 or D20Q20 is applied to cases varying PUC quality (see Figure 5.13). A breakpoint in both scenarios

occurs at X100Q20 whereupon higher levels of quality drive the objective function to zero. For the D20Q20 cases, as more paths are observed for PUCs, it is minutely harder to reconcile the PUCs with the sparsely populated, poor quality OD matrix. Even with the D20Q20 OD flows matrix, PUC quality is observed to affect the objective function values. Perfect data in yields a perfect objective function value, but as PUC quality drops, it quickly raises the objective function to peak values at approximately 20 percent PUC quality. This suggests that at least a level of 20 percent (preferably much higher) quality for PUCs should be required before relying on the model to yield reasonable PUC estimates.

Parameter Estimates. Now compare Figure 5.6 with Figure 5.14 and Figure 5.7 with Figure 5.15 to examine how an OD matrix can affect parameter estimates. One general trend visible is the widening and lowering of the range of correlations from the good to bad OD matrix and PUC coverage. For example, in Figure 5.6 correlations range from 0.2 to 0.8 while PUC coverage is less than 20 percent whereas in Figure 5.14 the correlations range between –0.2 to +0.6 until 60 percent PUC coverage is achieved. Thus, estimates of all three parameters are generally worse with the bad OD matrix. Likewise, as PUC quality varies Figure 5.7 has a tight cluster of correlations in each graph (diameter < 0.4) while Figure 5.15 has more dispersed clusters (diameter > 0.6). The individual parameters are examined below.

While the given OD matrix is sparsely populated and of poor quality (D20Q20), parameter correlations begin to shift upward rising above their earlier ceiling of 0.6 once PUC coverage is at 60 percent (see trend in Figure 5.14). So reasonable PUC and LUC estimates are

possible with a poor and sparse OD matrix if there are enough paths sensed (see top graph in Figure 5.15). However, even when there is 100 percent PUC coverage with perfect sensors, good arc flow estimates were not possible with the current input data.

Unfortunately, $\rho(v_a, \hat{v}_a)$ is less than 0.6) for all ten networks and the D20Q20 OD flows (see the top chart in Figure 5.15). Hence, we find a ceiling on what observed data can contribute to this picture; going above this ceiling will likely require an increase in inference.

Further recognize in the Figure 5.15 charts the slow increase in objective function value as the PUC quality is decreased; there is a similar trend of worsening seen with the parameter correlations for x and y. Contrarily, $\rho(v_a, \hat{v}_a)$ was rather stable with values between –0.2 and +0.6 regardless of changes in PUC quality. Therefore, inexpensive PUC sensors can be used without compromising arc flow estimates.

If observed PUCs and OD flows are model inputs (cases 2 to 11 in Table 5.5), then the true PUCs picture is well-estimated (objective function = 0, correlation (ρ) = 1.0) when 100 percent of PUCs are observed with 0 percent error (see Figure 5.3b). Likewise, the estimated LUCs are found to be well-correlated with the truth. However, unless the OD flow data are complete and correct, such a model does not estimate the arc flows with high accuracy (e.g. arc flow correlations ranged from -0.340 to +1.0 for Network 10 as the sensed OD flows were varied according to the experimental design).

Not until PUC coverage achieves 60 percent (see Figure 5.6) do the majority of networks obtain a large shift in correlation values for all three parameters (v, x, y). So notice that this breakpoint occurs whether the OD matrix is densely or sparsely populated and in perfect or poor condition.

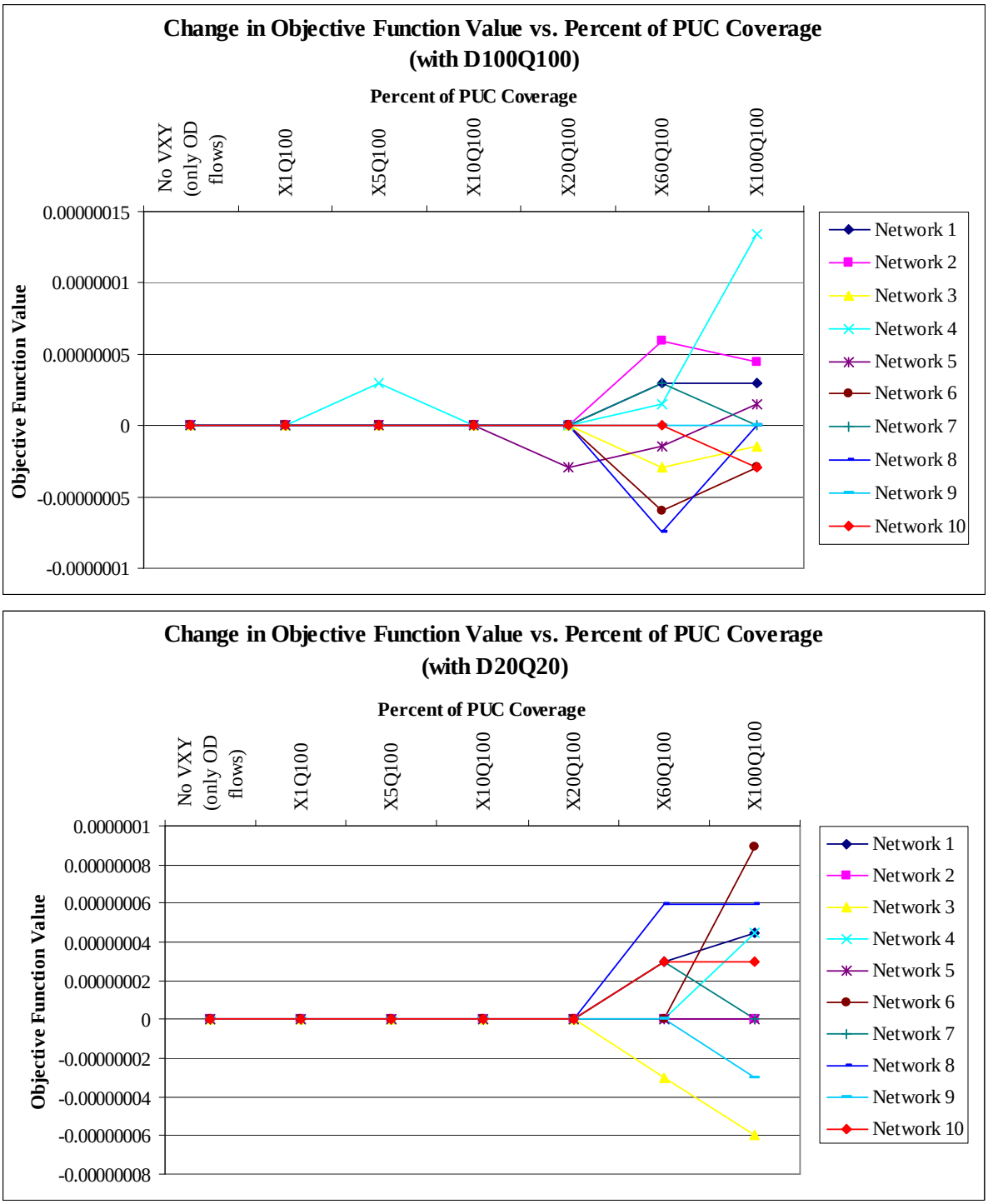
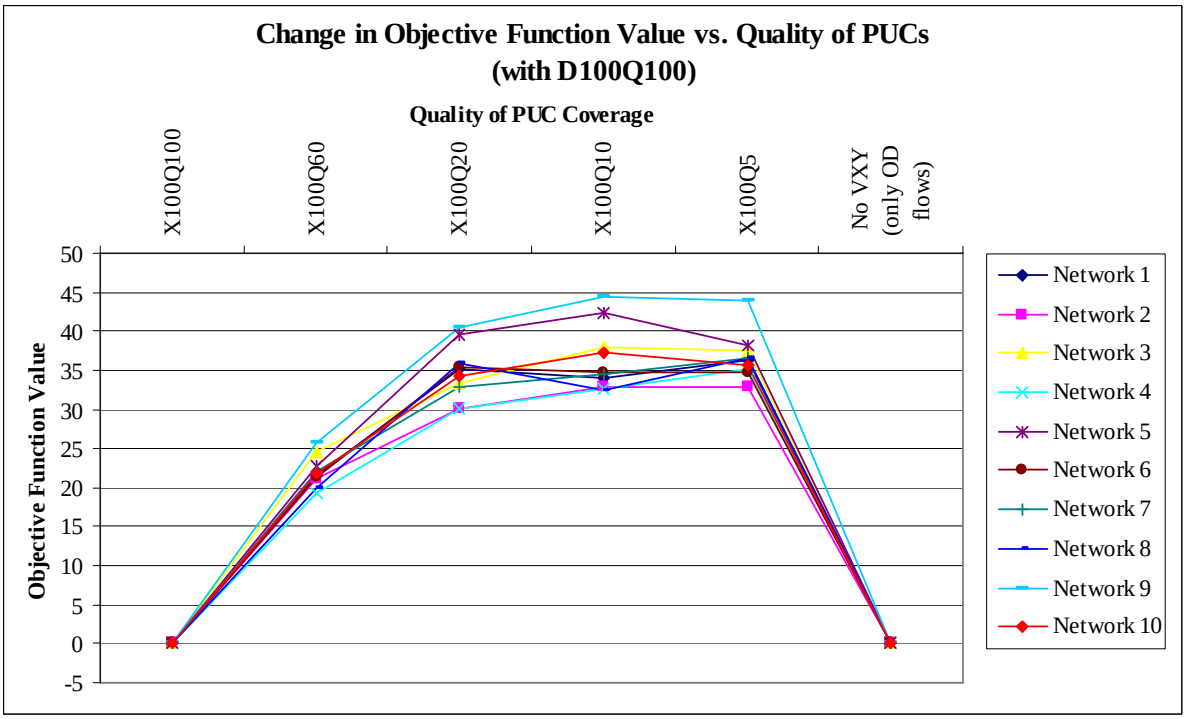


Figure 5.12 Objective Function Values for D100Q100 versus D20Q20 Cases with X?Q100



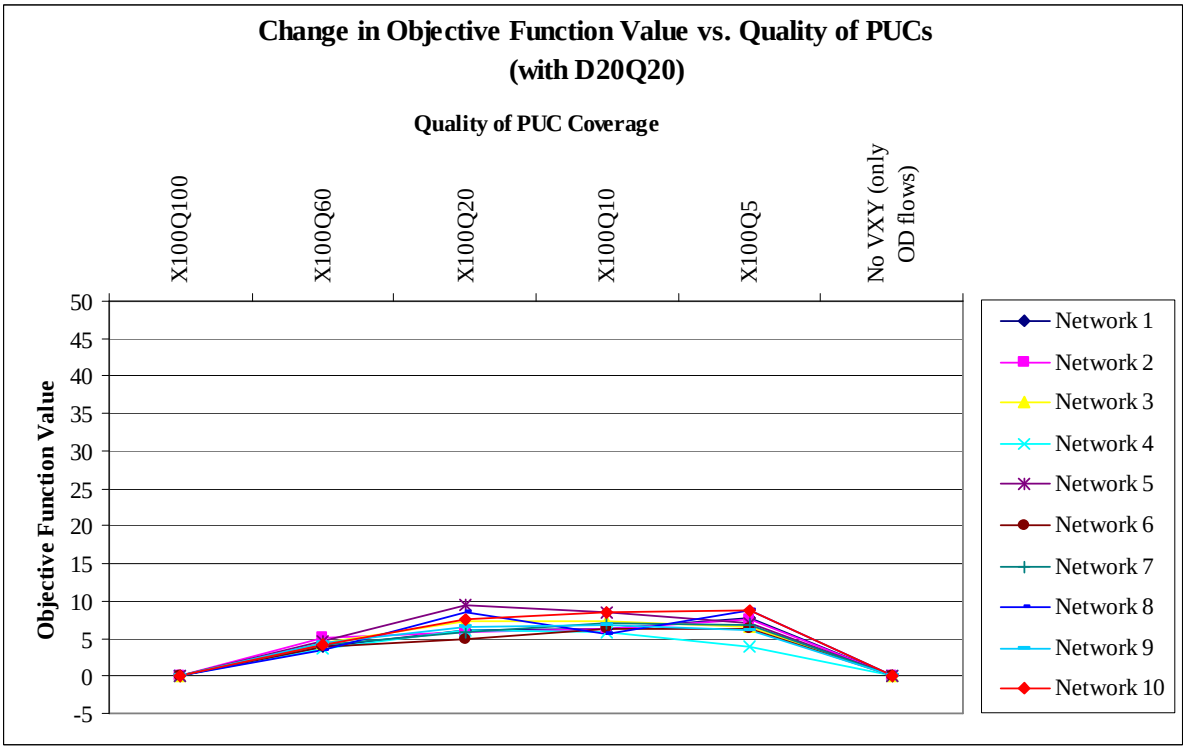


Figure 5.13 Objective Function Values for D100Q100 versus D20Q20 Cases with X100Q?

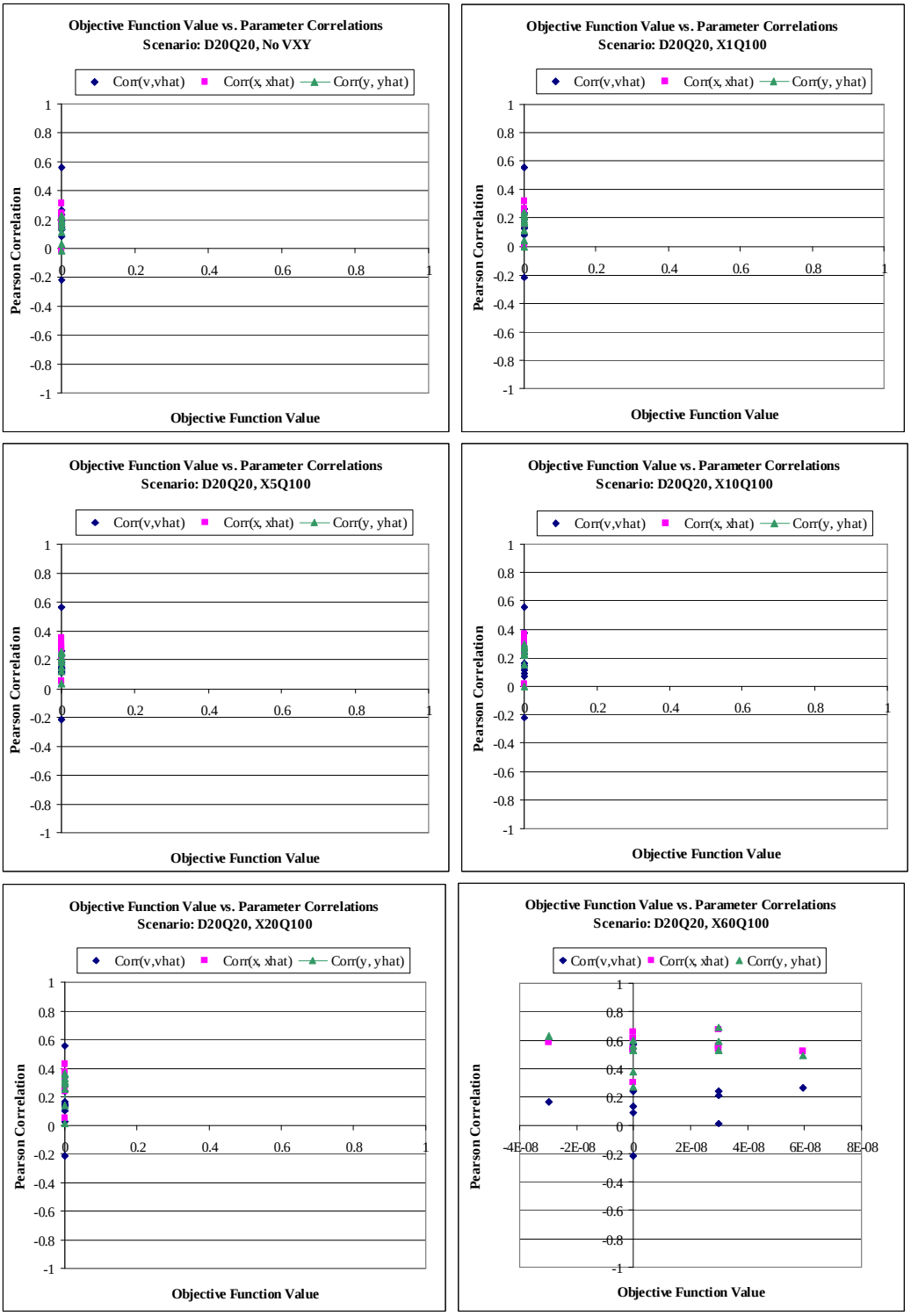


Figure 5.14 Relationships between Objective Function and Correlations as PUC Coverage Increases (D20Q20 for all cases)

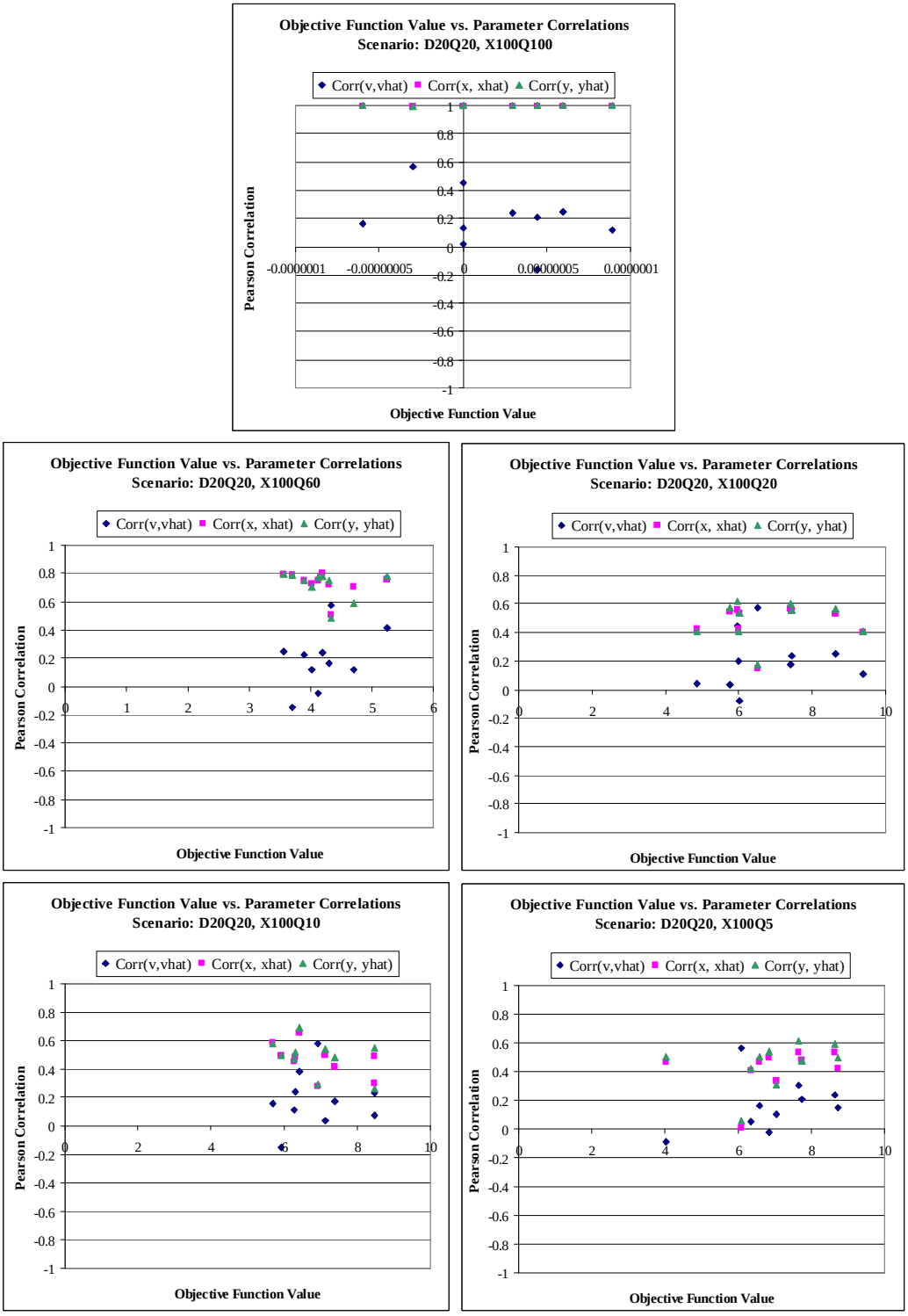


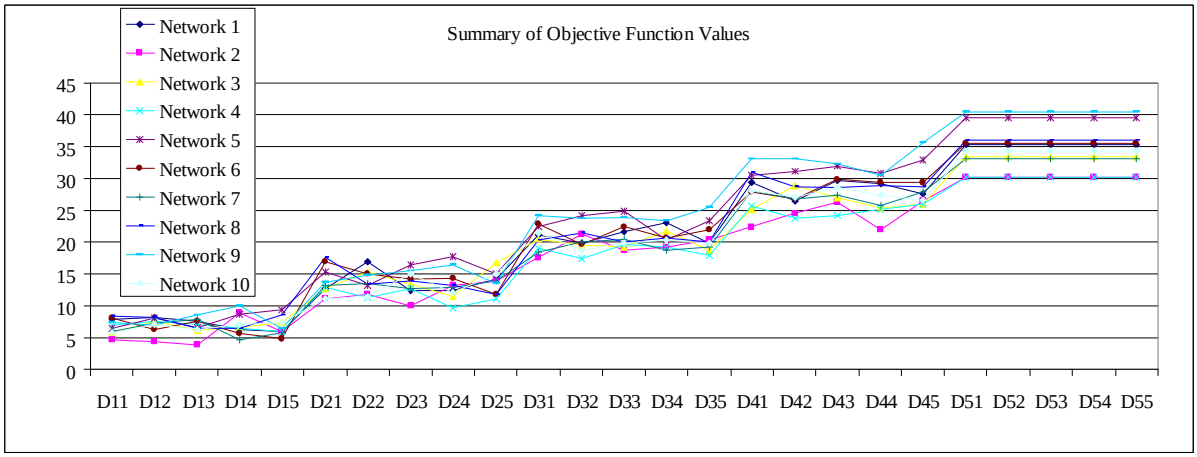
Figure 5.15 Relationships between Objective Function and Correlations as PUC Quality Decreases (D20Q20 for all cases)

5.2.3.3 Complete Block Design of OD Matrices

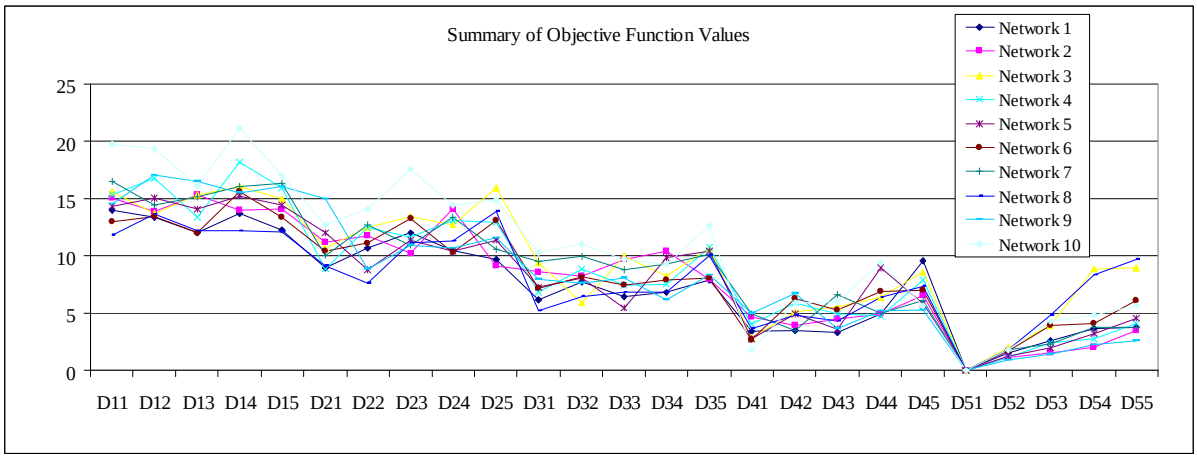
Returning to the question posed in the last section, "… how good of an OD matrix is needed when estimating traffic parameters such as $\hat{x}_p$, $\hat{v}_a$, and $\hat{y}_{oda}$?", a wide array of OD matrices are tried. While D100Q100 and D20Q20 are the extremes of an experimental design the full design has 2 factors (OD coverage, OD quality) and five levels each (20%, 40%, 60%, 80%, 100%). Here, the full experimental design is now visible for two conditions, (1) all X?Q? cases in Figure 5.17 and (2) the V100Q100 case in Figure 5.18.

5.2.3.3.1 Example Results

As expected, the objective function of the model in most cases showed improvements as more OD flows were available and as the quality of them increased. However, when sensor bundles' data quality in a model were low, the objective function values suffered, illuminating the necessity to encourage technology advancements. Two examples of objective function performance are presented in Figure 5.16 one for case 4 X100Q20 and one for case 11 V100Q100, X20Q100.



a. Case 4 X100Q20



b. Case 11 V100Q100, X20Q100

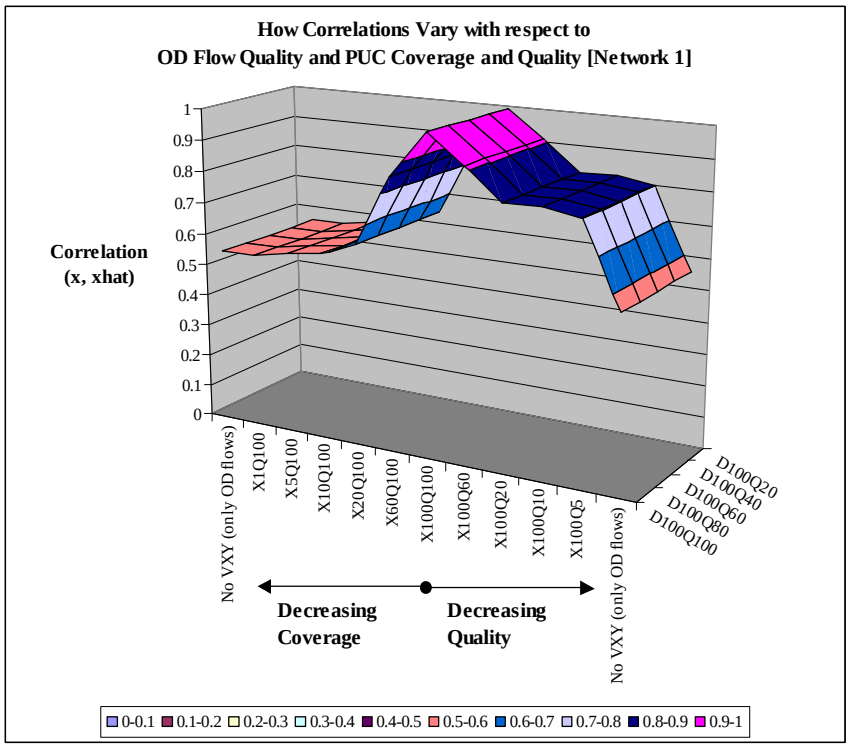
Figure 5.16 Examples of Objective Function Behavior as Available OD Flows Change

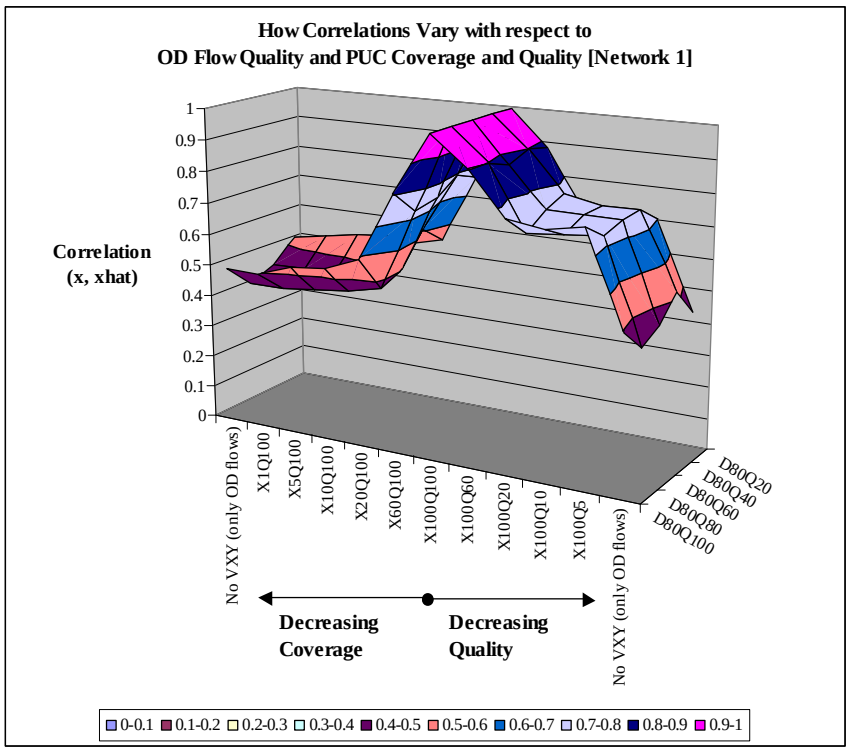
Note for interpreting Dij: (best scenario is D51, worst scenario is D15)
i = OD flow coverage factor (1 = 20% flows available, 2 = 40%, 3 = 60%, 4 = 80%, 5 = 100%)
j = OD flow error factor (1 = 0% error in flows, 2 = 20%, 3 = 40%, 4 = 60%, 5 = 80%)

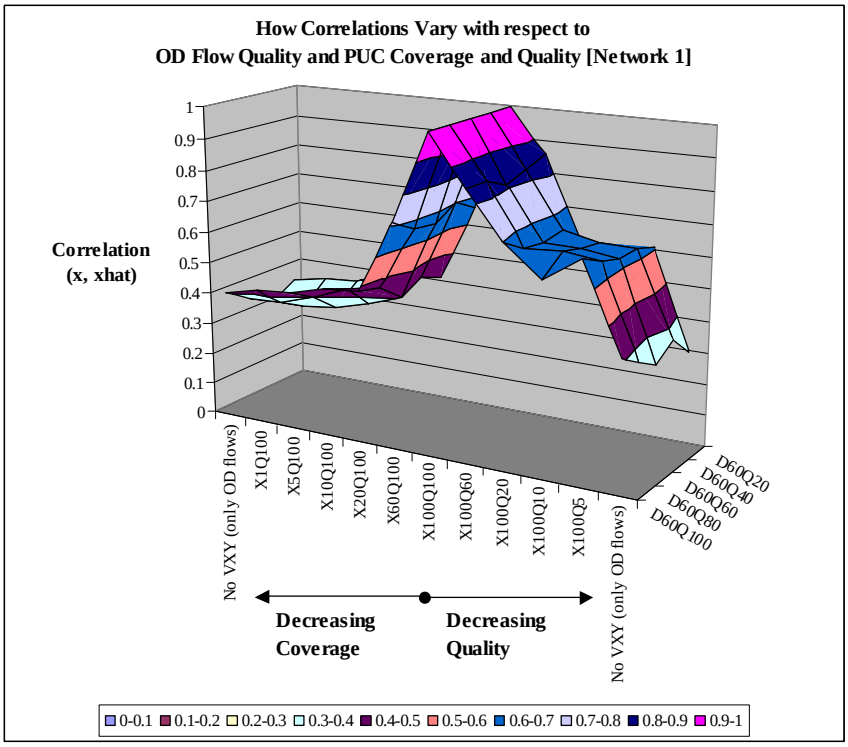
5.2.3.3.2 PUC Data Cases (D?Q?, X?Q?)

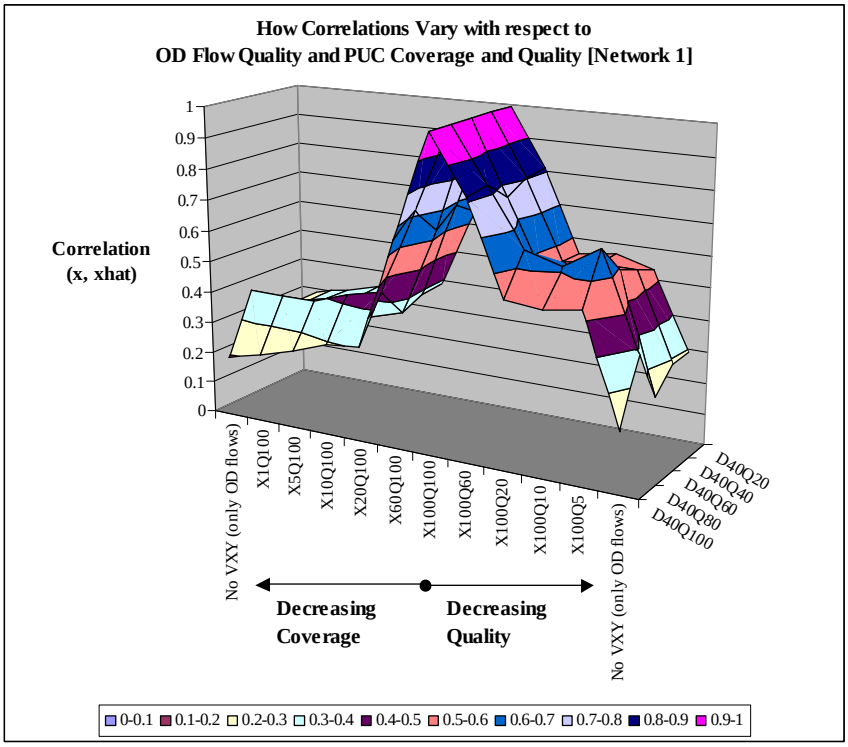
Visible in the first condition is the downward shift in $\rho(x_p, \hat{x}_p)$ by about 0.2 each time OD flow coverage is decreased by 20 percent. Overall, the curves for each OD matrix follow the same shape. From 0 to 20 percent PUC coverage the curves remain rather flat and unresponsive. From 20 to 100 percent PUC coverage the model responds strongly to the increase of PUC sensors and $\rho(x_p, \hat{x}_p)$ reaches its maximum value of 1.0 when the X100Q100 case is tested. Maintaining PUC coverage at 100 percent but dropping PUC quality, $\rho(x_p, \hat{x}_p)$ is observed to plateau between 20 and 5 percent PUC quality after quickly decreasing when PUC quality changed from 100 to 60 to 20 percent. Unfortunately, except when the OD matrix is complete (D100Q?), the correlations associated with the plateau are lower than the desired level of 0.8 for reasonable parameter estimates.

Figure 5.17 Effect of Quality and Coverage on Correlation (x, xhat)


How Correlations Vary with respect to
OD Flow Quality and PUC Coverage and Quality [Network 1]
Correlation
(x, xhat)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
No VXY (only OD flows)
X1Q100
X5Q100
X10Q100
X20Q100
X60Q100
X100Q100
X100Q60
X100Q20
X100Q10
X100Q5
No VXY (only OD flows)
D100Q20
D100Q40
D100Q60
D100Q80
D100Q100
Decreasing
Coverage
Decreasing
Quality
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
0.7-0.8
0.8-0.9
0.9-1


How Correlations Vary with respect to
OD Flow Quality and PUC Coverage and Quality [Network 1]
Correlation
(x, xhat)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
No VXY (only OD flows)
X1Q100
X5Q100
X10Q100
X20Q100
X60Q100
X100Q100
X100Q60
X100Q20
X100Q10
X100Q5
No VXY (only OD flows)
D80Q20
D80Q40
D80Q60
D80Q80
D80Q100
Decreasing
Coverage
Decreasing
Quality
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
0.7-0.8
0.8-0.9
0.9-1


How Correlations Vary with respect to
OD Flow Quality and PUC Coverage and Quality [Network 1]
Correlation
(x, xhat)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
No VXY (only OD flows)
X1Q100
X5Q100
X10Q100
X20Q100
X60Q100
X100Q100
X100Q60
X100Q20
X100Q10
X100Q5
No VXY (only OD flows)
D60Q20
D60Q40
D60Q60
D60Q80
D60Q100
Decreasing
Coverage
Decreasing
Quality
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
0.7-0.8
0.8-0.9
0.9-1


How Correlations Vary with respect to
OD Flow Quality and PUC Coverage and Quality [Network 1]
Correlation
(x, xhat)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
No VXY (only OD flows)
X1Q100
X5Q100
X10Q100
X20Q100
X60Q100
X100Q100
X100Q60
X100Q20
X100Q10
X100Q5
No VXY (only OD flows)
D40Q20
D40Q40
D40Q60
D40Q80
D40Q100
Decreasing
Coverage
Decreasing
Quality
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
0.7-0.8
0.8-0.9
0.9-1

5.2.3.3.3 Arc Flow Case (D?Q?, V100Q100)

From the graph (Figure 5.18), it looks like OD coverage has a definite positive effect on PUC estimates – notice the overall upward trend from D11 to D55. However, it is unclear from the graph whether OD quality also has an impact on PUC estimates. Therefore, a two-way ANOVA is run to determine the relationship.

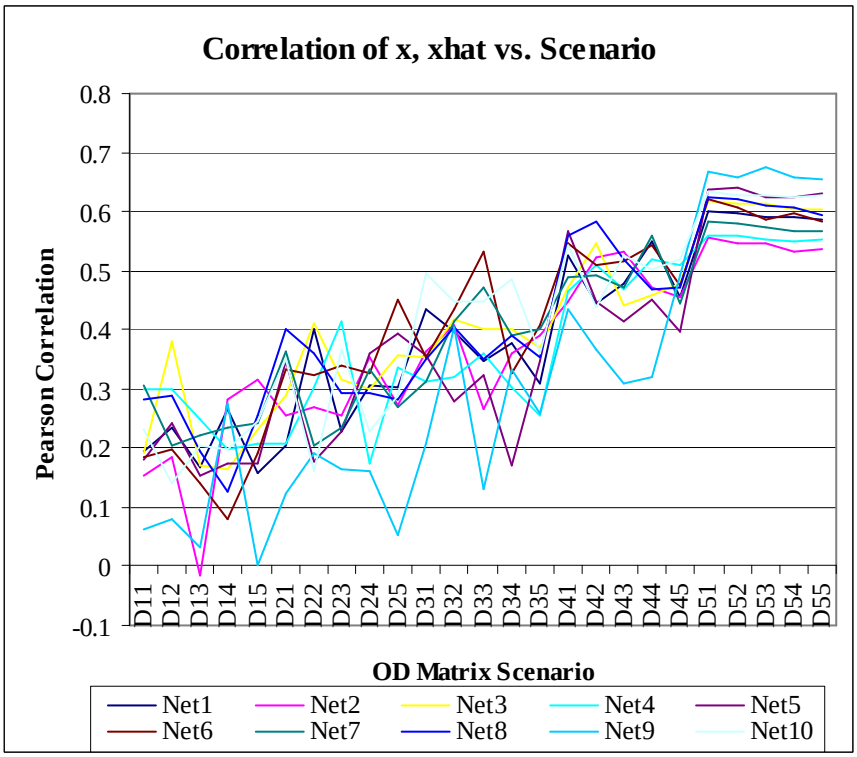


Figure 5.18 Correlation of x, xhat versus OD Scenario for the V100Q100 Case

Ten observations of each treatment (OD coverage, OD quality combination) are tested in this two-way ANOVA. Each factor has five levels.

- Factor Q = OD matrix quality, 5 levels (20%, 40%, 60%, 80%, 100%)
- Factor C = OD matrix coverage, 5 levels (20%, 40%, 60%, 80%, 100%)
- Response variable = $\rho(x_p, \hat{x}_p)$

Hypotheses to test:

Ho_{QC}: $\gamma_{ij} = 0$ for all i, j	versus	Ha_{QC}: at least one $\gamma_{ij} \neq 0$
Ho_{Q}: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 0$	versus	Ha_{Q}: at least one $\alpha_i \neq 0$
Ho_{C}: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$	versus	Ha_{C}: at least one $\beta_j \neq 0$

With:

Ho = null hypothesis

Ha = alternative hypothesis

γ_{ij} = interaction parameter

α_i = main effects for factor Q (OD matrix quality)

β_j = main effects for factor C (network coverage of the OD matrix)

Table 5.7 Two-way ANOVA Table for the V100Q100, D?Q? Set of Cases

Source of Variation	SS	df	MS	F	P-value	F crit
Differences between OD Coverage	5.073074	4	1.268268	255.262	2.2E-82	2.411767
Differences between OD Quality	0.018672	4	0.004668	0.939513	0.441828	2.411767
Interaction	0.038595	16	0.002412	0.485497	0.952579	1.688626
Within	1.117912	225	0.004968			
Total	6.248253	249				

Notes: SS = Sum of Squares, df = degrees of freedom, MS = Mean Square = SS/df, F = F-distribution statistic, F crit = critical F-statistic below which the null hypothesis cannot be rejected.

Based on the ANOVA results, only one null hypothesis is rejected at the 0.05 level or smaller levels, the other two cannot be rejected. In other words, for the V100Q100 case, interaction effects do not exist and are not significant, and OD quality does not significantly effect PUC estimates when arc flow data are model inputs. However, OD coverage does effect PUC estimates under these conditions. Furthermore, the mean square for OD coverage is much greater than that for OD quality, so it can be concluded that the differences between OD coverage levels are more important than the differences between OD quality levels.

Tukey's Procedure (or the T Method) is now applied because the no-interaction hypothesis Ho_{QC} is not rejected and one of the main effects null hypotheses, Ho_C, is rejected. This method enables the identification of significant differences in factor levels. Unfortunately, both factors did not show any significant differences in levels although differences are nearly significant for OD coverage levels of 60, 80, and 100 percent (see Figure 5.19).

1. For comparing levels of factor Q, obtain Qa,I,(I-1)(J-1)
Q0.05,5,16 = 4.33(from Table A.10 in Devore)
2. Compute w = Q*sqrt(MSE/J)
w = 0.136495
3. Underscore pairs of levels where Diff < w. These levels are not significantly different from one another.

	DQ60	DQ20	DQ40	DQ100	DQ80
Avg	0.373323	0.382223	0.383283	0.392974	0.397936
Diff		0.0089	0.00106	0.009691	0.004961

1. For comparing levels of factor C, obtain Qa,J,(I-1)(J-1)
Q0.05,5,16 = 4.33
2. Compute w = Q*sqrt(MSE/I)
w = 0.136495
3. Underscore pairs of levels where Diff < w. These levels are not significantly different from one another.

	DC20	DC40	DC60	DC80	DC100
Avg	0.197377	0.287057	0.361841	0.482552	0.600912
Diff		0.089681	0.074784	0.120711	0.11836

Figure 5.19 Tukey Procedure on V100Q100, D?Q?

5.2.4 Results Summary

Based on the analyses conducted, the following information has been generated to summarize the analyses.

Sensor Quality & Coverage

- More sensors yields better path flow estimation
- Higher quality sensors yield better path flow estimation
- Higher sensor quality instead of higher coverage yields better path flow estimation

- Using multiple sensor types yields better path flow estimation
- Differences between OD quality levels are more important than the differences between OD coverage levels when arc flows are also observed.

OD Matrices

- OD matrices with higher coverage yield better path flow estimation
- Higher quality OD matrices yield better path flow estimation

Physical Network Characteristics

- Less-connected networks (g=links/nodes) yield better path flow estimation
- Networks with fewer paths yield better path flow estimation
- The model behaves as expected.
- If no field data are collected, then a cloudy picture is possible if the available OD matrix is good. For the ten 10-node networks tested, correlations of all parameters could achieve values exceeding 0.5 under this condition.
- More sensors are better than fewer – In fact, if PUC sensors are used, then a high percentage of paths must be measured (PUCs sensed) if all three parameters are to be estimated with reasonable accuracy (say $\rho > 0.8$) so about 80 percent of the estimates match their associated true values.
- High quality sensors are an improvement over low quality ones – For estimating PUCs, the quality of PUC sensors is of little consequence as compared to covering the network.

- Sensor bundles capturing the most information (AVL) are better than those collecting the least information (loop detectors) – not always.
- The PUC picture degrades when either the quality of PUC sensors or the percentage of them in the field is decreased with the model being more sensitive to the latter. A PUC coverage breakpoint of 60 percent is found crucial for estimating all three parameters. Moreover, this breakpoint occurs whether the OD matrix is densely or sparsely populated and in perfect or poor condition.
- If arc flows are collected and a poor OD matrix is available, then better estimates of true arc flows are obtained as compared to models with only PUCs or LUCs collected.

5.2.5 Early Conclusions

New technologies can have a profound effect on our ability to predict path utilization coefficients and path flows by reducing our dependence on inference and increasing network observability. Specifically, observed arc and OD flows input to this model were inadequate at properly estimating path utilization coefficients for 10-node networks; therefore, extrapolating to larger networks suggests yet worse PUC estimation. Models that included either some PUC or LUC sensor data along with available OD flows proved to be better estimators of PUCs, so as technologies evolve and we depend less on point sensors such as loops there is hope for increasingly accurate path flow estimation. Combining a mix of sensor bundles with available OD flows yielded the best overall network picture – but it was recognized that only two types of sensors were necessary (point sensors and AVI or point sensors and AVL), not all three to achieve this picture.

Other statistical results and conclusions based on this model can be found in the dissertation that is the basis for this paper. Upcoming in this ongoing research are refined models such as one incorporating the secondary OD matrix associated with AVI tag readers, as well as consideration of time-dependence. Future research endeavors of interest include network design work such as the formulation of a bi-level programming model to determine the best locations of the optimal number of sensor bundles throughout a given network.

6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

6.1.1 Motivations Revisited

Path flows are a necessary piece of information for decision-makers of all types. Long-range planners' decision quality can be enhanced by path flows that quantify how the transportation network is changing over time (say year-to-year); decisions include where to guide land development and what network facilities to change (remove/add, maintain/enhance, restrict/open up). Path flow information on an hourly or daily basis (or smaller time units) can inform traffic engineers' decisions on signal system timing (coordination, platooning, forward and reverse progression), variable lane use assignments (such as when to reverse lane directions, open carpool lanes, or alter congestion prices), and especially aid in prioritizing which facilities should receive attention first. Therefore, path flow data can improve system efficiency through betterment of long- and short-term decisions. Logistics specialists working for truck fleets may benefit from similar short-term path flow information to design truckers' routes. Because of these needs for path flow data, this dissertation research was conducted. The author explored the effects of network observability on path flow estimates. Ten independent networks that were both small and virtual were the testing grounds on which different combinations of sensors were overlaid stochastically with respect to sensor type, network coverage, and quality of coverage.

6.1.2 Contributions to Knowledge

Through this doctoral work, three significant contributions to knowledge have been made. First, the predictability of path utilization rates and the extent to which that predictability is dependent upon the data available and the quality of that data was quantified. This relationship was explored both in deterministic and stochastic manners to see how degrees of uncertainty affect the resulting path utilization rates.

Second, a methodology was created for addressing the predictability of path flow rates which in some ways inverts the origin-destination estimation process. When thinking about the needs of decision makers with respect to network traffic flows, it is evident that path flows are an essential piece of information. Therefore, path flows or path utilization rates must be quantified. Thus, it was important to puzzle out how best to observe or estimate the path utilization coefficients.

Third, an improved understanding was reached of the interplay between observations and inferences in determining the path utilization coefficients. This contribution was driven by a desire to articulate whether an applied path flow estimation method had a reliance on inferred data, observed data, or both to discover how each one influences the choice of method and the quality of the outcome. The focus here was on exploring observed data, although in the future it would be interesting to develop a taxonomy of inference which could further shape the inference versus observability tradeoff concept that was presented and explored here on a small scale.

6.1.3 Results in Perspective

This dissertation can be characterized as implementing and then testing a methodology for determining path flows in a network based on the available sensor instrumentation and OD data. There are three main parts to the underlying research – methodology validation, robustness assessment, and model enhancement or compromised network analysis. The first two have been addressed using small, virtual networks. Throughout this research, three data conditions have been examined to test the methodology's predictions – error-free data, stochasticity in demands coverage (such as in OD flows, link volumes, *a priori* path utilizations, and *a priori* link utilizations), and stochasticity in the demand measurements.

One of the motivations was that technologies that have become available ought to have a profound effect on our ability to predict path utilization coefficients and path flows by reducing our dependence on inference and increasing network observability. AVL and AVI sensor data, along with available OD flows, ought to improve the estimates of PUCs, so as technologies evolve and we depend less on point sensors, such as loops, there is hope for increasingly accurate path flow estimation. The research demonstrates that models including either AVL or AVI sensor data prove to be better estimators of PUCs. Specifically, observed arc and OD flows input to this model were inadequate at properly estimating path utilization coefficients for 10-node networks; therefore, extrapolating to larger networks suggests yet worse PUC estimation. Combining a mix of sensor bundles with available OD flows yielded the best overall network picture – but it was recognized that only two types of sensors were

necessary (point sensors and AVL or point sensors and AVI), not all three to achieve this picture.

Returning to the objectives of this research, a credible picture of path flows is needed for decision-making. And for accuracy, one based on observed data is preferable to using inference to arrive at estimated traffic flows that are defensible. Focusing on three cohorts, note how the results affect the necessary decisions.

Decision Support Tool Developers. It was demonstrated that the ability to correctly predict path utilization coefficients was poor in the absence of direct observations of PUCs or LUCs. In essence, by looking at the inverse of the OD estimation problem (predicting PUCs instead of the ODs), it was found that the use of *observed* link flows and *assumed* OD flows results in deficient estimates of the link utilization coefficients. Said another way, the key to better traffic flow tools was found not to be more perceptive models (i.e. those with more inference)[20], but rather ones with the right mix of observable data. Moreover, modeling OD flows, PUCs, and link volumes together still needs exploration.

Capital Investment Decision Makers. If an agency wants to do a better job of deciding what investments to make, it needs to know the path flow rates to accomplish this task. Here it was learned that inference alone will not be enough to predict credible rates. Typically,

[20] Going in a direction of applying more inference leads to further uncertainty because of the reliance on assumptions of human behavior.

OD flows based on assumed LUCs are given to the agency for a macroscopic view of travel patterns. Unfortunately, this level of detail is not always enough to make strategic decisions for facility location and expansion. Especially in short- to mid-term planning, a view of existing path flows provides richer detail. With the recent advent of AVL sensors and continuing implementation of AVI systems, technology enables quantifying of path flows, as shown through this research. For example, it was found that increasing the number of AVI devices and relying less on point sensors improves the accuracy of path flow estimation. Therefore, the capital investment agency should focus less energies on modeling and more on data collection such as (a) partnering with a cell phone company for general GPS data, (b) sharing data with the local toll and automated parking authorities to collect AVI data, and (c) partnering with a real-time navigation company such as DASH or ALK (maker of CoPilot) for AVL probe data.

Operational Decision Makers. Even in terms of an operational environment, where it is already understood that path flows are important, this research reinforces the notion and shows that arriving at path flow rates requires more than just inference. Consider timing an isolated intersection – this requires only knowledge of the approach volumes and turning movement counts. Now consider timing an entire network of signals – this requires far more knowledge of the traffic to create an efficient signal system. Recognition of the multitude of paths on which traffic between a given OD pair can traverse the network can enhance the decision quality because the traffic engineer can determine how drivers may alter their current routes based on signal timing changes. To support such work, how path flows

change over time is important - which points to a need to translate this current research into a time-dependent tool.

6.2 Future Work

6.2.1 Simple Networks

Modeling. Simple networks like the 3-node toy in the preliminary findings and the 10-node networks explored in-depth are defined here as small, randomly-designed networks that are static in nature. It is assumed these networks are static and unchanging in their traffic flows during the analysis. Exploring the lower level math program is underway for simple networks – that of determining how well available sensor data can discern path flows at a macroscopic level. Currently it is assumed in the model that the determined path and link flows should match those observed; this assumption may be changed as ideas are tried out and points are plotted on the inference versus observability graph. Continuing in this direction leads to answering the following research questions:

- *Sample Size.* Do the conclusions found herein hold true when a larger sample of networks is tested? Create at least 30 new 10-node networks so a statistically "large" sample size is attained. Run the model again. Compare the new results with the original results to determine if there are significant differences. If not, maintain a sample size of 10 for initial testing of other concepts; otherwise, make the sample size of 30 networks standard.

- *Solution Uniqueness, part 1.* Are the linear programming solutions found in this research unique? Test the uniqueness of the estimated path flow vectors for the original 10 networks. If the solutions are not unique, discuss the implications for determining the best path flow vector.
- *Solution Uniqueness, part 2.* If the linear programming solutions found are not unique, create a search strategy for finding the best path flow vector for a given network. Going back to the linear programming issue that multiple solutions can exist for one objective function, examine the line of objective function solutions testing for the PUC vector that has the best correlation with known data.
- *Network Size.* Do the conclusions already found hold constant when larger networks are considered? What trends occur in the results as networks become larger (like do the PUC correlations decrease)?
- *Data Preprocessing.* What effect does choosing the best available data from that observed have on determining path flows? Recognize that the four data sets (OD, AVL, AVI, point sensors) have some overlapping information that may be capitalized upon to strengthen the input data prior to running the model. Preprocess the data based on confidence or knowledge that one data set is of superior quality to another, then apply the model to determine path flows. For instance, a researcher may be confident that AVL data is better than the available OD data because the AVL instruments typically have very low error rates so the researcher would replace duplicate OD data with the AVL OD data. A second

example would be the adding of a sub-OD matrix based on AVI data, again preprocessing the ODs.

- *Model Variations – Objective Function.* What changes to the objective function can create a more robust model? Edit the γ_v, γ_x, and γ_y weights. Edit the three summations, moving back toward the nonlinear formulation.

- *Overlapping vs. Non-overlapping Sensor Regions.* Is some spatial overlap of the sensors' regions necessary? What overlaps are helpful? Which are redundant? If two types of sensors are on a given path, how much stronger is the correlation between true and estimated data?

- *Mesoscopic Analysis.* How many sensors and probe vehicles, instead of percentages of sensors, are needed for adequate path flow estimates? Assign each vehicle in a network an OD pair and a path, then randomly select those vehicles that are or are not revealed. Simulate actual sensor coverage that could happen and determine how many sensors are needed in a network. One caveat, planners and traffic engineers cannot control where probe vehicles (AVLs) are driven.

- *Benefit Cost Analysis.* Based on the mesoscopic analysis conducted, what is the cost-benefit differential between using instrumentation to capture path flows versus using assignment models? Obtain current costs for each sensor type from vendors, use these to estimate observation costs. Obtain costs of developing OD patterns from local planning agencies based on planner-hours expended and survey costs they incur to collect data.

Network Design. The other goal of this step of work is to create and test the upper level sensor placement optimizations based on the simple networks for application to a portfolio of random network designs in the following step. For example, the following three questions are of interest:

- *Where do you place one detector in a network to maximize observability?*
- *Where do you place a second detector in a network to maximize additional observability?*
- *Where do you move both detectors in a network to further increase observability?*

In other words, where do you place sensors to move the operating point the furthest toward Direct Observation and away from Inference? These three questions help show that this is a combinatorial optimization problem with the solutions to the three problems often being quite different from one another. In the realm of facility location, this has been constructed as a p-median problem while in the realm of sensors it has been constructed as an edge-covering problem; both will be examined for applicability.

6.2.2 Validation & Robustness of Technique

To expand the usefulness of the math program, it is crucial to validate it and explore its limits to gauge the robustness of it. To pursue that goal, it is proposed to test the math program on general networks, such as the Irvine, California test bed that is widely used for simulation analyses and OD estimation technique testing because of the data set's richness. Depending

on the timing of the experiment, AVL and AVI data may also be soon available for the RPI test bed in Upstate New York.

6.2.3 More Complex Networks

Future work could also include examination of these and other issues with respect to discerning path flows.

- arc restrictions
- the addition of congestion and incidents
- different sensor attribute bundles
- other constraints (budgetary in time to solve and money, limited information, detectors in preset locations)
- time – how path flows change over time

6.2.4 Discovering Paths within a Compromised Network

Finally, it is important to determine how well paths can be discerned if the original network is somehow compromised. Consider the following situation:

- What if emergency response personnel poorly predict traffic flows?
  - Additional time may be required to reach an incident.
  - More or less personnel may be needed to manage the incident clean-up.
  - Rerouting traffic around an incident and onto parallel routes may not be possible if the alternate route is already fully congested.

Such a situation highlights the need for research questions such as:

- *How well does the original sensor placement work?*
- *How much loss on the direct observation-inference curve is sustained?*

One reference to sort roadway links by significance is (Sohn 2006) which can aid in ensuring redundancy exists in the sensor structure. Siefu, Salon, and List also wrote a paper on creating redundancy in network structure (Siefu, Salon et al. 1989).

6.3 Wrap-Up

To sum up, this dissertation was presented to explore the relationship between observed data and inferred data as it impacts the discernment of path flows. The lower level of a bi-level math program was developed to determine path flows that occurred in a portfolio of small, random networks and offer the best sensor strategies.

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APPENDIX

8 APPENDIX A: MATH PROGRAM IN LINGO CODE

This LINGO v10 code runs inside of an extensive VBA code that swaps the appropriate variables into and out of the optimization program for the Monte Carlo simulation.

```
MODEL:
  ! Path Choice Model - All variables included - modelAll;
  ! Created 10/6/2006 by Alixandra Demers, edited by Dr. List on 11/12/2007;
SETS:
  objectives/1..5/: obj;
  onodes/1..10/;
  dnodes/1..10/;
  paths/1..12/: xphat, xptilda, xflag, pfr, pto, xpplus, xpminus;
  arcs/1..6/: vkhat, vktilda, mess2p, mess2n, vflag, vkplus, vkminus;
  oda/1..246/: yhat, ytilda, mess3p, mess3n, yflag, on, dn, an, yn, ynplus, ynminus;
  odpa/1..479/: oj, dj, pj, aj;
  od(onodes,dnodes): Dod, Dflag;

ENDSETS
min = objfcn;
  objfcn= @sum(objectives(k): obj(k));
  obj(1)= @sum( paths(j)| xflag(j) #EQ# 1: xpplus(j) + xpminus(j));
  obj(2)= @sum( arcs(a)| vflag(a) #EQ# 1: .0005*(vkplus(a) + vkminus(a)));
  obj(3)= @sum( oda(k)| yflag(k) #EQ# 1: ynplus(k) + ynminus(k));
  obj(4)= @sum( arcs(a): 10*(mess2p(a) + mess2n(a)));
  obj(5)= @sum( oda(k): 10*(mess3p(k) + mess3n(k)));

  @ for (paths(j)| xflag(j) #EQ# 1: xphat(j) + xpminus(j) - xpplus(j) = xptilda(j));
  @ for (arcs(k)| vflag(k) #EQ# 1: vkhat(k) + vkminus(k) - vkplus(k) = vktilda(k));
  @ for (oda(n)| yflag(n) #EQ# 1: yhat(n) + ynminus(n) - ynplus(n) = ytilda(n));

! Constraint1 - The path utilization coefficients must sum to 1 for each od pair;
  @for( od(o,d)| o #NE# d #AND# Dflag(o,d) #GT# 0: [PUCsum]
      @sum( paths(p) | (pfr #EQ# o) #AND# (pto #EQ# d): xphat(p)) = 1);

! Constraint2 - The link volumes must equal the PUCs times the OD demand;
  @for( arcs(a)| vflag(a) #EQ# 1: [linkvol2]
      @sum( odpa(j)| aj(j) #EQ# a: xphat(pj(j)) * Dod(oj(j),dj(j))) + mess2p(a) –
            mess2n(a) = vkhat(a));

! Constraint3 - For a particular link for a given od pair, the link utilization;
!               coefficients must equal the sum of PUCs crossing that link;
!               for that od pair;
  @for( oda(k)| yflag(k) #EQ# 1: [LUCsum]
      @sum( odpa(j) |(oj(j) #EQ# on(k)) #AND# (dj(j) #EQ# dn(k)) #AND# (aj(j) #EQ# an(k)):
```

```
            xphat(pj(j))) + mess3p(k) - mess3n(k) = yhat(k));

! Constraint4 - each link has a finite capacity (add later);
! Constraint5 - all variables (except mess vars) must have a lower bound of zero (add later);
DATA:
  Dod = @OLE( 'C:\Temp\GenNets10.xls','Dod');
  xptilda = @OLE( 'C:\Temp\GenNets10.xls','xptilda');
  ytilda = @OLE( 'C:\Temp\GenNets10.xls','ytilda');
  vktilda = @OLE( 'C:\Temp\GenNets10.xls','vktilda');
  Dflag = @OLE( 'C:\Temp\GenNets10.xls','Dflag');
  xflag = @OLE( 'C:\Temp\GenNets10.xls','xflag');
  yflag = @OLE( 'C:\Temp\GenNets10.xls','yflag');
  vflag = @OLE( 'C:\Temp\GenNets10.xls','vflag');
  on = @OLE( 'C:\Temp\GenNets10.xls',orign');
  dn = @OLE( 'C:\Temp\GenNets10.xls','dn');
  an = @OLE( 'C:\Temp\GenNets10.xls','an');
  oj = @OLE( 'C:\Temp\GenNets10.xls','oj');
  dj = @OLE( 'C:\Temp\GenNets10.xls','dj');
  pj = @OLE( 'C:\Temp\GenNets10.xls',pj');
  aj = @OLE( 'C:\Temp\GenNets10.xls','aj');
  pfr = @OLE( 'C:\Temp\GenNets10.xls',pfr');
  pto = @OLE( 'C:\Temp\GenNets10.xls',pto');
! Send results data to the spreadsheet;
  @OLE( 'C:\Temp\GenNets10.xls') = objfcn;
  @OLE( 'C:\Temp\GenNets10.xls') = vkhat;
  @OLE( 'C:\Temp\GenNets10.xls') = mess2p;
  @OLE( 'C:\Temp\GenNets10.xls') = mess2n;
  @OLE( 'C:\Temp\GenNets10.xls') = xphat;
  @OLE( 'C:\Temp\GenNets10.xls') = yhat;
  @OLE( 'C:\Temp\GenNets10.xls') = mess3p;
  @OLE( 'C:\Temp\GenNets10.xls') = mess3n;
  @OLE( 'C:\Temp\GenNets10.xls') = obj;
ENDDATA
END

TERSE
GO
QUIT
```

9 APPENDIX B: VBA CODE SUBROUTINE SUMMARY

To generate a series of networks, Visual Basic for Applications (VBA) code was written inside Microsoft Excel. A series of subroutines can be activated through command buttons to step through the procedure; this method was chosen so that each routine could run entirely independent of the others, thereby enabling an analyst to change any component for creating further variations without impacting the remainder of the code. The VBA code starts by creating a workbook with one worksheet per network. Then the remaining subroutines make passes through the workbook, adding data each time. A map of the subroutines is shown on the following page.

Steps in the Generate Networks code to create the networks:

- Generate Random Network Sizes
- Generate Node Set
- Generate Link Set
- Generate an Arc Set & Arc Flows
- Calculate Arc Costs (cst)
- Generate Path Set
- Calculate temp PUCs (xp) with logit (lambda = 0.01)
- Generate Path-Arc Map
- Renumber Paths so consecutive: pnum & pk
- Generate OD-Arc Map & Compute LUCs (yodk)
- Generate Target OD vector (zero vector to start)
- Run "calibrate" LINGO code to estimate OD flows ("true" Dod)
- Generate ODA & ODPA

Treatment Design 1

Experimental Units

- Generate sensor scenarios by randomly selecting (CV, % coverage) combos
- Generate sensor traffic vectors va1, xp1, yn1

Block Design

- Generate 25 Dod vectors treatments from 5 levels of Cv(noise) and 5 levels of % coverage blocks

Running the Model code to optimize the estimated path flows:

- Optimize
  Run Model 1

For models: D, Dx, Dy, Dxy [no vxy, x only, y only]

- Calc vhat for models omitting this estimate

For models: D, Dv, Dx, Dvx [no vxy, v only, x only, no y]

- Calc yhat for models omitting this estimate

Analyzing the results: Calculating ANOVAs and performance measures.

- Summarize Objective Function Values
- Create Net# sheets for output
- Calculate SAEs for D, v, x, & y
- Calculate CVs, avg, var, skew, kurt, corr for D, v, x, & y
- Calculate RMSEs for D, v, x, & y
- Create RMSE Charts
- Calculate Path-related metrics
- **Calc All Metrics**

file in: X60Q20-b
file out: X60Q20-ba

10 APPENDIX C: SAMPLE DATA SET – NETWORK 4

This appendix includes one of the ten networks (Network 4) that were randomly generated using the VBA and LINGO codes presented in other appendices. The spreadsheet includes the "true", realized, and estimated data for the given network under the X100Q60 conditions.

TRUE DATA

NetNum = current network number	4
MaxNode = total # of nodes	10
MaxLink = total # of links (up to twice as many arcs)	18
ConnectRatio = MaxNode / MaxLink	0.555555556
MaxDist = maximum link distance	200
MaxOD = total # of OD pairs	100
KMax = K paths per OD pair	5
MaxOver = max dist path is longer than shortest path	50%
MaxPath = total # of paths for network	215
MaxPA = total # of path-arc incidences	526
MaxODA = total # of ODK triplets (k = arc #)	417
MaxArc = total # of arcs	36
AvgYodk = average of all yn values (avg ytilda)	0.444542462
PossibleODA = MaxOD x MaxArc	3600
MaxODPA = total # of non-zero quads	526
ObjAssign = objective fcn value	
Gap = diff btwn obs path cost and est path cost (gap)	
CapInv = req'd capacity investment (capinv)	
ObjCalibrate = objective fcn value	11733927.17

NNum	x	y	NUsed
1	97	54	1
2	98	8	1
3	24	14	1
4	65	33	1
5	83	85	1
6	90	9	1
7	48	26	1
8	20	55	1
9	43	77	1
10	81	11	1

Alixandra Demers:
The above list of variables and their values are the lengths of the dynamic ranges (columns C to AB) in the VBA code.

Alixandra Demers:
this is allowable paths NOT possible paths. So some paths may be excluded b/c they are unreasonable.

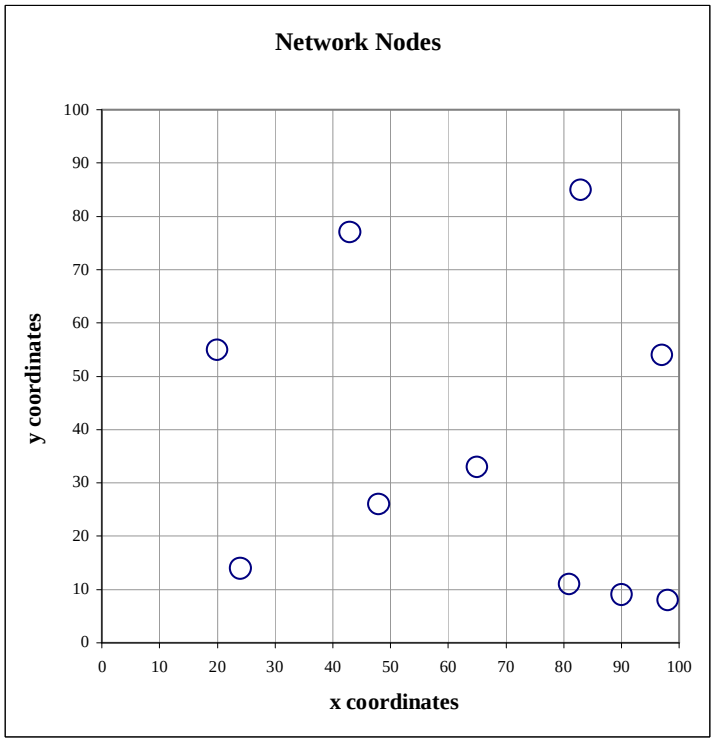
Experimental Design 1 (develops v1, x1, y1)

Number of arc volume sensors (SensVnum)	0
Number of path sensors or AVL (SensXnum)	215
Number of arc utilization sensors or AVI (SensYnum)	0
Quality of arc volume sensors (SensVqual)	0
Quality of path sensors (SensXqual)	60
Quality of arc utilization sensors (SensYqual)	0

Model Results

objfcn	obj1	obj2	obj3	obj4	obj5
19.23888015	19.239	0	0	0	0
3.28602985	3.286	0	0	0	0
3.78025497	3.7803	0	0	0	0
4.825431873	4.8254	0	0	0	0
4.506064382	4.5061	0	0	0	0
3.700756834	3.7008	0	0	0	0
6.840471794	6.8405	0	0	0	0
7.456333479	7.4563	0	0	0	0
7.954435057	7.9544	0	0	0	0
6.556312767	6.5563	0	0	0	0
6.713151268	6.7132	0	0	0	0
9.731513717	9.7315	0	0	0	0
9.956212317	9.9562	0	0	0	0
10.38931452	10.389	0	0	0	0
11.04892551	11.049	0	0	0	0
10.33363031	10.334	0	0	0	0
15.56120901	15.561	0	0	0	0
14.36612474	14.366	0	0	0	0
16.8357688	16.836	0	0	0	0
17.06657025	17.067	0	0	0	0
14.67795188	14.678	0	0	0	0
19.23888015	19.239	0	0	0	0
19.23888015	19.239	0	0	0	0
19.23888015	19.239	0	0	0	0
19.23888015	19.239	0	0	0	0
19.23888015	19.239	0	0	0	0

LNum	TailN	HeadN	deltax	deltay	LDist	LinkUsed
1	10	6	-9	2	9	TRUE
2	8	6	-70	46	83	TRUE
3	8	3	-4	41	41	TRUE
4	7	6	-42	17	45	TRUE
5	9	6	-47	68	82	TRUE
6	6	1	-7	-45	45	TRUE
7	9	4	-22	44	49	TRUE
8	9	2	-55	69	88	TRUE
9	5	2	-15	77	78	TRUE
10	2	1	1	-46	46	TRUE
11	9	7	-5	51	51	TRUE
12	8	7	-28	29	40	TRUE
13	10	3	57	-3	57	TRUE
14	3	2	-74	6	74	TRUE
15	5	1	-14	31	34	TRUE
16	6	4	25	-24	34	TRUE
17	6	5	7	-76	76	TRUE
18	10	4	16	-22	27	TRUE



ANum	TailN	HeadN	ADist	cv	ca	cap	va	cst	ve
1	10	6	9	1	10	2000	373	4.75	373
2	8	6	83	1	10	2000	1900	20.76	1338.83
3	8	3	41	1	10	2000	1765	18.99	1765
4	7	6	45	1	10	2000	1325	14.63	1342.09
5	9	6	82	1	10	2000	113	2.88	629.641
6	6	1	45	1	10	2000	625	7.63	804.477
7	9	4	49	1	10	2000	1368	15.1	812.317
8	9	2	88	1	10	2000	940	11.21	940
9	5	2	78	1	10	2000	1267	14.38	1361.75
10	2	1	46	1	10	2000	286	4.25	753.665
11	9	7	51	1	10	2000	105	2.49	105
12	8	7	40	1	10	2000	1125	12.58	1125
13	10	3	57	1	10	2000	1190	13.4	1190
14	3	2	74	1	10	2000	517	6.84	517
15	5	1	34	1	10	2000	1214	13.41	680.193
16	6	4	34	1	10	2000	1402	15.29	1458.37
17	6	5	76	1	10	2000	1683	18.52	501.743
18	10	4	27	1	10	2000	1317	14.37	1292.52
19	6	10	9	1	10	2000	613	7.15	1124.71
20	6	8	83	1	10	2000	925	11.01	371.591
21	3	8	41	1	10	2000	354	4.88	354
22	6	7	45	1	10	2000	296	4.34	384.673
23	6	9	82	1	10	2000	470	6.45	1536.25
24	1	6	45	1	10	2000	1273	14.11	731.108
25	4	9	49	1	10	2000	1508	16.5	323.329
26	2	9	88	1	10	2000	1758	19.39	479.318
27	2	5	78	1	10	2000	1008	11.79	102.755
28	1	2	46	1	10	2000	1458	15.97	465.609
29	7	9	51	1	10	2000	1431	15.75	896.57
30	7	8	40	1	10	2000	188	3.21	633.915
31	3	10	57	1	10	2000	316	4.66	904.43
32	2	3	74	1	10	2000	412	5.79	450.9
33	1	5	34	1	10	2000	123	2.5	1029.72
34	4	6	34	1	10	2000	989	11.16	1120.65
35	5	6	76	1	10	2000	1516	16.85	1516
36	4	10	27	1	10	2000	1258	13.78	643.134

PathNo	PFr	PTo	K	cp	predp	xp	PathNo	PFr	PTo	K	cp	predp	xp
1	1	2	1	15.97	0	0.502	36	2	6	1	15.2	49	0.262
2	1	2	2	16.88	10	0.498	37	2	6	2	18.36	27	0.254
3	1	3	1	21.76	1	0.502	38	2	6	3	22.27	46	0.244
4	1	3	2	22.67	2	0.498	39	2	6	4	23.6	34	0.241
5	1	4	1	29.4	11	0.212	40	2	7	1	19.54	36	0.206
6	1	4	2	34.64	12	0.201	41	2	7	2	21.88	46	0.201
7	1	4	3	35.63	23	0.199	42	2	7	3	22.7	37	0.199
8	1	4	4	35.66	21	0.199	43	2	7	4	23.25	45	0.198
9	1	4	5	40.79	24	0.189	44	2	7	5	24.14	47	0.196
10	1	5	1	2.5	0	1	45	2	8	1	10.67	28	1
11	1	6	1	14.11	0	0.513	46	2	9	1	19.39	0	0.342
12	1	6	2	19.35	10	0.487	47	2	9	2	21.65	36	0.334
13	1	7	1	18.45	11	0.344	48	2	9	3	24.81	37	0.324
14	1	7	2	23.05	21	0.329	49	2	10	1	10.45	28	1
15	1	7	3	23.69	12	0.327	50	3	1	1	11.09	51	1
16	1	8	1	21.66	13	0.207	51	3	2	1	6.84	0	1
17	1	8	2	25.12	11	0.2	52	3	4	1	19.03	64	0.514
18	1	8	3	26.26	14	0.198	53	3	4	2	24.7	57	0.486
19	1	8	4	26.64	3	0.197	54	3	5	1	13.59	50	0.355
20	1	8	5	26.9	15	0.197	55	3	5	2	18.63	51	0.338
21	1	9	1	20.56	11	0.513	56	3	5	3	27.93	57	0.308
22	1	9	2	25.8	12	0.487	57	3	6	1	9.41	64	1
23	1	10	1	21.26	11	0.26	58	3	7	1	13.75	57	0.343
24	1	10	2	26.42	3	0.247	59	3	7	2	17.46	61	0.33
25	1	10	3	26.5	12	0.247	60	3	7	3	18.35	62	0.327
26	1	10	4	27.33	4	0.245	61	3	8	1	4.88	0	1
27	2	1	1	4.25	0	1	62	3	9	1	15.86	57	0.526
28	2	3	1	5.79	0	1	63	3	9	2	26.23	51	0.474
29	2	4	1	24.82	49	0.215	64	3	10	1	4.66	0	1
30	2	4	2	30.49	36	0.203	65	4	1	1	18.79	78	1
31	2	4	3	33.65	37	0.197	66	4	2	1	27.71	86	0.209
32	2	4	4	34.49	46	0.195	67	4	2	2	28.82	87	0.207
33	2	4	5	36.75	47	0.191	68	4	2	3	34.02	71	0.196
34	2	5	1	6.75	27	0.513	69	4	2	4	34.76	65	0.195
35	2	5	2	11.79	0	0.487	70	4	2	5	35.67	76	0.193

PathNo	PFr	PTo	K	cp	predp	xp	PathNo	PFr	PTo	K	cp	predp	xp
71	4	3	1	27.18	88	0.212	106	5	9	2	33.77	92	0.474
72	4	3	2	31.71	89	0.202	107	5	10	1	24	98	0.502
73	4	3	3	33.5	66	0.199	108	5	10	2	24.83	93	0.498
74	4	3	4	34.61	67	0.197	109	6	1	1	7.63	0	1
75	4	3	5	37.7	82	0.191	110	6	2	1	17.66	126	0.348
76	4	5	1	21.29	65	0.521	111	6	2	2	23.6	109	0.328
77	4	5	2	29.68	78	0.479	112	6	2	3	24.51	121	0.325
78	4	6	1	11.16	0	1	113	6	3	1	20.55	127	0.211
79	4	7	1	15.5	78	0.342	114	6	3	2	23.45	110	0.205
80	4	7	2	18.99	86	0.331	115	6	3	3	26.54	124	0.199
81	4	7	3	20.1	87	0.327	116	6	3	4	29.39	111	0.193
82	4	8	1	18.71	79	0.257	117	6	3	5	30	125	0.192
83	4	8	2	22.17	78	0.249	118	6	4	1	15.29	0	0.347
84	4	8	3	22.2	80	0.248	119	6	4	2	21.52	127	0.326
85	4	8	4	23.31	81	0.246	120	6	4	3	21.55	126	0.326
86	4	9	1	16.5	0	0.503	121	6	5	1	10.13	109	0.521
87	4	9	2	17.61	78	0.497	122	6	5	2	18.52	0	0.479
88	4	10	1	13.78	0	0.511	123	6	7	1	4.34	0	1
89	4	10	2	18.31	78	0.489	124	6	8	1	7.55	123	0.509
90	5	1	1	13.41	0	0.513	125	6	8	2	11.01	0	0.491
91	5	1	2	18.63	92	0.487	126	6	9	1	6.45	0	1
92	5	2	1	14.38	0	1	127	6	10	1	7.15	0	1
93	5	3	1	20.17	92	1	128	7	1	1	22.26	149	0.265
94	5	4	1	32.14	98	0.262	129	7	1	2	26.26	150	0.255
95	5	4	2	38.37	107	0.247	130	7	1	3	31.21	132	0.242
96	5	4	3	38.4	105	0.246	131	7	1	4	33.29	133	0.238
97	5	4	4	39.2	108	0.245	132	7	2	1	26.96	152	0.212
98	5	6	1	16.85	0	1	133	7	2	2	29.04	137	0.208
99	5	7	1	21.19	98	0.511	134	7	2	3	32.29	153	0.201
100	5	7	2	25.79	105	0.489	135	7	2	4	38.23	128	0.19
101	5	8	1	24.4	99	0.255	136	7	2	5	39.14	144	0.188
102	5	8	2	25.05	93	0.254	137	7	3	1	22.2	151	0.526
103	5	8	3	27.86	98	0.247	138	7	3	2	32.75	132	0.474
104	5	8	4	29	100	0.244	139	7	4	1	29.92	149	0.207
105	5	9	1	23.3	98	0.526	140	7	4	2	30.85	152	0.205

PathNo	PFr	PTo	K	cp	predp	xp	PathNo	PFr	PTo	K	cp	predp	xp
							176	8	6	3	28.4	182	0.323
							177	8	7	1	12.58	0	1
							178	8	9	1	27.21	174	0.26
							179	8	9	2	28.33	177	0.257
							180	8	9	3	33.66	175	0.243
141	7	4	3	33.92	150	0.199	181	8	9	4	34.85	176	0.24
142	7	4	4	36.15	154	0.195	182	8	10	1	23.65	163	0.35
143	7	4	5	36.18	153	0.194	183	8	10	2	27.91	174	0.335
144	7	5	1	24.76	128	0.213	184	8	10	3	34.36	175	0.314
145	7	5	2	28.76	129	0.205	185	9	1	1	10.51	196	0.512
146	7	5	3	33.15	149	0.196	186	9	1	2	15.46	187	0.488
147	7	5	4	33.71	130	0.195	187	9	2	1	11.21	0	1
148	7	5	5	35.79	131	0.191	188	9	3	1	17	187	0.349
149	7	6	1	14.63	0	0.51	189	9	3	2	23.43	199	0.327
150	7	6	2	18.63	152	0.49	190	9	3	3	24.69	198	0.323
151	7	8	1	3.21	0	1	191	9	4	1	15.1	0	0.508
152	7	9	1	15.75	0	0.513	192	9	4	2	18.17	196	0.492
153	7	9	2	21.08	149	0.487	193	9	5	1	13.01	185	0.348
154	7	10	1	21.78	149	0.343	194	9	5	2	17.96	186	0.331
155	7	10	2	25.78	150	0.33	195	9	5	3	21.4	196	0.32
156	7	10	3	26.86	137	0.326	196	9	6	1	2.88	0	1
157	8	1	1	28.39	174	0.26	197	9	7	1	2.49	0	1
158	8	1	2	30.08	161	0.256	198	9	8	1	5.7	197	1
159	8	1	3	34.84	175	0.244	199	9	10	1	10.03	196	1
160	8	1	4	36.03	176	0.241	200	10	1	1	12.38	210	1
161	8	2	1	25.83	163	0.531	201	10	2	1	20.24	205	0.262
162	8	2	2	38.42	178	0.469	202	10	2	2	22.41	215	0.257
163	8	3	1	18.99	0	1	203	10	2	3	28.35	200	0.242
164	8	4	1	36.05	174	0.208	204	10	2	4	29.26	208	0.24
165	8	4	2	38.02	182	0.204	205	10	3	1	13.4	0	1
166	8	4	3	42.28	183	0.196	206	10	4	1	14.37	0	0.514
167	8	4	4	42.31	178	0.196	207	10	4	2	20.04	210	0.486
168	8	4	5	42.5	175	0.195	208	10	5	1	14.88	200	0.521
169	8	5	1	30.89	157	0.209	209	10	5	2	23.27	210	0.479
170	8	5	2	32.58	158	0.206	210	10	6	1	4.75	0	1
171	8	5	3	37.34	159	0.196	211	10	7	1	9.09	210	1
172	8	5	4	37.62	161	0.196	212	10	8	1	12.3	211	0.344
173	8	5	5	38.53	160	0.194	213	10	8	2	15.76	210	0.332
174	8	6	1	20.76	0	0.349	214	10	8	3	18.28	205	0.324
175	8	6	2	27.21	177	0.327	215	10	9	1	11.2	210	1

pk	ak	pk	ak	pk	ak	pk	ak	pk	ak	pk	ak
1	28	16	30	29	18	41	26	55	27	69	34
2	9	16	22	29	31	42	22	55	14	70	9
2	33	16	24	29	32	42	24	56	17	70	33
3	32	17	20	30	16	42	10	56	1	70	6
3	28	17	24	30	1	43	12	56	31	70	34
4	32	18	30	30	31	43	21	57	1	71	13
4	9	18	11	30	32	43	32	57	31	71	36
4	33	18	23	31	16	44	11	58	22	72	13
5	16	18	24	31	24	44	23	58	1	72	19
5	24	19	21	31	10	44	1	58	31	72	34
6	16	19	32	32	7	44	31	59	12	73	32
6	35	19	28	32	26	44	32	59	21	73	8
6	33	20	30	33	7	45	21	60	11	73	25
7	18	20	22	33	23	45	32	60	23	74	32
7	19	20	35	33	1	46	26	60	1	74	8
7	24	20	33	33	31	47	23	60	31	74	23
8	7	21	23	33	32	47	1	61	21	74	34
8	23	21	24	34	33	47	31	62	23	75	3
8	24	22	23	34	10	47	32	62	1	75	30
9	18	22	35	35	27	48	23	62	31	75	22
9	31	22	33	36	1	48	24	63	26	75	34
9	32	23	19	36	31	48	10	63	14	76	33
9	28	23	24	36	32	49	31	64	31	76	6
10	33	24	31	37	24	49	32	65	6	76	34
11	24	24	32	37	10	50	10	65	34	77	17
12	35	24	28	38	5	50	14	66	8	77	34
12	33	25	19	38	26	51	14	66	25	78	34
13	22	25	35	39	35	52	18	67	8	79	22
13	24	25	33	39	33	52	31	67	23	79	34
14	11	26	31	39	10	53	16	67	34	80	11
14	23	26	32	40	22	53	1	68	14	80	25
14	24	26	9	40	1	53	31	68	13	81	11
15	22	26	33	40	31	54	33	68	36	81	23
15	35	27	10	40	32	54	10	69	28	81	34
15	33	28	32	41	11	54	14	69	6	82	30

pk	ak	pk	ak	pk	ak	pk	ak	pk	ak	pk	ak
82	22	98	35	113	13	131	10	143	23	157	6
82	34	99	22	113	19	131	14	143	4	157	2
83	20	99	35	114	32	131	3	144	33	158	10
83	34	100	11	114	8	131	30	144	6	158	14
84	30	100	23	114	23	132	8	144	4	158	3
84	11	100	35	115	3	132	29	145	33	159	6
84	25	101	30	115	30	133	14	145	6	159	4
85	30	101	22	115	22	133	3	145	5	159	12
85	11	101	35	116	32	133	30	145	29	160	6
85	23	102	21	116	28	134	8	146	17	160	1
85	34	102	32	116	6	134	23	146	4	160	31
86	25	102	9	117	3	134	4	147	33	160	3
87	23	103	20	117	20	135	28	147	10	161	14
87	34	103	35	118	16	135	6	147	8	161	3
88	36	104	30	119	18	135	4	147	29	162	8
89	19	104	11	119	19	136	9	148	33	162	23
89	34	104	23	120	7	136	33	148	10	162	2
90	15	104	35	120	23	136	6	148	14	163	3
91	10	105	23	121	33	136	4	148	3	164	16
91	9	105	35	121	6	137	3	148	30	164	2
92	9	106	26	122	17	137	30	149	4	165	18
93	32	106	9	123	22	138	32	150	5	165	31
93	9	107	19	124	30	138	8	150	29	165	3
94	16	107	35	124	22	138	29	151	30	166	18
94	35	108	31	125	20	139	16	152	29	166	19
95	18	108	32	126	23	139	4	153	23	166	2
95	19	108	9	127	19	140	7	153	4	167	7
95	35	109	6	128	6	140	29	154	19	167	23
96	7	110	8	128	4	141	16	154	4	167	2
96	23	110	23	129	6	141	5	155	19	168	16
96	35	111	28	129	5	141	29	155	5	168	4
97	18	111	6	129	29	142	18	155	29	168	12
97	31	112	9	130	10	142	19	156	31	169	33
97	32	112	33	130	8	142	4	156	3	169	6
97	9	112	6	130	29	143	7	156	30	169	2

pk	ak	pk	ak	pk	ak	pk	ak
170	33	182	3	199	5	215	1
170	10	183	19	200	6		
170	14	183	2	200	1		
170	3	184	19	201	14		
171	33	184	4	201	13		
171	6	184	12	202	8		
171	4	185	6	202	23		
171	12	185	5	202	1		
172	27	186	10	203	28		
172	14	186	8	203	6		
172	3	187	8	203	1		
173	33	188	32	204	9		
173	6	188	8	204	33		
173	1	189	13	204	6		
173	31	189	19	204	1		
173	3	189	5	205	13		
174	2	190	3	206	18		
175	4	190	30	207	16		
175	12	190	11	207	1		
176	1	191	7	208	33		
176	31	192	16	208	6		
176	3	192	5	208	1		
177	12	193	33	209	17		
178	23	193	6	209	1		
178	2	193	5	210	1		
179	29	194	33	211	22		
179	12	194	10	211	1		
180	23	194	8	212	30		
180	4	195	17	212	22		
180	12	195	5	212	1		
181	23	196	5	213	20		
181	1	197	11	213	1		
181	31	198	30	214	21		
181	3	198	11	214	13		
182	31	199	19	215	23		

odnum	Orig	Dest	TgtVod	EstVod	odnum	Orig	Dest	TgtVod	EstVod
1	1	1	0	0	36	4	6	0	0
2	1	2	0	115.18	37	4	7	0	0
3	1	3	0	0	38	4	8	0	0
4	1	4	0	1198.71	39	4	9	0	256.484
5	1	5	0	0	40	4	10	0	900.889
6	1	6	0	0	41	5	1	0	1325.79
7	1	7	0	0	42	5	2	0	0
8	1	8	0	0	43	5	3	0	0
9	1	9	0	0	44	5	4	0	0
10	1	10	0	0	45	5	5	0	0
11	2	1	0	0	46	5	6	0	742.788
12	2	2	0	0	47	5	7	0	0
13	2	3	0	0	48	5	8	0	0
14	2	4	0	0	49	5	9	0	1011.54
15	2	5	0	0	50	5	10	0	0
16	2	6	0	0	51	6	1	0	0
17	2	7	0	0	52	6	2	0	0
18	2	8	0	0	53	6	3	0	0
19	2	9	0	0	54	6	4	0	0
20	2	10	0	0	55	6	5	0	775.321
21	3	1	0	0	56	6	6	0	0
22	3	2	0	123.69	57	6	7	0	0
23	3	3	0	0	58	6	8	0	756.265
24	3	4	0	0	59	6	9	0	0
25	3	5	0	304.451	60	6	10	0	0
26	3	6	0	0	61	7	1	0	0
27	3	7	0	0	62	7	2	0	0
28	3	8	0	354	63	7	3	0	473.528
29	3	9	0	0	64	7	4	0	412.93
30	3	10	0	0	65	7	5	0	0
31	4	1	0	0	66	7	6	0	1031.54
32	4	2	0	929.738	67	7	7	0	0
33	4	3	0	0	68	7	8	0	0
34	4	4	0	0	69	7	9	0	0
35	4	5	0	0	70	7	10	0	0

odnum	Orig	Dest	TgtVod	EstVod
71	8	1	0	0
72	8	2	0	0
73	8	3	0	931.571
74	8	4	0	1866.15
75	8	5	0	0
76	8	6	0	626.764
77	8	7	0	555.097
78	8	8	0	0
79	8	9	0	0
80	8	10	0	0
81	9	1	0	0
82	9	2	0	329.11
83	9	3	0	0
84	9	4	0	85.4121
85	9	5	0	0
86	9	6	0	0
87	9	7	0	105
88	9	8	0	0
89	9	9	0	0
90	9	10	0	0
91	10	1	0	0
92	10	2	0	0
93	10	3	0	1007.51
94	10	4	0	0
95	10	5	0	76.6237
96	10	6	0	0
97	10	7	0	0
98	10	8	0	0
99	10	9	0	0
100	10	10	0	0

onr	dnr	anr	ynr	onr	dnr	anr	ynr	onr	dnr	anr	ynr
1	2	28	0.5	1	8	30	0.6	2	4	18	0.21
1	2	9	0.5	1	8	22	0.4	2	4	31	0.61
1	2	33	0.5	1	8	24	0.61	2	4	32	0.61
1	3	32	1	1	8	20	0.2	2	4	16	0.4
1	3	28	0.5	1	8	24	0.61	2	4	1	0.39
1	3	32	1	1	8	30	0.6	2	4	31	0.61
1	3	9	0.5	1	8	11	0.2	2	4	32	0.61
1	3	33	0.5	1	8	23	0.2	2	4	16	0.4
1	4	16	0.41	1	8	24	0.61	2	4	24	0.2
1	4	24	0.61	1	8	21	0.2	2	4	10	0.2
1	4	16	0.41	1	8	32	0.2	2	4	7	0.39
1	4	35	0.2	1	8	28	0.2	2	4	26	0.19
1	4	33	0.2	1	8	30	0.6	2	4	7	0.39
1	4	18	0.39	1	8	22	0.4	2	4	23	0.19
1	4	19	0.2	1	8	35	0.2	2	4	1	0.39
1	4	24	0.61	1	8	33	0.2	2	4	31	0.61
1	4	7	0.2	1	9	23	1	2	4	32	0.61
1	4	23	0.2	1	9	24	0.51	2	5	33	0.51
1	4	24	0.61	1	9	23	1	2	5	10	0.51
1	4	18	0.39	1	9	35	0.49	2	5	27	0.49
1	4	31	0.19	1	9	33	0.49	2	6	1	0.26
1	4	32	0.19	1	10	19	0.51	2	6	31	0.26
1	4	28	0.19	1	10	24	0.26	2	6	32	0.26
1	5	33	1	1	10	31	0.49	2	6	24	0.25
1	6	24	0.51	1	10	32	0.49	2	6	10	0.49
1	6	35	0.49	1	10	28	0.25	2	6	5	0.24
1	6	33	0.49	1	10	19	0.51	2	6	26	0.24
1	7	22	0.67	1	10	35	0.25	2	6	35	0.24
1	7	24	0.67	1	10	33	0.49	2	6	33	0.24
1	7	11	0.33	1	10	31	0.49	2	6	10	0.49
1	7	23	0.33	1	10	32	0.49	2	7	22	0.4
1	7	24	0.67	1	10	9	0.25	2	7	1	0.4
1	7	22	0.67	1	10	33	0.49	2	7	31	0.4
1	7	35	0.33	2	1	10	1	2	7	32	0.6
1	7	33	0.33	2	3	32	1	2	7	11	0.4

onr	dnr	anr	ynr	onr	dnr	anr	ynr	onr	dnr	anr	ynr
2	7	26	0.2	3	5	27	0.34	4	2	34	0.59
2	7	22	0.4	3	5	14	0.69	4	2	9	0.19
2	7	24	0.2	3	5	17	0.31	4	2	33	0.19
2	7	10	0.2	3	5	1	0.31	4	2	6	0.39
2	7	12	0.2	3	5	31	0.31	4	2	34	0.59
2	7	21	0.2	3	6	1	1	4	3	13	0.41
2	7	32	0.6	3	6	31	1	4	3	36	0.21
2	7	11	0.4	3	7	22	0.34	4	3	13	0.41
2	7	23	0.2	3	7	1	0.67	4	3	19	0.2
2	7	1	0.4	3	7	31	0.67	4	3	34	0.59
2	7	31	0.4	3	7	12	0.33	4	3	32	0.4
2	7	32	0.6	3	7	21	0.33	4	3	8	0.4
2	8	21	1	3	7	11	0.33	4	3	25	0.2
2	8	32	1	3	7	23	0.33	4	3	32	0.4
2	9	26	0.34	3	7	1	0.67	4	3	8	0.4
2	9	23	0.66	3	7	31	0.67	4	3	23	0.2
2	9	1	0.33	3	8	21	1	4	3	34	0.59
2	9	31	0.33	3	9	23	0.53	4	3	3	0.19
2	9	32	0.33	3	9	1	0.53	4	3	30	0.19
2	9	23	0.66	3	9	31	0.53	4	3	22	0.19
2	9	24	0.32	3	9	26	0.47	4	3	34	0.59
2	9	10	0.32	3	9	14	0.47	4	5	33	0.52
2	10	31	1	3	10	31	1	4	5	6	0.52
2	10	32	1	4	1	6	1	4	5	34	1
3	1	10	1	4	1	34	1	4	5	17	0.48
3	1	14	1	4	2	8	0.42	4	5	34	1
3	2	14	1	4	2	25	0.21	4	6	34	1
3	4	18	0.51	4	2	8	0.42	4	7	22	0.34
3	4	31	1	4	2	23	0.21	4	7	34	0.67
3	4	16	0.49	4	2	34	0.59	4	7	11	0.66
3	4	1	0.49	4	2	14	0.2	4	7	25	0.33
3	4	31	1	4	2	13	0.2	4	7	11	0.66
3	5	33	0.35	4	2	36	0.2	4	7	23	0.33
3	5	10	0.35	4	2	28	0.19	4	7	34	0.67
3	5	14	0.69	4	2	6	0.39	4	8	30	0.75

onr	dnr	anr	ynr
4	8	22	0.26
4	8	34	0.75
4	8	20	0.25
4	8	34	0.75
4	8	30	0.75
4	8	11	0.49
4	8	25	0.25
4	8	30	0.75
4	8	11	0.49
4	8	23	0.25
4	8	34	0.75
4	9	25	0.5
4	9	23	0.5
4	9	34	0.5
4	10	36	0.51
4	10	19	0.49
4	10	34	0.49
5	1	15	0.51
5	1	10	0.49
5	1	9	0.49
5	2	9	1
5	3	32	1
5	3	9	1
5	4	16	0.26
5	4	35	0.76
5	4	18	0.49
5	4	19	0.25
5	4	35	0.76
5	4	7	0.25
5	4	23	0.25
5	4	35	0.76
5	4	18	0.49
5	4	31	0.24
5	4	32	0.24
5	4	9	0.24
5	6	35	1
5	7	22	0.51
5	7	35	1
5	7	11	0.49
5	7	23	0.49
5	7	35	1
5	8	30	0.5
5	8	22	0.26
5	8	35	0.75
5	8	21	0.25
5	8	32	0.25
5	8	9	0.25
5	8	20	0.25
5	8	35	0.75
5	8	30	0.5
5	8	11	0.24
5	8	23	0.24
5	8	35	0.75
5	9	23	0.53
5	9	35	0.53
5	9	26	0.47
5	9	9	0.47
5	10	19	0.5
5	10	35	0.5
5	10	31	0.5
5	10	32	0.5
5	10	9	0.5
6	1	6	1
6	2	8	0.35
6	2	23	0.35
6	2	28	0.33
6	2	6	0.65
6	2	9	0.32
6	2	33	0.32
6	2	6	0.65
6	3	13	0.21
6	3	19	0.21
6	3	32	0.4
6	3	8	0.21
6	3	23	0.21
6	3	3	0.39
6	3	30	0.2
6	3	22	0.2
6	3	32	0.4
6	3	28	0.19
6	3	6	0.19
6	3	3	0.39
6	3	20	0.19
6	4	16	0.35
6	4	18	0.33
6	4	19	0.33
6	4	7	0.33
6	4	23	0.33
6	5	33	0.52
6	5	6	0.52
6	5	17	0.48
6	7	22	1
6	8	30	0.51
6	8	22	0.51
6	8	20	0.49
6	9	23	1
6	10	19	1
7	1	6	0.52
7	1	4	0.27
7	1	6	0.52
7	1	5	0.25
7	1	29	0.5
7	1	10	0.48
7	1	8	0.24
7	1	29	0.5

onr	dnr	anr	ynr	onr	dnr	anr	ynr	onr	dnr	anr	ynr
7	1	10	0.48	7	4	23	0.19	8	1	6	0.74
7	1	14	0.24	7	4	4	0.6	8	1	2	0.26
7	1	3	0.24	7	5	33	0.8	8	1	10	0.26
7	1	30	0.24	7	5	6	0.42	8	1	14	0.26
7	2	8	0.41	7	5	4	0.41	8	1	3	0.5
7	2	29	0.21	7	5	33	0.8	8	1	6	0.74
7	2	14	0.21	7	5	6	0.42	8	1	4	0.24
7	2	3	0.21	7	5	5	0.2	8	1	12	0.24
7	2	30	0.21	7	5	29	0.4	8	1	6	0.74
7	2	8	0.41	7	5	17	0.2	8	1	1	0.24
7	2	23	0.2	7	5	4	0.41	8	1	31	0.24
7	2	4	0.58	7	5	33	0.8	8	1	3	0.5
7	2	28	0.19	7	5	10	0.39	8	2	14	0.53
7	2	6	0.38	7	5	8	0.19	8	2	3	0.53
7	2	4	0.58	7	5	29	0.4	8	2	8	0.47
7	2	9	0.19	7	5	33	0.8	8	2	23	0.47
7	2	33	0.19	7	5	10	0.39	8	2	2	0.47
7	2	6	0.38	7	5	14	0.19	8	3	3	1
7	2	4	0.58	7	5	3	0.19	8	4	16	0.4
7	3	3	0.53	7	5	30	0.19	8	4	2	0.6
7	3	30	0.53	7	6	4	0.51	8	4	18	0.4
7	3	32	0.47	7	6	5	0.49	8	4	31	0.2
7	3	8	0.47	7	6	29	0.49	8	4	3	0.2
7	3	29	0.47	7	8	30	1	8	4	18	0.4
7	4	16	0.41	7	9	29	0.51	8	4	19	0.2
7	4	4	0.6	7	9	23	0.49	8	4	2	0.6
7	4	7	0.4	7	9	4	0.49	8	4	7	0.2
7	4	29	0.4	7	10	19	0.67	8	4	23	0.2
7	4	16	0.41	7	10	4	0.34	8	4	2	0.6
7	4	5	0.2	7	10	19	0.67	8	4	16	0.4
7	4	29	0.4	7	10	5	0.33	8	4	4	0.2
7	4	18	0.19	7	10	29	0.33	8	4	12	0.2
7	4	19	0.19	7	10	31	0.33	8	5	33	0.8
7	4	4	0.6	7	10	3	0.33	8	5	6	0.6
7	4	7	0.4	7	10	30	0.33	8	5	2	0.21

onr	dnr	anr	ynr
8	5	33	0.8
8	5	10	0.21
8	5	14	0.4
8	5	3	0.59
8	5	33	0.8
8	5	6	0.6
8	5	4	0.2
8	5	12	0.2
8	5	27	0.2
8	5	14	0.4
8	5	3	0.59
8	5	33	0.8
8	5	6	0.6
8	5	1	0.19
8	5	31	0.19
8	5	3	0.59
8	6	2	0.35
8	6	4	0.33
8	6	12	0.33
8	6	1	0.32
8	6	31	0.32
8	6	3	0.32
8	7	12	1
8	9	23	0.74
8	9	2	0.26
8	9	29	0.26
8	9	12	0.5
8	9	23	0.74
8	9	4	0.24
8	9	12	0.5
8	9	23	0.74
8	9	1	0.24
8	9	31	0.24
8	9	3	0.24
8	10	31	0.35
8	10	3	0.35
8	10	19	0.65
8	10	2	0.34
8	10	19	0.65
8	10	4	0.31
8	10	12	0.31
9	1	6	0.51
9	1	5	0.51
9	1	10	0.49
9	1	8	0.49
9	2	8	1
9	3	32	0.35
9	3	8	0.35
9	3	13	0.33
9	3	19	0.33
9	3	5	0.33
9	3	3	0.32
9	3	30	0.32
9	3	11	0.32
9	4	7	0.51
9	4	16	0.49
9	4	5	0.49
9	5	33	0.68
9	5	6	0.35
9	5	5	0.67
9	5	33	0.68
9	5	10	0.33
9	5	8	0.33
9	5	17	0.32
9	5	5	0.67
9	6	5	1
9	7	11	1
9	8	30	1
9	8	11	1
9	10	19	1
9	10	5	1
10	1	6	1
10	1	1	1
10	2	14	0.26
10	2	13	0.26
10	2	8	0.26
10	2	23	0.26
10	2	1	0.74
10	2	28	0.24
10	2	6	0.48
10	2	1	0.74
10	2	9	0.24
10	2	33	0.24
10	2	6	0.48
10	2	1	0.74
10	3	13	1
10	4	18	0.51
10	4	16	0.49
10	4	1	0.49
10	5	33	0.52
10	5	6	0.52
10	5	1	1
10	5	17	0.48
10	5	1	1
10	6	1	1
10	7	22	1
10	7	1	1
10	8	30	0.34
10	8	22	0.34
10	8	1	0.68
10	8	20	0.33
10	8	1	0.68
10	8	21	0.32
10	8	13	0.32
10	9	23	1
10	9	1	1

odanum	on	dn	an	yn
1	1	2	28	0.5
2	1	2	9	0.5
3	1	2	33	0.5
4	1	3	32	1
5	1	3	28	0.5
6	1	3	9	0.5
7	1	3	33	0.5
8	1	4	16	0.41
9	1	4	24	0.61
10	1	4	35	0.2
11	1	4	33	0.2
12	1	4	18	0.39
13	1	4	19	0.2
14	1	4	7	0.2
15	1	4	23	0.2
16	1	4	31	0.19
17	1	4	32	0.19
18	1	4	28	0.19
19	1	5	33	1
20	1	6	24	0.51
21	1	6	35	0.49
22	1	6	33	0.49
23	1	7	22	0.67
24	1	7	24	0.67
25	1	7	11	0.33
26	1	7	23	0.33
27	1	7	35	0.33
28	1	7	33	0.33
29	1	8	30	0.6
30	1	8	22	0.4
31	1	8	24	0.61
32	1	8	20	0.2
33	1	8	11	0.2
34	1	8	23	0.2
35	1	8	21	0.2
36	1	8	32	0.2
37	1	8	28	0.2
38	1	8	35	0.2
39	1	8	33	0.2
40	1	9	23	1
41	1	9	24	0.51
42	1	9	35	0.49
43	1	9	33	0.49
44	1	10	19	0.51
45	1	10	24	0.26
46	1	10	31	0.49
47	1	10	32	0.49
48	1	10	28	0.25
49	1	10	35	0.25
50	1	10	33	0.49
51	1	10	9	0.25
52	2	1	10	1
53	2	3	32	1
54	2	4	18	0.21
55	2	4	31	0.61
56	2	4	32	0.61
57	2	4	16	0.4
58	2	4	1	0.39
59	2	4	24	0.2
60	2	4	10	0.2
61	2	4	7	0.39
62	2	4	26	0.19
63	2	4	23	0.19
64	2	5	33	0.51
65	2	5	10	0.51
66	2	5	27	0.49
67	2	6	1	0.26
68	2	6	31	0.26
69	2	6	32	0.26
70	2	6	24	0.25
71	2	6	10	0.49
72	2	6	5	0.24
73	2	6	26	0.24
74	2	6	35	0.24
75	2	6	33	0.24
76	2	7	22	0.4
77	2	7	1	0.4
78	2	7	31	0.4
79	2	7	32	0.6
80	2	7	11	0.4
81	2	7	26	0.2
82	2	7	24	0.2
83	2	7	10	0.2
84	2	7	12	0.2
85	2	7	21	0.2
86	2	7	23	0.2
87	2	8	21	1
88	2	8	32	1
89	2	9	26	0.34
90	2	9	23	0.66
91	2	9	1	0.33
92	2	9	31	0.33
93	2	9	32	0.33
94	2	9	24	0.32
95	2	9	10	0.32
96	2	10	31	1
97	2	10	32	1
98	3	1	10	1
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101	3	4	18	0.51
102	3	4	31	1
103	3	4	16	0.49
104	3	4	1	0.49
105	3	5	33	0.35
106	3	5	10	0.35
107	3	5	14	0.69
108	3	5	27	0.34
109	3	5	17	0.31
110	3	5	1	0.31
111	3	5	31	0.31
112	3	6	1	1
113	3	6	31	1
114	3	7	22	0.34
115	3	7	1	0.67
116	3	7	31	0.67
117	3	7	12	0.33
118	3	7	21	0.33
119	3	7	11	0.33
120	3	7	23	0.33

ɒdanum	on	dn	an	yn	ɒdanum	on	dn	an	yn	ɒdanum	on	dn	an	yn
121	3	8	21	1	161	4	7	23	0.33	201	5	8	20	0.25
122	3	9	23	0.53	162	4	8	30	0.75	202	5	8	11	0.24
123	3	9	1	0.53	163	4	8	22	0.26	203	5	8	23	0.24
124	3	9	31	0.53	164	4	8	34	0.75	204	5	9	23	0.53
125	3	9	26	0.47	165	4	8	20	0.25	205	5	9	35	0.53
126	3	9	14	0.47	166	4	8	11	0.49	206	5	9	26	0.47
127	3	10	31	1	167	4	8	25	0.25	207	5	9	9	0.47
128	4	1	6	1	168	4	8	23	0.25	208	5	10	19	0.5
129	4	1	34	1	169	4	9	25	0.5	209	5	10	35	0.5
130	4	2	8	0.42	170	4	9	23	0.5	210	5	10	31	0.5
131	4	2	25	0.21	171	4	9	34	0.5	211	5	10	32	0.5
132	4	2	23	0.21	172	4	10	36	0.51	212	5	10	9	0.5
133	4	2	34	0.59	173	4	10	19	0.49	213	6	1	6	1
134	4	2	14	0.2	174	4	10	34	0.49	214	6	2	8	0.35
135	4	2	13	0.2	175	5	1	15	0.51	215	6	2	23	0.35
136	4	2	36	0.2	176	5	1	10	0.49	216	6	2	28	0.33
137	4	2	28	0.19	177	5	1	9	0.49	217	6	2	6	0.65
138	4	2	6	0.39	178	5	2	9	1	218	6	2	9	0.32
139	4	2	9	0.19	179	5	3	32	1	219	6	2	33	0.32
140	4	2	33	0.19	180	5	3	9	1	220	6	3	13	0.21
141	4	3	13	0.41	181	5	4	16	0.26	221	6	3	19	0.21
142	4	3	36	0.21	182	5	4	35	0.76	222	6	3	32	0.4
143	4	3	19	0.2	183	5	4	18	0.49	223	6	3	8	0.21
144	4	3	34	0.59	184	5	4	19	0.25	224	6	3	23	0.21
145	4	3	32	0.4	185	5	4	7	0.25	225	6	3	3	0.39
146	4	3	8	0.4	186	5	4	23	0.25	226	6	3	30	0.2
147	4	3	25	0.2	187	5	4	31	0.24	227	6	3	22	0.2
148	4	3	23	0.2	188	5	4	32	0.24	228	6	3	28	0.19
149	4	3	3	0.19	189	5	4	9	0.24	229	6	3	6	0.19
150	4	3	30	0.19	190	5	6	35	1	230	6	3	20	0.19
151	4	3	22	0.19	191	5	7	22	0.51	231	6	4	16	0.35
152	4	5	33	0.52	192	5	7	35	1	232	6	4	18	0.33
153	4	5	6	0.52	193	5	7	11	0.49	233	6	4	19	0.33
154	4	5	34	1	194	5	7	23	0.49	234	6	4	7	0.33
155	4	5	17	0.48	195	5	8	30	0.5	235	6	4	23	0.33
156	4	6	34	1	196	5	8	22	0.26	236	6	5	33	0.52
157	4	7	22	0.34	197	5	8	35	0.75	237	6	5	6	0.52
158	4	7	34	0.67	198	5	8	21	0.25	238	6	5	17	0.48
159	4	7	11	0.66	199	5	8	32	0.25	239	6	7	22	1
160	4	7	25	0.33	200	5	8	9	0.25	240	6	8	30	0.51

odanum	on	dn	an	yn
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242	6	8	20	0.49
243	6	9	23	1
244	6	10	19	1
245	7	1	6	0.52
246	7	1	4	0.27
247	7	1	5	0.25
248	7	1	29	0.5
249	7	1	10	0.48
250	7	1	8	0.24
251	7	1	14	0.24
252	7	1	3	0.24
253	7	1	30	0.24
254	7	2	8	0.41
255	7	2	29	0.21
256	7	2	14	0.21
257	7	2	3	0.21
258	7	2	30	0.21
259	7	2	23	0.2
260	7	2	4	0.58
261	7	2	28	0.19
262	7	2	6	0.38
263	7	2	9	0.19
264	7	2	33	0.19
265	7	3	3	0.53
266	7	3	30	0.53
267	7	3	32	0.47
268	7	3	8	0.47
269	7	3	29	0.47
270	7	4	16	0.41
271	7	4	4	0.6
272	7	4	7	0.4
273	7	4	29	0.4
274	7	4	5	0.2
275	7	4	18	0.19
276	7	4	19	0.19
277	7	4	23	0.19
278	7	5	33	0.8
279	7	5	6	0.42
280	7	5	4	0.41
281	7	5	5	0.2
282	7	5	29	0.4
283	7	5	17	0.2
284	7	5	10	0.39
285	7	5	8	0.19
286	7	5	14	0.19
287	7	5	3	0.19
288	7	5	30	0.19
289	7	6	4	0.51
290	7	6	5	0.49
291	7	6	29	0.49
292	7	8	30	1
293	7	9	29	0.51
294	7	9	23	0.49
295	7	9	4	0.49
296	7	10	19	0.67
297	7	10	4	0.34
298	7	10	5	0.33
299	7	10	29	0.33
300	7	10	31	0.33
301	7	10	3	0.33
302	7	10	30	0.33
303	8	1	6	0.74
304	8	1	2	0.26
305	8	1	10	0.26
306	8	1	14	0.26
307	8	1	3	0.5
308	8	1	4	0.24
309	8	1	12	0.24
310	8	1	1	0.24
311	8	1	31	0.24
312	8	2	14	0.53
313	8	2	3	0.53
314	8	2	8	0.47
315	8	2	23	0.47
316	8	2	2	0.47
317	8	3	3	1
318	8	4	16	0.4
319	8	4	2	0.6
320	8	4	18	0.4
321	8	4	31	0.2
322	8	4	3	0.2
323	8	4	19	0.2
324	8	4	7	0.2
325	8	4	23	0.2
326	8	4	4	0.2
327	8	4	12	0.2
328	8	5	33	0.8
329	8	5	6	0.6
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331	8	5	10	0.21
332	8	5	14	0.4
333	8	5	3	0.59
334	8	5	4	0.2
335	8	5	12	0.2
336	8	5	27	0.2
337	8	5	1	0.19
338	8	5	31	0.19
339	8	6	2	0.35
340	8	6	4	0.33
341	8	6	12	0.33
342	8	6	1	0.32
343	8	6	31	0.32
344	8	6	3	0.32
345	8	7	12	1
346	8	9	23	0.74
347	8	9	2	0.26
348	8	9	29	0.26
349	8	9	12	0.5
350	8	9	4	0.24
351	8	9	1	0.24
352	8	9	31	0.24
353	8	9	3	0.24
354	8	10	31	0.35
355	8	10	3	0.35
356	8	10	19	0.65
357	8	10	2	0.34
358	8	10	4	0.31
359	8	10	12	0.31
360	9	1	6	0.51

ɔdanum	on	dn	an	yn
361	9	1	5	0.51
362	9	1	10	0.49
363	9	1	8	0.49
364	9	2	8	1
365	9	3	32	0.35
366	9	3	8	0.35
367	9	3	13	0.33
368	9	3	19	0.33
369	9	3	5	0.33
370	9	3	3	0.32
371	9	3	30	0.32
372	9	3	11	0.32
373	9	4	7	0.51
374	9	4	16	0.49
375	9	4	5	0.49
376	9	5	33	0.68
377	9	5	6	0.35
378	9	5	5	0.67
379	9	5	10	0.33
380	9	5	8	0.33
381	9	5	17	0.32
382	9	6	5	1
383	9	7	11	1
384	9	8	30	1
385	9	8	11	1
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387	9	10	5	1
388	10	1	6	1
389	10	1	1	1
390	10	2	14	0.26
391	10	2	13	0.26
392	10	2	8	0.26
393	10	2	23	0.26
394	10	2	1	0.74
395	10	2	28	0.24
396	10	2	6	0.48
397	10	2	9	0.24
398	10	2	33	0.24
399	10	3	13	1
400	10	4	18	0.51
401	10	4	16	0.49
402	10	4	1	0.49
403	10	5	33	0.52
404	10	5	6	0.52
405	10	5	1	1
406	10	5	17	0.48
407	10	6	1	1
408	10	7	22	1
409	10	7	1	1
410	10	8	30	0.34
411	10	8	22	0.34
412	10	8	1	0.68
413	10	8	20	0.33
414	10	8	21	0.32
415	10	8	13	0.32
416	10	9	23	1
417	10	9	1	1

oj	dj	pj	aj	oj	dj	pj	aj	oj	dj	pj	aj
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1	2	2	9	1	8	16	22	2	4	29	31
1	2	2	33	1	8	16	24	2	4	29	32
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oj	dj	pj	aj	oj	dj	pj	aj	oj	dj	pj	aj
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2	7	42	22	3	5	55	14	4	2	70	9
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oj	dj	pj	aj
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oj	dj	pj	aj
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6	2	111	28
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oj	dj	pj	aj
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6	3	113	19
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6	9	126	23
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7	1	129	29
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7	1	130	29

oj	dj	pj	aj	oj	dj	pj	aj	oj	dj	pj	aj
7	1	131	10	7	4	143	23	8	1	157	6
7	1	131	14	7	4	143	4	8	1	157	2
7	1	131	3	7	5	144	33	8	1	158	10
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7	2	132	8	7	5	144	4	8	1	158	3
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7	2	136	9	7	5	148	33	8	2	162	23
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7	4	142	18	7	10	155	29	8	4	168	12
7	4	142	19	7	10	156	31	8	5	169	33
7	4	142	4	7	10	156	3	8	5	169	6
7	4	143	7	7	10	156	30	8	5	169	2

oj	dj	pj	aj
8	5	170	33
8	5	170	10
8	5	170	14
8	5	170	3
8	5	171	33
8	5	171	6
8	5	171	4
8	5	171	12
8	5	172	27
8	5	172	14
8	5	172	3
8	5	173	33
8	5	173	6
8	5	173	1
8	5	173	31
8	5	173	3
8	6	174	2
8	6	175	4
8	6	175	12
8	6	176	1
8	6	176	31
8	6	176	3
8	7	177	12
8	9	178	23
8	9	178	2
8	9	179	29
8	9	179	12
8	9	180	23
8	9	180	4
8	9	180	12
8	9	181	23
8	9	181	1
8	9	181	31
8	9	181	3
8	10	182	31

oj	dj	pj	aj
8	10	182	3
8	10	183	19
8	10	183	2
8	10	184	19
8	10	184	4
8	10	184	12
9	1	185	6
9	1	185	5
9	1	186	10
9	1	186	8
9	2	187	8
9	3	188	32
9	3	188	8
9	3	189	13
9	3	189	19
9	3	189	5
9	3	190	3
9	3	190	30
9	3	190	11
9	4	191	7
9	4	192	16
9	4	192	5
9	5	193	33
9	5	193	6
9	5	193	5
9	5	194	33
9	5	194	10
9	5	194	8
9	5	195	17
9	5	195	5
9	6	196	5
9	7	197	11
9	8	198	30
9	8	198	11
9	10	199	19

oj	dj	pj	aj
9	10	199	5
10	1	200	6
10	1	200	1
10	2	201	14
10	2	201	13
10	2	202	8
10	2	202	23
10	2	202	1
10	2	203	28
10	2	203	6
10	2	203	1
10	2	204	9
10	2	204	33
10	2	204	6
10	2	204	1
10	3	205	13
10	4	206	18
10	4	207	16
10	4	207	1
10	5	208	33
10	5	208	6
10	5	208	1
10	5	209	17
10	5	209	1
10	6	210	1
10	7	211	22
10	7	211	1
10	8	212	30
10	8	212	22
10	8	212	1
10	8	213	20
10	8	213	1
10	8	214	21
10	8	214	13
10	9	215	23
10	9	215	1

REVEALED DATA

va1	vflag	xp1	xflag	xp1	xflag	xp1	xflag	xp1	xflag
999999	0								
999999	0	0.281	1	0.204	1	0.234	1	0.645	1
999999	0	0.692	1	0.385	1	0.191	1	0.695	1
999999	0	0.469	1	0.286	1	0.098	1	0.341	1
999999	0	0.706	1	0.147	1	0.277	1	0.283	1
999999	0	0.212	1	0.127	1	0.176	1	0.454	1
999999	0	0.257	1	0.373	1	0.445	1	0.388	1
999999	0	0.208	1	0.091	1	0.05	1	0.222	1
999999	0	0.244	1	0.29	1	0.671	1	0.096	1
999999	0	0.155	1	0.172	1	0.292	1	0.143	1
999999	0	0.729	1	0.455	1	0.46	1	0.159	1
999999	0	0.572	1	0.161	1	0.205	1	0.258	1
999999	0	0.339	1	0.408	1	0.417	1	0.214	1
999999	0	0.587	1	0.322	1	0.284	1	0.35	1
999999	0	0.332	1	0.533	1	0.318	1	0.457	1
999999	0	0.358	1	0.633	1	0.182	1	0.393	1
999999	0	0.129	1	0.456	1	0.694	1	0.561	1
999999	0	0.21	1	0.47	1	0.607	1	0.376	1
999999	0	0.141	1	0.335	1	0.403	1	0.817	1
999999	0	0.186	1	0.5	1	0.568	1	0.561	1
999999	0	0.207	1	0.467	1	0.358	1	0.29	1
999999	0	0.467	1	0.199	1	0.651	1	0.96	1
999999	0	0.576	1	0.637	1	0.56	1	0.699	1
999999	0	0.289	1	0.469	1	0.804	1	0.047	1
999999	0	0.344	1	0.535	1	0.39	1	0.351	1
999999	0	0.382	1	0.281	1	0.199	1	0.112	1
999999	0	0.159	1	0.898	1	0.076	1	0.323	1
999999	0	0.793	1	0.336	1	0.181	1	0.231	1
999999	0	0.929	1	0.363	1	0.107	1	0.198	1
999999	0	0.222	1	0.049	1	0.493	1	0.211	1
999999	0	0.058	1	0.879	1	0.363	1	0.157	1
999999	0	0.217	1	0.214	1	0.275	1	0.335	1
999999	0	0.204	1	0.084	1	0.204	1	0.609	1
999999	0	0.37	1	0.208	1	0.454	1	0.302	1
999999	0	0.675	1	0.15	1	0.387	1	0.104	1
		0.196	1	0.136	1	0.279	1	0.211	1

xp1	xflag	xp1	xflag	xp1	xflag	yn1	yflag	yn1	yflag
0.058	1	0.403	1	0.238	1	999999	0	999999	0
0.254	1	0.988	1	0.416	1	999999	0	999999	0
0.134	1	0.177	1	0.43	1	999999	0	999999	0
0.278	1	0.206	1	0.44	1	999999	0	999999	0
0.345	1	0.366	1	0.952	1	999999	0	999999	0
0.214	1	0.233	1			999999	0	999999	0
0.205	1	0.4	1			999999	0	999999	0
0.159	1	0.375	1			999999	0	999999	0
0.776	1	0.557	1			999999	0	999999	0
0.282	1	0.369	1			999999	0	999999	0
0.92	1	0.477	1			999999	0	999999	0
0.377	1	0.952	1			999999	0	999999	0
0.065	1	0.33	1			999999	0	999999	0
0.621	1	0.25	1			999999	0	999999	0
0.534	1	0.134	1			999999	0	999999	0
0.416	1	0.584	1			999999	0	999999	0
0.238	1	0.877	1			999999	0	999999	0
0.289	1	0.377	1			999999	0	999999	0
0.27	1	0.422	1			999999	0	999999	0
0.183	1	0.297	1			999999	0	999999	0
0.521	1	0.803	1			999999	0	999999	0
0.317	1	0.814	1			999999	0	999999	0
0.905	1	0.562	1			999999	0	999999	0
0.192	1	0.54	1			999999	0	999999	0
0.188	1	0.968	1			999999	0	999999	0
0.214	1	0.264	1			999999	0	999999	0
0.268	1	0.294	1			999999	0	999999	0
0.079	1	0.291	1			999999	0	999999	0
0.313	1	0.207	1			999999	0	999999	0
0.173	1	0.77	1			999999	0	999999	0
0.201	1	0.548	1			999999	0	999999	0
0.084	1	0.272	1			999999	0	999999	0
0.029	1	0.596	1			999999	0	999999	0
0.251	1	0.41	1			999999	0	999999	0
0.236	1	0.877	1			999999	0	999999	0

yn1	yflag	yn1	yflag	yn1	yflag	yn1	yflag	yn1	yflag
999999	0	999999	0	999999	0	999999	0	999999	0

yn1	yflag	yn1	yflag	yn1	yflag	yn1	yflag	yn1	yflag
999999	0	999999	0	999999	0	999999	0	999999	0

n	D11	D12	D13	D14	D15	D21	D22	D23	D24	D25
1	0	0	0	0	0	0	0	0	0	0
2	999999	999999	999999	999999	999999	115.18	999999	999999	127	999999
3	999999	0	999999	999999	0	999999	999999	0	0	999999
4	999999	999999	445	537	999999	1198.71	1394	999999	999999	999999
5	999999	999999	0	999999	999999	999999	0	999999	999999	0
6	999999	0	999999	999999	999999	999999	0	0	0	999999
7	999999	999999	999999	999999	999999	999999	999999	0	0	999999
8	999999	999999	999999	999999	999999	999999	999999	999999	999999	999999
9	999999	999999	0	999999	999999	0	0	999999	999999	999999
10	0	0	999999	999999	999999	0	999999	999999	0	0
11	0	999999	0	999999	999999	999999	999999	0	999999	0
12	0	0	0	0	0	0	0	0	0	0
13	0	999999	999999	0	999999	0	0	999999	0	0
14	0	999999	999999	999999	999999	999999	0	999999	999999	0
15	999999	0	999999	999999	999999	999999	999999	999999	0	999999
16	999999	999999	999999	999999	0	0	0	0	999999	0
17	999999	999999	0	999999	999999	0	999999	999999	999999	0
18	999999	999999	0	0	999999	999999	0	999999	999999	999999
19	999999	999999	999999	999999	999999	999999	999999	0	0	999999
20	999999	999999	0	999999	999999	999999	0	999999	999999	999999
21	999999	999999	999999	999999	999999	999999	0	999999	0	999999
22	999999	999999	163	221	999999	999999	999999	999999	999999	115
23	0	0	0	0	0	0	0	0	0	0
24	999999	999999	0	0	0	0	0	0	999999	0
25	999999	999999	999999	215	999999	999999	999999	999999	999999	999999
26	0	999999	999999	999999	999999	999999	999999	0	999999	999999
27	999999	999999	0	999999	999999	0	999999	999999	999999	999999
28	999999	999999	999999	999999	999999	999999	999999	999999	999999	999999
29	999999	999999	999999	999999	0	0	999999	0	999999	0
30	999999	0	999999	999999	0	999999	999999	0	999999	999999
31	0	999999	999999	999999	999999	0	999999	0	0	999999
32	999999	999999	999999	999999	999999	929.738	620	999999	999999	999999
33	999999	999999	999999	999999	999999	999999	0	999999	0	0
34	0	0	0	0	0	0	0	0	0	0
35	999999	999999	999999	0	999999	0	999999	999999	0	0

n	D11	D12	D13	D14	D15	D21	D22	D23	D24	D25
36	999999	999999	999999	0	0	999999	999999	0	999999	999999
37	999999	0	0	0	0	0	0	0	999999	999999
38	999999	0	999999	999999	999999	999999	999999	999999	999999	999999
39	999999	999999	999999	999999	999999	256.484	248	999999	999999	135
40	999999	999999	495	999999	999999	999999	999999	999999	1174	999999
41	1325.79	999999	999999	999999	999999	1325.79	1533	1577	2001	3434
42	999999	999999	0	999999	999999	0	0	999999	999999	0
43	999999	999999	0	999999	999999	999999	999999	999999	999999	0
44	999999	999999	999999	999999	0	999999	999999	999999	0	999999
45	0	0	0	0	0	0	0	0	0	0
46	999999	999999	999999	999999	999999	742.788	942	858	1177	999999
47	0	999999	999999	999999	999999	999999	999999	999999	999999	999999
48	0	999999	0	999999	999999	999999	999999	999999	999999	0
49	999999	999999	999999	999999	999999	1011.54	999999	1453	999999	179
50	999999	999999	999999	999999	999999	999999	0	999999	0	999999
51	999999	0	999999	0	999999	999999	999999	999999	999999	0
52	0	999999	999999	999999	999999	0	0	999999	999999	0
53	999999	999999	999999	999999	999999	999999	999999	999999	0	999999
54	999999	999999	999999	999999	999999	999999	0	999999	999999	999999
55	999999	999999	999999	781	999999	999999	633	999999	1029	771
56	0	0	0	0	0	0	0	0	0	0
57	999999	999999	999999	999999	999999	0	999999	0	999999	0
58	999999	999999	999999	999999	999999	756.265	999999	999999	267	576
59	999999	999999	999999	999999	0	999999	0	0	999999	999999
60	0	999999	999999	0	0	999999	999999	999999	999999	999999
61	999999	999999	999999	999999	999999	0	999999	999999	999999	999999
62	999999	999999	999999	999999	999999	999999	999999	0	0	999999
63	999999	999999	999999	999999	999999	473.528	999999	999999	999999	999999
64	999999	999999	999999	126	999999	412.93	999999	999999	999999	464
65	999999	999999	999999	0	0	0	0	0	0	999999
66	999999	999999	1947	999999	999999	1031.54	999999	999999	598	999999
67	0	0	0	0	0	0	0	0	0	0
68	0	0	999999	999999	999999	999999	999999	0	999999	0
69	999999	999999	999999	999999	999999	999999	999999	0	0	999999
70	999999	999999	0	999999	999999	999999	0	999999	999999	999999

n	D11	D12	D13	D14	D15	D21	D22	D23	D24	D25
71	999999	999999	999999	0	999999	999999	0	999999	0	999999
72	999999	999999	999999	999999	999999	0	999999	999999	999999	999999
73	999999	826	999999	999999	999999	999999	773	766	1129	2000
74	999999	999999	999999	999999	999999	999999	999999	999999	189	2876
75	0	999999	999999	999999	999999	999999	999999	0	0	999999
76	999999	520	999999	1105	999999	626.764	999999	999999	152	999999
77	555.097	508	999999	999999	999999	999999	367	544	999999	535
78	0	0	0	0	0	0	0	0	0	0
79	0	999999	999999	999999	999999	999999	999999	999999	999999	999999
80	999999	999999	999999	0	999999	999999	0	0	999999	999999
81	999999	999999	999999	999999	999999	0	999999	0	999999	999999
82	329.11	999999	999999	291	999999	329.11	348	999999	999999	999999
83	0	0	0	999999	999999	999999	999999	0	999999	999999
84	999999	999999	999999	999999	999999	999999	110	999999	134	27
85	999999	999999	999999	999999	0	999999	0	999999	999999	0
86	999999	999999	0	999999	999999	999999	999999	999999	999999	999999
87	999999	999999	999999	999999	999999	999999	999999	176	999999	115
88	999999	999999	999999	999999	999999	0	0	999999	0	0
89	0	0	0	0	0	0	0	0	0	0
90	999999	999999	999999	999999	999999	0	0	999999	0	999999
91	0	0	999999	999999	999999	999999	999999	0	999999	0
92	999999	999999	999999	999999	999999	0	999999	999999	999999	0
93	999999	924	999999	999999	999999	1007.51	999999	536	74	999999
94	999999	999999	999999	999999	999999	0	0	0	999999	999999
95	999999	999999	999999	999999	92	76.6237	999999	105	999999	999999
96	999999	0	999999	999999	0	999999	999999	0	999999	999999
97	0	999999	999999	999999	0	999999	999999	0	999999	999999
98	999999	0	999999	999999	999999	999999	999999	999999	999999	999999
99	999999	0	999999	999999	999999	999999	999999	999999	999999	999999
100	0	0	0	0	0	0	0	0	0	0

n	D31	D32	D33	D34	D35	D41	D42	D43	D44	D45
1	0	0	0	0	0	0	0	0	0	0
2	115.18	999999	28	77	194	115.18	130	84	999999	110
3	0	999999	0	0	999999	0	0	0	0	999999
4	999999	1115	603	180	999999	1198.71	1104	470	974	999999
5	0	999999	999999	0	0	0	0	0	0	999999
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	999999	0	0	999999
8	0	0	0	0	0	0	0	0	0	999999
9	0	0	0	0	999999	999999	0	999999	0	0
10	999999	999999	999999	999999	0	0	999999	0	0	0
11	999999	999999	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0
13	0	0	999999	0	0	999999	0	0	0	0
14	0	999999	999999	999999	0	0	999999	0	999999	999999
15	999999	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	999999	0	0	999999	999999	0	0	0	0	0
18	0	0	0	999999	999999	0	0	0	0	0
19	0	999999	0	999999	999999	0	0	0	0	0
20	999999	999999	0	0	999999	0	0	0	0	0
21	999999	999999	0	999999	0	0	0	0	0	0
22	999999	999999	111	70	999999	123.69	115	131	295	95
23	0	0	0	0	0	0	0	0	0	0
24	0	0	0	999999	0	0	999999	0	0	0
25	304.451	999999	128	999999	999999	999999	262	999999	576	580
26	0	999999	999999	0	0	0	999999	999999	0	999999
27	0	0	0	0	0	0	0	0	999999	0
28	354	369	999999	999999	999999	999999	383	226	456	274
29	0	0	0	0	999999	0	0	0	0	0
30	0	999999	999999	999999	999999	0	999999	0	0	999999
31	0	999999	0	999999	0	0	999999	0	0	999999
32	929.738	999999	614	1210	1058	929.738	830	757	999999	1336
33	0	999999	999999	0	0	0	0	999999	0	999999
34	0	0	0	0	0	0	0	0	0	0
35	999999	999999	0	999999	0	0	0	0	0	999999

n	D31	D32	D33	D34	D35	D41	D42	D43	D44	D45
36	999999	0	0	0	0	0	0	0	0	0
37	0	0	0	0	999999	0	999999	0	0	0
38	999999	0	999999	999999	0	0	0	0	0	0
39	256.484	208	145	999999	93	999999	311	232	502	377
40	900.889	615	1012	808	151	900.889	1283	999	999999	997
41	1325.79	1011	1177	933	399	999999	1555	999999	999999	902
42	999999	0	999999	0	0	999999	999999	0	0	999999
43	0	0	999999	999999	0	0	0	0	0	0
44	0	999999	999999	0	0	0	0	999999	0	0
45	0	0	0	0	0	0	0	0	0	0
46	999999	790	999999	999999	999999	742.788	826	448	840	1146
47	999999	0	999999	0	0	0	0	999999	0	0
48	999999	999999	0	999999	0	0	0	0	0	0
49	1011.54	1041	999999	709	1560	1011.54	947	1505	999999	1663
50	999999	0	999999	999999	0	0	0	999999	0	0
51	999999	999999	0	0	999999	999999	0	0	0	0
52	999999	0	0	0	999999	999999	999999	0	999999	0
53	0	0	0	0	0	999999	0	0	0	0
54	999999	999999	999999	0	999999	0	0	0	999999	0
55	999999	696	999999	999999	999999	775.321	719	965	4	203
56	0	0	0	0	0	0	0	0	0	0
57	0	0	999999	999999	0	0	999999	0	0	0
58	999999	769	999999	999999	1408	756.265	957	799	347	270
59	0	999999	0	999999	999999	0	0	999999	0	0
60	999999	999999	999999	0	999999	0	0	0	0	0
61	0	0	999999	999999	0	0	999999	999999	0	999999
62	0	999999	999999	0	999999	999999	0	0	0	0
63	999999	314	562	999999	100	473.528	999999	624	263	107
64	412.93	999999	999999	588	999999	412.93	999999	470	24	71
65	999999	0	0	0	999999	0	0	0	0	0
66	1031.54	999999	999999	999999	999999	1031.54	999999	1491	999999	973
67	0	0	0	0	0	0	0	0	0	0
68	999999	0	0	0	0	0	0	999999	0	0
69	0	0	999999	0	0	0	999999	0	999999	0
70	0	999999	999999	999999	0	0	0	0	0	0

n	D31	D32	D33	D34	D35	D41	D42	D43	D44	D45
71	0	999999	0	999999	0	0	999999	0	0	999999
72	0	0	0	999999	0	0	0	0	0	999999
73	931.571	999999	999999	999999	2130	931.571	822	920	999999	604
74	1866.15	1429	2592	999999	5568	999999	1824	1171	1531	4825
75	0	999999	999999	0	0	0	0	0	999999	0
76	999999	565	287	672	107	626.764	999999	766	195	600
77	555.097	999999	358	999999	999999	999999	526	332	1031	589
78	0	0	0	0	0	0	0	0	0	0
79	0	999999	999999	0	999999	0	0	999999	0	999999
80	0	0	999999	0	0	0	0	0	0	999999
81	999999	0	0	0	0	999999	0	0	0	0
82	329.11	233	342	350	999999	329.11	272	324	999999	477
83	999999	999999	0	0	0	0	0	0	0	0
84	999999	84	75	112	999999	999999	999999	91	105	999999
85	0	999999	0	0	0	0	0	999999	0	0
86	0	0	0	999999	999999	0	0	999999	0	0
87	105	134	999999	3	999999	105	127	101	999999	79
88	999999	999999	0	999999	0	0	0	0	0	0
89	0	0	0	0	0	0	0	0	0	0
90	0	999999	0	999999	999999	0	0	0	0	0
91	999999	0	0	0	0	0	0	0	0	0
92	999999	0	999999	0	0	999999	0	999999	999999	0
93	1007.51	992	999999	1516	999999	1007.51	741	1732	1723	717
94	0	0	999999	0	0	0	0	0	0	0
95	76.6237	79	100	160	35	76.6237	73	105	59	1
96	999999	999999	0	999999	0	0	0	0	0	0
97	999999	0	999999	0	999999	999999	0	999999	0	0
98	999999	0	0	0	0	0	999999	0	0	0
99	999999	999999	0	0	999999	0	0	999999	0	0
100	0	0	0	0	0	0	0	0	0	0

n	D51	D52	D53	D54	D55	Dod	Dflag
1	0	0	0	0	0	0	1
2	115	92	63	327	228	228	1
3	0	0	0	0	0	0	1
4	1199	1596	713	913	2847	2847	1
5	0	0	0	0	0	0	1
6	0	0	0	0	0	0	1
7	0	0	0	0	0	0	1
8	0	0	0	0	0	0	1
9	0	0	0	0	0	0	1
10	0	0	0	0	0	0	1
11	0	0	0	0	0	0	1
12	0	0	0	0	0	0	1
13	0	0	0	0	0	0	1
14	0	0	0	0	0	0	1
15	0	0	0	0	0	0	1
16	0	0	0	0	0	0	1
17	0	0	0	0	0	0	1
18	0	0	0	0	0	0	1
19	0	0	0	0	0	0	1
20	0	0	0	0	0	0	1
21	0	0	0	0	0	0	1
22	124	93	75	6	253	253	1
23	0	0	0	0	0	0	1
24	0	0	0	0	0	0	1
25	304	308	539	594	175	175	1
26	0	0	0	0	0	0	1
27	0	0	0	0	0	0	1
28	354	248	583	217	300	300	1
29	0	0	0	0	0	0	1
30	0	0	0	0	0	0	1
31	0	0	0	0	0	0	1
32	930	697	1186	776	1633	1633	1
33	0	0	0	0	0	0	1
34	0	0	0	0	0	0	1
35	0	0	0	0	0	0	1

n	D51	D52	D53	D54	D55	Dod	Dflag
36	0	0	0	0	0	0	1
37	0	0	0	0	0	0	1
38	0	0	0	0	0	0	1
39	256	246	472	324	150	150	1
40	901	1022	215	901	1438	1438	1
41	1326	1183	1267	1882	845	845	1
42	0	0	0	0	0	0	1
43	0	0	0	0	0	0	1
44	0	0	0	0	0	0	1
45	0	0	0	0	0	0	1
46	743	733	101	201	677	677	1
47	0	0	0	0	0	0	1
48	0	0	0	0	0	0	1
49	1012	1084	461	363	969	969	1
50	0	0	0	0	0	0	1
51	0	0	0	0	0	0	1
52	0	0	0	0	0	0	1
53	0	0	0	0	0	0	1
54	0	0	0	0	0	0	1
55	775	766	1157	22	360	360	1
56	0	0	0	0	0	0	1
57	0	0	0	0	0	0	1
58	756	833	771	464	2098	2098	1
59	0	0	0	0	0	0	1
60	0	0	0	0	0	0	1
61	0	0	0	0	0	0	1
62	0	0	0	0	0	0	1
63	474	469	271	283	421	421	1
64	413	517	718	102	194	194	1
65	0	0	0	0	0	0	1
66	1032	866	896	582	1462	1462	1
67	0	0	0	0	0	0	1
68	0	0	0	0	0	0	1
69	0	0	0	0	0	0	1
70	0	0	0	0	0	0	1

n	D51	D52	D53	D54	D55	Dod	Dflag
71	0	0	0	0	0	0	1
72	0	0	0	0	0	0	1
73	932	777	1081	1418	601	601	1
74	1866	1301	1843	2773	932	932	1
75	0	0	0	0	0	0	1
76	627	636	766	475	1175	1175	1
77	555	739	371	35	339	339	1
78	0	0	0	0	0	0	1
79	0	0	0	0	0	0	1
80	0	0	0	0	0	0	1
81	0	0	0	0	0	0	1
82	329	303	385	566	235	235	1
83	0	0	0	0	0	0	1
84	85.4	80	55	53	107	107	1
85	0	0	0	0	0	0	1
86	0	0	0	0	0	0	1
87	105	139	111	138	84	84	1
88	0	0	0	0	0	0	1
89	0	0	0	0	0	0	1
90	0	0	0	0	0	0	1
91	0	0	0	0	0	0	1
92	0	0	0	0	0	0	1
93	1008	1389	1184	1607	240	240	1
94	0	0	0	0	0	0	1
95	76.6	96	74	89	100	100	1
96	0	0	0	0	0	0	1
97	0	0	0	0	0	0	1
98	0	0	0	0	0	0	1
99	0	0	0	0	0	0	1
100	0	0	0	0	0	0	1

ESTIMATED DATA

vkh12	vkh13	vkh14	vkh15	vkh21	vkh22	vkh23	vkh24	vkh25	vkh31	vkh32	vkh33
210	0	452	92	329	0	105	61	0	137	307	241
188	0	399	0	226	0	0	193	2107	1367	1251	2003
1036	0	445	0	584	773	766	1226	2542	1284	716	996
123	1398	353	0	1191	0	0	480	566	1190	246	273
0	549	7	0	315	96	0	287	51	315	74	66
0	0	487	54	312	572	62	642	481	312	481	235
0	108	175	0	434	354	0	67	935	643	666	852
0	0	291	0	943	662	0	0	0	800	328	822
0	0	0	0	1723	1082	1964	1390	2350	1723	1330	869
0	0	107	0	863	998	1026	1302	2234	965	658	809
0	0	0	0	0	0	176	0	115	105	134	0
631	0	261	0	148	367	544	51	762	702	246	631
924	0	0	0	1201	129	536	74	0	1201	992	128
0	163	428	0	193	129	0	0	115	437	0	342
0	0	0	0	463	535	551	699	1200	463	353	411
0	208	302	0	637	643	0	180	1157	780	983	1157
0	0	301	38	31	238	43	387	290	92	294	66
0	128	186	0	540	506	0	76	1275	856	979	1261
0	374	144	0	354	290	0	706	733	1015	886	1253
0	0	0	0	219	0	0	77	167	0	223	0
0	0	0	0	0	0	0	0	0	354	369	0
0	0	0	0	537	0	0	190	409	0	546	0
0	108	148	0	940	543	515	51	979	1149	1151	982
0	295	357	0	704	819	0	0	0	0	655	354
0	0	0	0	494	359	0	0	53	494	82	316
0	0	0	0	653	0	938	0	116	653	672	0
0	0	100	0	0	0	0	0	0	142	0	60
0	35	42	0	362	309	0	39	0	176	173	195
0	549	34	0	545	0	0	169	125	402	95	170
0	0	0	0	868	0	0	190	409	0	765	392
210	35	494	0	439	216	0	97	542	413	670	723
0	35	42	0	329	216	0	0	0	0	268	264
0	114	732	54	560	837	62	730	481	354	768	360
0	281	0	0	501	380	0	666	82	1012	475	889
0	114	138	0	1410	1300	1373	1177	63	359	1446	155
0	214	0	0	193	129	0	508	0	583	266	566

vkh34	vkh35	vkh41	vkh42	vkh43	vkh44	vkh45	vkh51	vkh52	vkh53	vkh54	vkh55
431	78	329	125	414	253	358	390	413	490	398	609
243	4119	226	1337	1134	1191	3751	1593	1183	1628	2202	1106
271	3292	1516	1166	1886	551	1830	1868	1605	1926	2329	1545
589	465	1191	144	1686	184	1274	1338	1253	1494	824	1543
132	0	315	0	528	93	278	390	344	342	216	517
441	324	795	729	881	37	511	795	735	1104	288	750
261	1495	434	759	602	669	1320	945	926	924	1010	1024
962	565	943	692	895	79	1185	943	798	1067	1044	1188
1283	1545	860	1826	1132	0	1918	1723	1629	1326	1791	1555
607	260	0	1099	0	192	781	965	873	1004	1423	608
3	0	105	127	101	0	79	105	139	111	138	84
159	465	148	670	605	1198	1112	850	992	697	366	690
1767	220	1201	913	1889	1723	995	1201	1534	1430	1768	579
321	220	317	496	288	756	838	561	485	753	642	732
326	139	0	543	0	0	315	463	413	443	657	295
404	1835	637	1035	838	987	1617	1326	1334	1223	1359	1598
66	14	323	353	406	141	191	384	388	573	163	212
214	2239	540	1135	761	975	1958	1291	1234	1182	1473	1458
645	1276	865	1348	1034	536	1615	1264	1321	846	1320	1656
0	408	219	278	232	101	78	219	242	224	135	608
0	0	0	383	226	456	274	354	248	583	217	300
0	1000	537	679	567	246	192	537	591	547	329	1490
475	2192	784	1353	1230	956	2236	1441	1398	1315	1372	1541
105	0	704	649	277	572	0	704	938	419	537	1673
511	484	393	473	411	197	712	494	392	686	455	749
458	1007	653	611	971	0	1073	653	700	297	234	625
0	0	0	122	0	269	271	142	144	252	277	82
234	219	362	336	213	151	235	362	381	308	359	757
158	30	545	0	735	85	325	545	525	528	277	591
0	1070	868	679	1003	430	267	868	918	736	527	1784
299	1092	439	567	603	633	1266	852	810	874	973	1127
28	30	329	171	261	230	32	329	390	193	227	569
358	299	1043	1065	946	479	580	1145	1207	1333	831	1453
907	533	856	1224	988	305	1290	1012	987	847	995	1510
297	553	1410	1446	1103	1090	1736	1410	1527	448	565	1753
600	285	583	727	589	0	709	583	587	339	551	961

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
1	0.2805	0.2805	0.2805	0.2805	0.2805	0.3084	0.2805	0.2805	0.3084	0.2805	0.3084	0.2805	0.3084
2	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916
3	0.4687	0.2942	0.4687	0.4687	0.2942	0.4687	0.4687	0.2942	0.2942	0.4687	0.2942	0.4687	0.2942
4	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058
5	0.2123	0.2123	0.2123	0.2123	0.2123	0.1359	0.1359	0.2123	0.2123	0.2123	0.2123	0.1359	0.1359
6	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571
7	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
8	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437
9	0.1552	0.1552	0.0788	0.0788	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552
10	0.7286	0.7286	1	0.7286	0.7286	0.7286	1	0.7286	0.7286	1	1	0.7286	0.7286
11	0.5721	0.6609	0.5721	0.5721	0.5721	0.5721	0.6609	0.6609	0.6609	0.5721	0.6609	0.6609	0.6609
12	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391
13	0.5867	0.5867	0.5867	0.5867	0.5867	0.5867	0.5867	0.3095	0.3095	0.5867	0.3095	0.3095	0.3095
14	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323
15	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582
16	0.1291	0.1291	0.1291	0.1291	0.1291	0.1291	0.1291	0.1291	0.1291	0.1291	0.2548	0.2548	0.2548
17	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104
18	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409
19	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864
20	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075
21	0.4667	0.4667	0.4243	0.4667	0.4667	0.4243	0.4243	0.4667	0.4667	0.4667	0.4243	0.4243	0.4243
22	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757
23	0.2737	0.2737	0.2894	0.2894	0.2894	0.1142	0.2894	0.2894	0.2737	0.2737	0.2894	0.2894	0.2894
24	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443
25	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382
26	0	0	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0	0	0.1594	0.1594	0.1594
27	1	0.7935	1	0.7935	0.7935	0.7935	0.7935	1	0.7935	1	0.7935	0.7935	1
28	1	0.9294	0.9294	1	0.9294	1	1	0.9294	1	1	1	1	0.9294
29	0.2225	0.2225	0.2225	0.2225	0.2225	0.2225	0.1512	0.2225	0.2225	0.1512	0.1512	0.2225	0.2225
30	0	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579
31	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173
32	0.1905	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038
33	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698
34	0.6749	0.8042	0.6749	0.6749	0.6749	0.6749	0.6749	0.6749	0.8042	0.6749	0.6749	0.8042	0.8042
35	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
36	0.2039	0.2039	0.2039	0.2039	0.2039	0.1812	0.1812	0.1812	0.2039	0.1812	0.1812	0.1812	0.1812
37	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853
38	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864
39	0.1471	0.1471	0.1471	0.1471	0.1245	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471
40	0.1268	0.1268	0.1268	0.1268	0.1268	0.0743	0.1268	0.1268	0.1268	0.0743	0.1268	0.0743	0.0743
41	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733
42	0.0906	0.0906	0.0381	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906
43	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903
44	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716
45	0.4548	0.4548	1	1	0.4548	0.4548	1	0.4548	0.4548	0.4548	1	1	1
46	0.1611	0.1611	0.1611	0.1611	0.1611	0.1611	0.1611	0.2702	0.2702	0.1611	0.2702	0.1611	0.2702
47	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082
48	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216
49	0.5328	0.5328	1	0.5328	0.5328	0.5328	1	0.5328	0.5328	0.5328	0.5328	0.5328	1
50	0.6329	0.6329	0.6329	0.6329	0.6329	0.6329	1	0.6329	1	0.6329	0.6329	0.6329	1
51	0.4556	0.4556	1	1	0.4556	0.4556	0.4556	0.4556	0.4556	1	0.4556	0.4556	1
52	0.4698	0.4698	0.6651	0.6651	0.6651	0.6651	0.6651	0.6651	0.4698	0.6651	0.6651	0.6651	0.6651
53	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349
54	0.4996	0.4996	0.4996	0.4996	0.4996	0.4996	0.4996	0.4996	0.4996	0.4996	0.3339	0.4996	0.3339
55	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467
56	0.1991	0.1991	0.1991	0.0333	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991
57	1	0.6368	0.6368	0.6368	0.6368	0.6368	0.6368	1	0.6368	0.6368	1	0.6368	0.6368
58	0.4691	0.4691	0.184	0.4691	0.4691	0.184	0.4691	0.4691	0.4691	0.4691	0.184	0.184	0.184
59	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354
60	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806
61	0.8981	0.8981	0.8981	0.8981	0.8981	0.8981	0.8981	0.8981	0.8981	0.8981	1	1	0.8981
62	0.3362	0.3362	0.3362	0.3362	0.6375	0.6375	0.3362	0.6375	0.3362	0.6375	0.6375	0.6375	0.6375
63	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625
64	0.0492	1	0.0492	0.0492	1	0.0492	0.0492	1	0.0492	0.0492	1	0.0492	0.0492
65	1	0.8788	0.8788	0.8788	0.8788	1	0.8788	1	1	0.8788	1	0.8788	1
66	0.2141	0.2141	0.2141	0.2141	0.2141	0.4225	0.4225	0.2141	0.2141	0.2141	0.4225	0.2141	0.4225
67	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836
68	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077
69	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501
70	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
71	0.2336	0.2336	0.2336	0.2336	0.2336	0.2336	0.2586	0.2336	0.2586	0.2586	0.2586	0.2336	0.2336
72	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908
73	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976
74	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766
75	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764
76	0.4451	0.4451	0.4451	0.9497	0.4451	0.9497	0.4451	0.4451	0.9497	0.9497	0.4451	0.4451	0.9497
77	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503
78	0.6715	0.6715	0.6715	1	1	0.6715	0.6715	1	0.6715	0.6715	0.6715	1	1
79	0.292	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.292	0.292	0.3349	0.3349	0.3349
80	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597
81	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054
82	0.4165	0.2166	0.4165	0.4165	0.4165	0.4165	0.4165	0.4165	0.4165	0.4165	0.4165	0.2166	0.4165
83	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284
84	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179
85	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815
86	0.6939	0.6939	0.6939	0.6939	0.6939	0.3926	0.3926	0.6939	0.6939	0.3926	0.3926	0.3926	0.3926
87	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074
88	0.403	0.403	0.4325	0.403	0.403	0.403	0.403	0.403	0.4325	0.403	0.4325	0.4325	0.4325
89	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675
90	0.3493	0.3579	0.3579	0.3579	0.3579	0.3493	0.3493	0.3493	0.3493	0.3493	0.3493	0.3493	0.3493
91	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507
92	0.5601	0.5601	1	0.5601	0.5601	1	1	0.5601	0.5601	1	0.5601	1	0.5601
93	0.8044	0.8044	1	0.8044	0.8044	0.8044	0.8044	0.8044	0.8044	1	1	1	0.8044
94	0.39	0.39	0.39	0.39	0.5442	0.39	0.39	0.39	0.5442	0.39	0.5442	0.39	0.39
95	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992
96	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759
97	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808
98	0.1069	0.1069	0.1069	0.1069	0.1069	1	1	1	1	0.1069	0.1069	1	0.1069
99	0.6371	0.4925	0.4925	0.4925	0.4925	0.4925	0.4925	0.4925	0.4925	0.4925	0.4925	0.6371	0.4925
100	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629
101	0.1597	0.2748	0.1597	0.2748	0.2748	0.2748	0.2748	0.2748	0.2748	0.1597	0.2748	0.2748	0
102	0	0.2044	0	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0	0.2044	0.2044	0.2044
103	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537
104	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3866	0.3418
105	0.2794	0.2794	0.2794	0.2794	0.2794	0.3547	0.2794	0.3547	0.2794	0.3547	0.3547	0.3547	0.2794

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
106	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453
107	0.6952	0.6952	0.6952	0.6952	0.6952	0.6952	0.659	0.6952	0.659	0.6952	0.6952	0.659	0.6952
108	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
109	0.2832	1	0.2832	1	0.2832	0.2832	0.2832	0.2832	0.2832	1	0.2832	0.2832	1
110	0.3897	0.4543	0.4543	0.4543	0.4543	0.3897	0.3897	0.4543	0.4543	0.3897	0.4543	0.3897	0.3897
111	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884
112	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219
113	0.0961	0.0961	0.0961	0.0961	0.0961	0.0961	0.0961	0.0961	0.226	0.0961	0.226	0.226	0.226
114	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433
115	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589
116	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577
117	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141
118	0.3503	0.3503	0.3503	0.3503	0.3503	0.3503	0.1498	0.3503	0.3503	0.3503	0.3503	0.3503	0.3503
119	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
120	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932
121	0.5606	0.5606	0.5606	0.6235	0.5606	0.5606	0.6235	0.5606	0.6235	0.6235	0.5606	0.6235	0.5606
122	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765
123	0.8167	0.8167	0.8167	0.8167	0.8167	1	0.8167	1	0.8167	1	1	1	0.8167
124	0.5608	0.5608	0.5608	0.5608	0.5608	0.71	0.5608	0.5608	0.71	0.71	0.5608	0.71	0.5608
125	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
126	0.9603	0.9603	0.9603	0.9603	1	0.9603	1	1	0.9603	0.9603	1	0.9603	1
127	1	0.6992	0.6992	1	1	0.6992	0.6992	0.6992	0.6992	0.6992	0.6992	0.6992	0.6992
128	0.047	0.047	0.047	0.047	0.047	0.2135	0.047	0.047	0.047	0.047	0.2135	0.2135	0.047
129	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512
130	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119
131	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234
132	0.2315	0.2315	0.2315	0.2315	0.2315	0.2315	0.2315	0.0994	0.0994	0.2315	0.0994	0.2315	0.2315
133	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979
134	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211
135	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566
136	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351
137	0.6093	0.6093	0.6093	0.6093	0.6093	0.6981	0.6093	0.6093	0.6093	0.6093	0.6093	0.6981	0.6981
138	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019
139	0.1036	0.1036	0.1036	0.3434	0.1036	0.3434	0.1036	0.1036	0.1036	0.3434	0.3434	0.1036	0.1036
140	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
141	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576
142	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536
143	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339
144	0.2777	0.2777	0.2777	0.2777	0.0766	0.0766	0.0766	0.0766	0.2356	0.2777	0.2777	0.0766	0.0766
145	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448
146	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142
147	0.2054	0.2054	0.2054	0.1633	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054
148	0.1591	0.1591	0.1591	0	0.1591	0.1591	0.1591	0.1591	0	0.1591	0.1591	0.1591	0.1591
149	0.7761	0.7761	0.7179	0.7761	0.7761	0.7179	0.7761	0.7761	0.7179	0.7761	0.7179	0.7761	0.7761
150	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821
151	1	1	0.9196	0.9196	0.9196	0.9196	0.9196	1	0.9196	1	0.9196	1	1
152	0.3773	0.3773	0.3773	0.3773	0.3773	0.3773	0.3773	0.9351	0.9351	0.3773	0.9351	0.9351	0.3773
153	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649
154	0.621	0.621	0.0504	0.621	0.621	0.621	0.0504	0.621	0.621	0.621	0.0504	0.621	0.621
155	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337
156	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159
157	0.2377	0.2377	0.2377	0.2576	0.2377	0.2377	0.2576	0.2377	0.2576	0.2377	0.2576	0.2377	0.2576
158	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888
159	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703
160	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833
161	0.5206	0.5206	0.5206	0.5206	0.5206	0.6825	0.5206	0.5206	0.5206	0.5206	0.6825	0.6825	0.6825
162	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175
163	0.9054	1	0.9054	0.9054	0.9054	0.9054	1	1	1	1	1	0.9054	0.9054
164	0.1917	0.1917	0.1917	0.1917	0.1917	0.1917	0.1917	0.1917	0.2505	0.2505	0.2505	0.2505	0.2505
165	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884
166	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137
167	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684
168	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789
169	0.5139	0.313	0.313	0.313	0.313	0.313	0.313	0.5139	0.5139	0.313	0.5139	0.313	0.313
170	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727
171	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
172	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836
173	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287
174	0.2508	0.361	0.2508	0.361	0.2508	0.361	0.2508	0.2508	0.361	0.2508	0.2508	0.361	0.361
175	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359

n	xph11	xph12	xph13	xph14	xph15	xph21	xph22	xph23	xph24	xph25	xph31	xph32	xph33
176	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031
177	1	1	0.9881	0.9881	0.9881	0.9881	1	1	0.9881	1	1	0.9881	1
178	0.1951	0.1774	0.1774	0.1774	0.1774	0.1774	0.1774	0.1774	0.1774	0.1774	0.1951	0.1774	0.1774
179	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057
180	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664
181	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328
182	0.3999	0.3999	0.3999	0.0673	0.3999	0.3999	0.0673	0.0673	0.3999	0.3999	0.0673	0.0673	0.3999
183	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752
184	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575
185	0.3692	0.3692	0.3692	0.3692	0.3692	0.5233	0.3692	0.5233	0.3692	0.3692	0.3692	0.5233	0.5233
186	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767
187	1	0.9519	0.9519	1	0.9519	1	1	0.9519	0.9519	0.9519	1	1	1
188	0.6165	0.6165	0.6165	0.3304	0.3304	0.3304	0.3304	0.6165	0.3304	0.3304	0.3304	0.3304	0.6165
189	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499
190	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336
191	0.5842	0.5842	0.5842	0.5842	0.5842	0.5842	0.1229	0.5842	0.1229	0.1229	0.5842	0.1229	0.1229
192	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771
193	0.3773	0.3773	0.3773	0.3773	0.2809	0.3773	0.2809	0.3773	0.3773	0.2809	0.2809	0.3773	0.2809
194	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221
195	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297
196	0.8034	0.8034	1	0.8034	0.8034	0.8034	0.8034	0.8034	0.8034	0.8034	1	1	1
197	0.814	0.814	0.814	0.814	0.814	0.814	0.814	1	0.814	1	1	1	0.814
198	0.5619	0.5619	0.5619	0.5619	0.5619	1	1	0.5619	1	1	0.5619	0.5619	1
199	0.5403	0.5403	0.5403	0.5403	0.5403	1	1	0.5403	1	0.5403	1	0.5403	1
200	1	1	0.9676	0.9676	0.9676	0.9676	0.9676	1	0.9676	1	0.9676	1	1
201	0.2638	0.2638	0.2638	0.2638	0.2638	0.2083	0.2638	0.2638	0.2638	0.2083	0.2638	0.2083	0.2638
202	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944
203	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906
204	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066
205	0.7704	1	0.7704	0.7704	0.7704	1	0.7704	1	1	0.7704	1	1	0.7704
206	0.5481	0.5481	0.5481	0.5481	0.5481	0.7285	0.7285	0.7285	0.5481	0.5481	0.7285	0.7285	0.5481
207	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715
208	0.5964	0.5964	0.5964	0.5964	0.5897	0.5897	0.5964	0.5897	0.5964	0.5964	0.5897	0.5897	0.5897
209	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103
210	0.8765	1	0.8765	0.8765	1	0.8765	0.8765	1	0.8765	0.8765	0.8765	0.8765	1
211	1	0.2376	0.2376	0.2376	1	0.2376	0.2376	1	0.2376	0.2376	0.2376	1	0.2376
212	0.416	0.1307	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.1307	0.1307
213	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297
214	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396
215	0.952	1	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	1

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
1	0.3084	0.3084	0.3084	0.3084	0.3084	0.2805	0.3084	0.3084	0.3084	0.3084	0.3084	0.3084
2	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916	0.6916
3	0.2942	0.4687	0.2942	0.2942	0.2942	0.2942	0.4687	0.2942	0.2942	0.2942	0.2942	0.2942
4	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058	0.7058
5	0.1359	0.2123	0.1359	0.1359	0.1359	0.1359	0.2123	0.1359	0.1359	0.1359	0.1359	0.1359
6	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571	0.2571
7	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
8	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437	0.2437
9	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552	0.1552
10	1	1	1	1	1	1	0.7286	1	1	1	1	1
11	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609	0.6609
12	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391
13	0.3095	0.3095	0.3095	0.5867	0.3095	0.3095	0.5867	0.3095	0.3095	0.3095	0.3095	0.3095
14	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323	0.3323
15	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582	0.3582
16	0.2548	0.2548	0.2548	0.2548	0.2548	0.2548	0.1291	0.2548	0.2548	0.2548	0.2548	0.2548
17	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104	0.2104
18	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409	0.1409
19	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864	0.1864
20	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075	0.2075
21	0.4243	0.4667	0.4667	0.4243	0.4667	0.4243	0.4243	0.4243	0.4243	0.4243	0.4243	0.4243
22	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757	0.5757
23	0.2894	0.1142	0.1142	0.2894	0.1142	0.1142	0.1142	0.1142	0.1142	0.1142	0.1142	0.1142
24	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443	0.3443
25	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382
26	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594	0.1594
27	1	1	1	1	1	1	1	1	1	1	1	1
28	1	1	0.9294	1	1	1	1	1	1	1	1	1
29	0.2225	0.1512	0.1512	0.2225	0.2091	0.2225	0.2225	0.1512	0.1512	0.1512	0.1512	0.1512
30	0.0579	0.0579	0.0579	0.0579	0	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579	0.0579
31	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173	0.2173
32	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038	0.2038
33	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698	0.3698
34	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042	0.8042
35	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958	0.1958

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
36	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812	0.1812
37	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853	0.3853
38	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864	0.2864
39	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471	0.1471
40	0.1268	0.1268	0.0743	0.0743	0.0743	0.0743	0.0743	0.0743	0.0743	0.0743	0.0743	0.0743
41	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733	0.3733
42	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906	0.0906
43	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903	0.2903
44	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716	0.1716
45	0.4548	0.4548	1	1	1	1	1	1	1	1	1	1
46	0.1611	0.1611	0.2702	0.2702	0.2702	0.2702	0.2702	0.2702	0.2702	0.2702	0.2702	0.2702
47	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082	0.4082
48	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216	0.3216
49	1	0.5328	1	1	1	1	1	1	1	1	1	1
50	0.6329	1	1	1	1	1	1	1	1	1	1	1
51	1	0.4556	1	1	1	1	1	1	1	1	1	1
52	0.4698	0.6651	0.6651	0.4698	0.6651	0.6651	0.6651	0.6651	0.6651	0.6651	0.6651	0.6651
53	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349
54	0.4996	0.4996	0.4996	0.3339	0.4996	0.3339	0.3339	0.3339	0.3339	0.3339	0.3339	0.3339
55	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467
56	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991	0.1991
57	1	1	1	0.6368	0.6368	1	0.6368	1	1	1	1	1
58	0.184	0.184	0.184	0.184	0.184	0.4691	0.184	0.184	0.184	0.184	0.184	0.184
59	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354	0.5354
60	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806	0.2806
61	0.8981	0.8981	0.8981	1	1	1	1	1	1	1	1	1
62	0.6375	0.3362	0.6375	0.6375	0.6375	0.6375	0.6375	0.6375	0.6375	0.6375	0.6375	0.6375
63	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625	0.3625
64	0.0492	0.0492	1	0.0492	1	1	0.0492	1	1	1	1	1
65	0.8788	1	1	0.8788	1	1	0.8788	1	1	1	1	1
66	0.4225	0.4225	0.4225	0.4225	0.4225	0.2141	0.4225	0.4225	0.4225	0.4225	0.4225	0.4225
67	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836
68	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077	0.2077
69	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501	0.1501
70	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361	0.1361

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
71	0.2586	0.2586	0.2586	0.2586	0.2336	0.2586	0.2336	0.2586	0.2586	0.2586	0.2586	0.2586
72	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908	0.1908
73	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976	0.0976
74	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766	0.2766
75	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764	0.1764
76	0.4451	0.9497	0.9497	0.9497	0.9497	0.9497	0.4451	0.9497	0.9497	0.9497	0.9497	0.9497
77	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503	0.0503
78	1	1	1	1	1	1	1	1	1	1	1	1
79	0.3349	0.292	0.3349	0.292	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349
80	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597	0.4597
81	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054
82	0.4165	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166	0.2166
83	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284
84	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179	0.3179
85	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815	0.1815
86	0.6939	0.3926	0.6939	0.3926	0.3926	0.3926	0.3926	0.3926	0.3926	0.3926	0.3926	0.3926
87	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074	0.6074
88	0.4325	0.4325	0.4325	0.4325	0.4325	0.403	0.4325	0.4325	0.4325	0.4325	0.4325	0.4325
89	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675	0.5675
90	0.3493	0.3493	0.3579	0.3493	0.3579	0.3579	0.3493	0.3493	0.3493	0.3493	0.3493	0.3493
91	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507	0.6507
92	1	1	0.5601	0.5601	1	1	0.5601	1	1	1	1	1
93	0.8044	1	1	1	1	1	1	1	1	1	1	1
94	0.5442	0.5442	0.5442	0.5442	0.39	0.5442	0.5442	0.5442	0.5442	0.5442	0.5442	0.5442
95	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992	0.1992
96	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759	0.0759
97	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808	0.1808
98	0.1069	0.1069	1	1	1	1	1	1	1	1	1	1
99	0.6371	0.6371	0.6371	0.6371	0.4925	0.6371	0.6371	0.6371	0.6371	0.6371	0.6371	0.6371
100	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629	0.3629
101	0.2748	0	0	0	0	0	0	0	0	0	0	0
102	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044	0.2044
103	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537	0.4537
104	0.3866	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
105	0.3547	0.3547	0.3547	0.3547	0.3547	0.2794	0.3547	0.3547	0.3547	0.3547	0.3547	0.3547

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
106	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453	0.6453
107	0.6952	0.659	0.659	0.659	0.6952	0.659	0.659	0.659	0.659	0.659	0.659	0.659
108	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
109	1	0.2832	0.2832	1	1	1	1	1	1	1	1	1
110	0.3897	0.4543	0.4543	0.4543	0.3897	0.4543	0.3897	0.3897	0.3897	0.3897	0.3897	0.3897
111	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884	0.3884
112	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219
113	0.226	0.226	0.0961	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226
114	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433	0.1433
115	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589	0.1589
116	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577
117	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141
118	0.1498	0.3503	0.1498	0.1498	0.1498	0.3503	0.1498	0.1498	0.1498	0.1498	0.1498	0.1498
119	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
120	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932	0.3932
121	0.5606	0.5606	0.6235	0.6235	0.6235	0.6235	0.6235	0.6235	0.6235	0.6235	0.6235	0.6235
122	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765	0.3765
123	0.8167	1	1	0.8167	1	1	1	1	1	1	1	1
124	0.5608	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
125	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
126	0.9603	0.9603	1	1	0.9603	1	1	1	1	1	1	1
127	1	0.6992	1	1	1	1	1	1	1	1	1	1
128	0.047	0.2135	0.2135	0.047	0.047	0.2135	0.047	0.2135	0.2135	0.2135	0.2135	0.2135
129	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512	0.3512
130	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119	0.1119
131	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234	0.3234
132	0.0994	0.2315	0.2315	0.0994	0.0994	0.0994	0.0994	0.0994	0.0994	0.0994	0.0994	0.0994
133	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979	0.1979
134	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211
135	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566	0.1566
136	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351	0.3351
137	0.6093	0.6981	0.6981	0.6093	0.6981	0.6981	0.6981	0.6981	0.6981	0.6981	0.6981	0.6981
138	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019	0.3019
139	0.3434	0.1036	0.3434	0.1036	0.3434	0.3434	0.3434	0.3434	0.3434	0.3434	0.3434	0.3434
140	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115	0.2115

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
141	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576	0.0576
142	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536	0.2536
143	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339	0.1339
144	0.0766	0.2777	0.0766	0.0766	0.0766	0.0766	0.0766	0.0766	0.0766	0.0766	0.0766	0.0766
145	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448	0.3448
146	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142	0.2142
147	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054	0.2054
148	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591	0.1591
149	0.7761	0.7761	0.7179	0.7761	0.7179	0.7761	0.7179	0.7179	0.7179	0.7179	0.7179	0.7179
150	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821	0.2821
151	1	1	1	1	0.9196	1	1	1	1	1	1	1
152	0.9351	0.9351	0.9351	0.3773	0.9351	0.3773	0.9351	0.9351	0.9351	0.9351	0.9351	0.9351
153	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649	0.0649
154	0.621	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504
155	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337	0.5337
156	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159	0.4159
157	0.2377	0.2576	0.2576	0.2377	0.2576	0.2576	0.2377	0.2576	0.2576	0.2576	0.2576	0.2576
158	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888	0.2888
159	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703	0.2703
160	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833	0.1833
161	0.5206	0.6825	0.6825	0.6825	0.6825	0.6825	0.5206	0.6825	0.6825	0.6825	0.6825	0.6825
162	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175	0.3175
163	0.9054	1	1	1	1	0.9054	1	1	1	1	1	1
164	0.1917	0.2505	0.1917	0.2505	0.2505	0.2505	0.2505	0.2505	0.2505	0.2505	0.2505	0.2505
165	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884	0.1884
166	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137	0.2137
167	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684	0.2684
168	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789	0.0789
169	0.5139	0.5139	0.5139	0.5139	0.5139	0.313	0.5139	0.5139	0.5139	0.5139	0.5139	0.5139
170	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727	0.1727
171	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
172	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836	0.0836
173	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287	0.0287
174	0.361	0.361	0.361	0.2508	0.361	0.361	0.361	0.361	0.361	0.361	0.361	0.361
175	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359	0.2359

n	xph34	xph35	xph41	xph42	xph43	xph44	xph45	xph51	xph52	xph53	xph54	xph55
176	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031	0.4031
177	0.9881	0.9881	0.9881	1	1	1	1	1	1	1	1	1
178	0.1951	0.1774	0.1951	0.1951	0.1774	0.1951	0.1774	0.1951	0.1951	0.1951	0.1951	0.1951
179	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057	0.2057
180	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664	0.3664
181	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328	0.2328
182	0.0673	0.0673	0.0673	0.0673	0.0673	0.0673	0.3999	0.0673	0.0673	0.0673	0.0673	0.0673
183	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752	0.3752
184	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575	0.5575
185	0.5233	0.5233	0.3692	0.5233	0.5233	0.5233	0.5233	0.5233	0.5233	0.5233	0.5233	0.5233
186	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767	0.4767
187	1	0.9519	1	1	1	0.9519	1	1	1	1	1	1
188	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165	0.6165
189	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499	0.2499
190	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336	0.1336
191	0.1229	0.5842	0.5842	0.5842	0.1229	0.1229	0.5842	0.1229	0.1229	0.1229	0.1229	0.1229
192	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771	0.8771
193	0.2809	0.2809	0.2809	0.2809	0.3773	0.2809	0.2809	0.2809	0.2809	0.2809	0.2809	0.2809
194	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221	0.4221
195	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297
196	0.8034	0.8034	1	1	0.8034	1	1	1	1	1	1	1
197	1	0.814	1	1	1	0.814	1	1	1	1	1	1
198	0.5619	1	1	1	1	1	1	1	1	1	1	1
199	0.5403	0.5403	1	1	1	1	1	1	1	1	1	1
200	1	1	1	1	1	1	1	1	1	1	1	1
201	0.2083	0.2083	0.2638	0.2083	0.2638	0.2638	0.2083	0.2083	0.2083	0.2083	0.2083	0.2083
202	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944	0.2944
203	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906	0.2906
204	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066	0.2066
205	1	0.7704	1	1	1	1	1	1	1	1	1	1
206	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285	0.7285
207	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715	0.2715
208	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897	0.5897
209	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103	0.4103
210	0.8765	1	1	1	1	1	1	1	1	1	1	1
211	1	0.2376	0.2376	1	0.2376	1	1	1	1	1	1	1
212	0.1307	0.1307	0.1307	0.416	0.1307	0.1307	0.1307	0.1307	0.1307	0.1307	0.1307	0.1307
213	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297	0.4297
214	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396	0.4396
215	1	0.952	1	1	0.952	1	1	1	1	1	1	1

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
1	0.281	0.281	0.281	0.281	0.281	0.308	0.281	0.281	0.308	0.281	0.308	0.281	0.308
2	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692
3	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692
4	1.174	1	1.174	1.174	1	1.174	1.174	1	1	1.174	1	1.174	1
5	0.469	0.294	0.469	0.469	0.294	0.469	0.469	0.294	0.294	0.469	0.294	0.469	0.294
6	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
7	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
8	0.469	0.469	0.469	0.469	0.469	0.393	0.393	0.469	0.469	0.469	0.469	0.393	0.393
9	0.664	0.664	0.664	0.664	0.664	0.588	0.588	0.664	0.664	0.664	0.664	0.588	0.588
10	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257
11	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257
12	0.363	0.363	0.287	0.287	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
13	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
14	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
15	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
16	0.155	0.155	0.079	0.079	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
17	0.155	0.155	0.079	0.079	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
18	0.155	0.155	0.079	0.079	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
19	0.729	0.729	1	0.729	0.729	0.729	1	0.729	0.729	1	1	0.729	0.729
20	0.572	0.661	0.572	0.572	0.572	0.572	0.661	0.661	0.661	0.572	0.661	0.661	0.661
21	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339
22	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339
23	0.945	0.945	0.945	0.945	0.945	0.945	0.945	0.668	0.668	0.945	0.668	0.668	0.668
24	0.919	0.919	0.919	0.919	0.919	0.919	0.919	0.642	0.642	0.919	0.642	0.642	0.642
25	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332
26	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332
27	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358
28	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358
29	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.603	0.603	0.603
30	0.337	0.337	0.337	0.337	0.337	0.337	0.337	0.337	0.337	0.337	0.462	0.462	0.462
31	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.606	0.606	0.606
32	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
33	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141
34	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141
35	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
36	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186
37	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186
38	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
39	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
40	1.042	1.042	1	1.042	1.042	1	1	1.042	1.042	1.042	1	1	1
41	0.467	0.467	0.424	0.467	0.467	0.424	0.424	0.467	0.467	0.467	0.424	0.424	0.424
42	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576
43	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576
44	0.656	0.656	0.671	0.671	0.671	0.496	0.671	0.671	0.656	0.656	0.671	0.671	0.671
45	0.274	0.274	0.289	0.289	0.289	0.114	0.289	0.289	0.274	0.274	0.289	0.289	0.289
46	0.344	0.344	0.504	0.504	0.504	0.504	0.504	0.504	0.344	0.344	0.504	0.504	0.504
47	0.344	0.344	0.504	0.504	0.504	0.504	0.504	0.504	0.344	0.344	0.504	0.504	0.504
48	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344
49	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382
50	0.382	0.382	0.541	0.541	0.541	0.541	0.541	0.541	0.382	0.382	0.541	0.541	0.541
51	0	0	0.159	0.159	0.159	0.159	0.159	0.159	0	0	0.159	0.159	0.159
52	1	0.793	1	0.793	0.793	0.793	0.793	1	0.793	1	0.793	0.793	1
53	1	0.929	0.929	1	0.929	1	1	0.929	1	1	1	1	0.929
54	0.222	0.222	0.222	0.222	0.222	0.222	0.151	0.222	0.222	0.151	0.151	0.222	0.222
55	0.592	0.65	0.65	0.65	0.65	0.65	0.579	0.65	0.65	0.579	0.579	0.65	0.65
56	0.592	0.65	0.65	0.65	0.65	0.65	0.579	0.65	0.65	0.579	0.579	0.65	0.65
57	0.217	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275
58	0.37	0.428	0.428	0.428	0.428	0.428	0.428	0.428	0.428	0.428	0.428	0.428	0.428
59	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217
60	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217
61	0.56	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574
62	0.19	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204
63	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
64	0.675	0.804	0.675	0.675	0.675	0.675	0.675	0.675	0.804	0.675	0.675	0.804	0.804
65	0.675	0.804	0.675	0.675	0.675	0.675	0.675	0.675	0.804	0.675	0.675	0.804	0.804
66	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196
67	0.204	0.204	0.204	0.204	0.204	0.181	0.181	0.181	0.204	0.181	0.181	0.181	0.181
68	0.204	0.204	0.204	0.204	0.204	0.181	0.181	0.181	0.204	0.181	0.181	0.181	0.181
69	0.204	0.204	0.204	0.204	0.204	0.181	0.181	0.181	0.204	0.181	0.181	0.181	0.181
70	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
71	0.532	0.532	0.532	0.532	0.51	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532
72	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
73	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
74	0.147	0.147	0.147	0.147	0.124	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
75	0.147	0.147	0.147	0.147	0.124	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
76	0.217	0.217	0.165	0.217	0.217	0.165	0.217	0.217	0.217	0.165	0.217	0.165	0.165
77	0.298	0.298	0.298	0.298	0.298	0.246	0.298	0.298	0.298	0.246	0.298	0.246	0.246
78	0.298	0.298	0.298	0.298	0.298	0.246	0.298	0.298	0.298	0.246	0.298	0.246	0.246
79	0.589	0.589	0.589	0.589	0.589	0.536	0.589	0.589	0.589	0.536	0.589	0.536	0.536
80	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545
81	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373
82	0.091	0.091	0.038	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
83	0.091	0.091	0.038	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
84	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
85	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
86	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172
87	0.455	0.455	1	1	0.455	0.455	1	0.455	0.455	0.455	1	1	1
88	0.455	0.455	1	1	0.455	0.455	1	0.455	0.455	0.455	1	1	1
89	0.161	0.161	0.161	0.161	0.161	0.161	0.161	0.27	0.27	0.161	0.27	0.161	0.27
90	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
91	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
92	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
93	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
94	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322
95	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322
96	0.533	0.533	1	0.533	0.533	0.533	1	0.533	0.533	0.533	0.533	0.533	1
97	0.533	0.533	1	0.533	0.533	0.533	1	0.533	0.533	0.533	0.533	0.533	1
98	0.633	0.633	0.633	0.633	0.633	0.633	1	0.633	1	0.633	0.633	0.633	1
99	0.633	0.633	0.633	0.633	0.633	0.633	1	0.633	1	0.633	0.633	0.633	1
100	0.456	0.456	1	1	0.456	0.456	0.456	0.456	0.456	1	0.456	0.456	1
101	0.47	0.47	0.665	0.665	0.665	0.665	0.665	0.665	0.47	0.665	0.665	0.665	0.665
102	0.805	0.805	1	1	1	1	1	1	0.805	1	1	1	1
103	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
104	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
105	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.334	0.5	0.334

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
106	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.334	0.5	0.334
107	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.801	0.967	0.801
108	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467
109	0.199	0.199	0.199	0.033	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
110	0.199	0.199	0.199	0.033	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
111	0.199	0.199	0.199	0.033	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
112	1	0.637	0.637	0.637	0.637	0.637	0.637	1	0.637	0.637	1	0.637	0.637
113	1	0.637	0.637	0.637	0.637	0.637	0.637	1	0.637	0.637	1	0.637	0.637
114	0.469	0.469	0.184	0.469	0.469	0.184	0.469	0.469	0.469	0.469	0.184	0.184	0.184
115	0.75	0.75	0.465	0.75	0.75	0.465	0.75	0.75	0.75	0.75	0.465	0.465	0.465
116	0.75	0.75	0.465	0.75	0.75	0.465	0.75	0.75	0.75	0.75	0.465	0.465	0.465
117	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535
118	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535
119	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281
120	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281
121	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898	0.898	1	1	0.898
122	0.336	0.336	0.336	0.336	0.637	0.637	0.336	0.637	0.336	0.637	0.637	0.637	0.637
123	0.336	0.336	0.336	0.336	0.637	0.637	0.336	0.637	0.336	0.637	0.637	0.637	0.637
124	0.336	0.336	0.336	0.336	0.637	0.637	0.336	0.637	0.336	0.637	0.637	0.637	0.637
125	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
126	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
127	0.049	1	0.049	0.049	1	0.049	0.049	1	0.049	0.049	1	0.049	0.049
128	1	0.879	0.879	0.879	0.879	1	0.879	1	1	0.879	1	0.879	1
129	1	0.879	0.879	0.879	0.879	1	0.879	1	1	0.879	1	0.879	1
130	0.298	0.298	0.298	0.298	0.298	0.506	0.506	0.298	0.298	0.298	0.506	0.298	0.506
131	0.214	0.214	0.214	0.214	0.214	0.423	0.423	0.214	0.214	0.214	0.423	0.214	0.423
132	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084
133	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
134	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
135	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
136	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
137	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
138	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
139	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136
140	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
141	0.424	0.424	0.424	0.424	0.424	0.424	0.449	0.424	0.449	0.449	0.449	0.424	0.424
142	0.234	0.234	0.234	0.234	0.234	0.234	0.259	0.234	0.259	0.259	0.259	0.234	0.234
143	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191
144	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644
145	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374
146	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374
147	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
148	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277
149	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
150	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
151	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
152	0.445	0.445	0.445	0.95	0.445	0.95	0.445	0.445	0.95	0.95	0.445	0.445	0.95
153	0.445	0.445	0.445	0.95	0.445	0.95	0.445	0.445	0.95	0.95	0.445	0.445	0.95
154	0.495	0.495	0.495	1	0.495	1	0.495	0.495	1	1	0.495	0.495	1
155	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
156	0.671	0.671	0.671	1	1	0.671	0.671	1	0.671	0.671	0.671	1	1
157	0.292	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.292	0.292	0.335	0.335	0.335
158	0.497	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.497	0.497	0.54	0.54	0.54
159	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665
160	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
161	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205
162	0.916	0.716	0.916	0.916	0.916	0.916	0.916	0.916	0.916	0.916	0.916	0.716	0.916
163	0.417	0.217	0.417	0.417	0.417	0.417	0.417	0.417	0.417	0.417	0.417	0.217	0.417
164	0.882	0.682	0.882	0.882	0.882	0.882	0.882	0.882	0.882	0.882	0.882	0.682	0.882
165	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284
166	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499
167	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318
168	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182
169	0.694	0.694	0.694	0.694	0.694	0.393	0.393	0.694	0.694	0.393	0.393	0.393	0.393
170	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607
171	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607
172	0.403	0.403	0.432	0.403	0.403	0.403	0.403	0.403	0.432	0.403	0.432	0.432	0.432
173	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568
174	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568
175	0.349	0.358	0.358	0.358	0.358	0.349	0.349	0.349	0.349	0.349	0.349	0.349	0.349

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
176	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651
177	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651
178	0.56	0.56	1	0.56	0.56	1	1	0.56	0.56	1	0.56	1	0.56
179	0.804	0.804	1	0.804	0.804	0.804	0.804	0.804	0.804	1	1	1	0.804
180	0.804	0.804	1	0.804	0.804	0.804	0.804	0.804	0.804	1	1	1	0.804
181	0.39	0.39	0.39	0.39	0.544	0.39	0.39	0.39	0.544	0.39	0.544	0.39	0.39
182	0.665	0.665	0.665	0.665	0.819	0.665	0.665	0.665	0.819	0.665	0.819	0.665	0.665
183	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
184	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
185	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
186	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
187	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
188	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
189	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
190	0.107	0.107	0.107	0.107	0.107	1	1	1	1	0.107	0.107	1	0.107
191	0.637	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.493	0.637	0.493
192	1	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	1	0.855
193	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
194	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
195	0.546	0.661	0.546	0.661	0.661	0.661	0.661	0.661	0.661	0.546	0.661	0.661	0.342
196	0.16	0.275	0.16	0.275	0.275	0.275	0.275	0.275	0.275	0.16	0.275	0.275	0
197	1	1.115	1	1.115	1.115	1.115	1.115	1.115	1.115	1	1.115	1.115	0.796
198	0	0.204	0	0.204	0.204	0.204	0.204	0.204	0.204	0	0.204	0.204	0.204
199	0	0.204	0	0.204	0.204	0.204	0.204	0.204	0.204	0	0.204	0.204	0.204
200	0	0.204	0	0.204	0.204	0.204	0.204	0.204	0.204	0	0.204	0.204	0.204
201	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454
202	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.342
203	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.387	0.342
204	0.279	0.279	0.279	0.279	0.279	0.355	0.279	0.355	0.279	0.355	0.355	0.355	0.279
205	0.279	0.279	0.279	0.279	0.279	0.355	0.279	0.355	0.279	0.355	0.355	0.355	0.279
206	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645
207	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645
208	0.695	0.695	0.695	0.695	0.695	0.695	0.659	0.695	0.659	0.695	0.695	0.659	0.695
209	0.695	0.695	0.695	0.695	0.695	0.695	0.659	0.695	0.659	0.695	0.695	0.659	0.695
210	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
211	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
212	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
213	0.283	1	0.283	1	0.283	0.283	0.283	0.283	0.283	1	0.283	0.283	1
214	0.39	0.454	0.454	0.454	0.454	0.39	0.39	0.454	0.454	0.39	0.454	0.39	0.39
215	0.39	0.454	0.454	0.454	0.454	0.39	0.39	0.454	0.454	0.39	0.454	0.39	0.39
216	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388
217	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
218	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222
219	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222
220	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.226	0.096	0.226	0.226	0.226
221	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.226	0.096	0.226	0.226	0.226
222	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401
223	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143
224	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143
225	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373
226	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
227	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
228	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258
229	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258
230	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
231	0.35	0.35	0.35	0.35	0.35	0.35	0.15	0.35	0.35	0.35	0.35	0.35	0.35
232	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
233	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
234	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393
235	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393
236	0.561	0.561	0.561	0.624	0.561	0.561	0.624	0.561	0.624	0.624	0.561	0.624	0.561
237	0.561	0.561	0.561	0.624	0.561	0.561	0.624	0.561	0.624	0.624	0.561	0.624	0.561
238	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376
239	0.817	0.817	0.817	0.817	0.817	1	0.817	1	0.817	1	1	1	0.817
240	0.561	0.561	0.561	0.561	0.561	0.71	0.561	0.561	0.71	0.71	0.561	0.71	0.561
241	0.561	0.561	0.561	0.561	0.561	0.71	0.561	0.561	0.71	0.71	0.561	0.71	0.561
242	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
243	0.96	0.96	0.96	0.96	1	0.96	1	1	0.96	0.96	1	0.96	1
244	1	0.699	0.699	1	1	0.699	0.699	0.699	0.699	0.699	0.699	0.699	0.699
245	0.398	0.398	0.398	0.398	0.398	0.565	0.398	0.398	0.398	0.398	0.565	0.565	0.398

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
246	0.047	0.047	0.047	0.047	0.047	0.213	0.047	0.047	0.047	0.047	0.213	0.213	0.047
247	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351
248	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
249	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435
250	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
251	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
252	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
253	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
254	0.443	0.443	0.443	0.443	0.443	0.443	0.443	0.31	0.31	0.443	0.31	0.443	0.443
255	0.231	0.231	0.231	0.231	0.231	0.231	0.231	0.099	0.099	0.231	0.099	0.231	0.231
256	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
257	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
258	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
259	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211
260	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703
261	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157
262	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492
263	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
264	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
265	0.609	0.609	0.609	0.609	0.609	0.698	0.609	0.609	0.609	0.609	0.609	0.698	0.698
266	0.609	0.609	0.609	0.609	0.609	0.698	0.609	0.609	0.609	0.609	0.609	0.698	0.698
267	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
268	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
269	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
270	0.161	0.161	0.161	0.401	0.161	0.401	0.161	0.161	0.161	0.401	0.401	0.161	0.161
271	0.491	0.491	0.491	0.731	0.491	0.731	0.491	0.491	0.491	0.731	0.731	0.491	0.491
272	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345
273	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269
274	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
275	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254
276	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254
277	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
278	0.987	0.987	0.987	0.786	0.786	0.786	0.786	0.786	0.786	0.987	0.987	0.786	0.786
279	0.623	0.623	0.623	0.623	0.421	0.421	0.421	0.421	0.58	0.623	0.623	0.421	0.421
280	0.492	0.492	0.492	0.492	0.291	0.291	0.291	0.291	0.45	0.492	0.492	0.291	0.291

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
281	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345
282	0.55	0.55	0.55	0.508	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
283	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
284	0.364	0.364	0.364	0.163	0.364	0.364	0.364	0.364	0.205	0.364	0.364	0.364	0.364
285	0.205	0.205	0.205	0.163	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205
286	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159
287	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159
288	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159	0	0.159	0.159	0.159	0.159
289	0.776	0.776	0.718	0.776	0.776	0.718	0.776	0.776	0.718	0.776	0.718	0.776	0.776
290	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282
291	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282
292	1	1	0.92	0.92	0.92	0.92	0.92	1	0.92	1	0.92	1	1
293	0.377	0.377	0.377	0.377	0.377	0.377	0.377	0.935	0.935	0.377	0.935	0.935	0.377
294	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
295	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
296	1.155	1.155	0.584	1.155	1.155	1.155	0.584	1.155	1.155	1.155	0.584	1.155	1.155
297	0.621	0.621	0.05	0.621	0.621	0.621	0.05	0.621	0.621	0.621	0.05	0.621	0.621
298	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534
299	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534
300	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
301	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
302	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
303	0.691	0.691	0.691	0.711	0.691	0.691	0.711	0.691	0.711	0.691	0.711	0.691	0.711
304	0.238	0.238	0.238	0.258	0.238	0.238	0.258	0.238	0.258	0.238	0.258	0.238	0.258
305	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289
306	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289
307	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472
308	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
309	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
310	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183
311	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183
312	0.521	0.521	0.521	0.521	0.521	0.683	0.521	0.521	0.521	0.521	0.683	0.683	0.683
313	0.521	0.521	0.521	0.521	0.521	0.683	0.521	0.521	0.521	0.521	0.683	0.683	0.683
314	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317
315	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
316	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317
317	0.905	1	0.905	0.905	0.905	0.905	1	1	1	1	1	0.905	0.905
318	0.271	0.271	0.271	0.271	0.271	0.271	0.271	0.271	0.329	0.329	0.329	0.329	0.329
319	0.674	0.674	0.674	0.674	0.674	0.674	0.674	0.674	0.733	0.733	0.733	0.733	0.733
320	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402
321	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188
322	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188
323	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
324	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268
325	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268
326	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
327	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
328	0.916	0.715	0.715	0.715	0.715	0.715	0.715	0.916	0.916	0.715	0.916	0.715	0.715
329	0.744	0.543	0.543	0.543	0.543	0.543	0.543	0.744	0.744	0.543	0.744	0.543	0.543
330	0.514	0.313	0.313	0.313	0.313	0.313	0.313	0.514	0.514	0.313	0.514	0.313	0.313
331	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173
332	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256
333	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285
334	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
335	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
336	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084
337	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
338	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
339	0.251	0.361	0.251	0.361	0.251	0.361	0.251	0.251	0.361	0.251	0.251	0.361	0.361
340	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
341	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
342	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
343	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
344	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
345	1	1	0.988	0.988	0.988	0.988	1	1	0.988	1	1	0.988	1
346	0.794	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.794	0.777	0.777
347	0.195	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.195	0.177	0.177
348	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206
349	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572
350	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
351	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
352	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
353	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
354	0.4	0.4	0.4	0.067	0.4	0.4	0.067	0.067	0.4	0.4	0.067	0.067	0.4
355	0.4	0.4	0.4	0.067	0.4	0.4	0.067	0.067	0.4	0.4	0.067	0.067	0.4
356	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933
357	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375
358	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557
359	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557
360	0.369	0.369	0.369	0.369	0.369	0.523	0.369	0.523	0.369	0.369	0.369	0.523	0.523
361	0.369	0.369	0.369	0.369	0.369	0.523	0.369	0.523	0.369	0.369	0.369	0.523	0.523
362	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477
363	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477
364	1	0.952	0.952	1	0.952	1	1	0.952	0.952	0.952	1	1	1
365	0.617	0.617	0.617	0.33	0.33	0.33	0.33	0.617	0.33	0.33	0.33	0.33	0.617
366	0.617	0.617	0.617	0.33	0.33	0.33	0.33	0.617	0.33	0.33	0.33	0.33	0.617
367	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
368	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
369	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
370	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
371	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
372	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
373	0.584	0.584	0.584	0.584	0.584	0.584	0.123	0.584	0.123	0.123	0.584	0.123	0.123
374	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877
375	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877
376	0.799	0.799	0.799	0.799	0.703	0.799	0.703	0.799	0.799	0.703	0.703	0.799	0.703
377	0.377	0.377	0.377	0.377	0.281	0.377	0.281	0.377	0.377	0.281	0.281	0.377	0.281
378	0.674	0.674	0.674	0.674	0.578	0.674	0.578	0.674	0.674	0.578	0.578	0.674	0.578
379	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422
380	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422
381	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297
382	0.803	0.803	1	0.803	0.803	0.803	0.803	0.803	0.803	0.803	1	1	1
383	0.814	0.814	0.814	0.814	0.814	0.814	0.814	1	0.814	1	1	1	0.814
384	0.562	0.562	0.562	0.562	0.562	1	1	0.562	1	1	0.562	0.562	1
385	0.562	0.562	0.562	0.562	0.562	1	1	0.562	1	1	0.562	0.562	1

n	yh11	yh12	yh13	yh14	yh15	yh21	yh22	yh23	yh24	yh25	yh31	yh32	yh33
386	0.54	0.54	0.54	0.54	0.54	1	1	0.54	1	0.54	1	0.54	1
387	0.54	0.54	0.54	0.54	0.54	1	1	0.54	1	0.54	1	0.54	1
388	1	1	0.968	0.968	0.968	0.968	0.968	1	0.968	1	0.968	1	1
389	1	1	0.968	0.968	0.968	0.968	0.968	1	0.968	1	0.968	1	1
390	0.264	0.264	0.264	0.264	0.264	0.208	0.264	0.264	0.264	0.208	0.264	0.208	0.264
391	0.264	0.264	0.264	0.264	0.264	0.208	0.264	0.264	0.264	0.208	0.264	0.208	0.264
392	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294
393	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294
394	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792
395	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291
396	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497
397	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
398	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
399	0.77	1	0.77	0.77	0.77	1	0.77	1	1	0.77	1	1	0.77
400	0.548	0.548	0.548	0.548	0.548	0.728	0.728	0.728	0.548	0.548	0.728	0.728	0.548
401	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272
402	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272
403	0.596	0.596	0.596	0.596	0.59	0.59	0.596	0.59	0.596	0.596	0.59	0.59	0.59
404	0.596	0.596	0.596	0.596	0.59	0.59	0.596	0.59	0.596	0.596	0.59	0.59	0.59
405	1.007	1.007	1.007	1.007	1	1	1.007	1	1.007	1.007	1	1	1
406	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
407	0.877	1	0.877	0.877	1	0.877	0.877	1	0.877	0.877	0.877	0.877	1
408	1	0.238	0.238	0.238	1	0.238	0.238	1	0.238	0.238	0.238	1	0.238
409	1	0.238	0.238	0.238	1	0.238	0.238	1	0.238	0.238	0.238	1	0.238
410	0.416	0.131	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.131	0.131
411	0.416	0.131	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.131	0.131
412	0.846	0.56	0.846	0.846	0.846	0.846	0.846	0.846	0.846	0.846	0.846	0.56	0.56
413	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
414	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
415	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
416	0.952	1	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	1
417	0.952	1	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	1

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
1	0.308	0.308	0.308	0.308	0.308	0.281	0.308	0.308	0.308	0.308	0.308	0.308
2	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692
3	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692
4	1	1.174	1	1	1	1	1.174	1	1	1	1	1
5	0.294	0.469	0.294	0.294	0.294	0.294	0.469	0.294	0.294	0.294	0.294	0.294
6	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
7	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706	0.706
8	0.393	0.469	0.393	0.393	0.393	0.393	0.469	0.393	0.393	0.393	0.393	0.393
9	0.588	0.664	0.588	0.588	0.588	0.588	0.664	0.588	0.588	0.588	0.588	0.588
10	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257
11	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257	0.257
12	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
13	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
14	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
15	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244	0.244
16	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
17	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
18	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
19	1	1	1	1	1	1	0.729	1	1	1	1	1
20	0.661	0.661	0.661	0.661	0.661	0.661	0.661	0.661	0.661	0.661	0.661	0.661
21	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339
22	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339	0.339
23	0.668	0.668	0.668	0.945	0.668	0.668	0.945	0.668	0.668	0.668	0.668	0.668
24	0.642	0.642	0.642	0.919	0.642	0.642	0.919	0.642	0.642	0.642	0.642	0.642
25	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332
26	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332	0.332
27	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358
28	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358	0.358
29	0.603	0.603	0.603	0.603	0.603	0.603	0.477	0.603	0.603	0.603	0.603	0.603
30	0.462	0.462	0.462	0.462	0.462	0.462	0.337	0.462	0.462	0.462	0.462	0.462
31	0.606	0.606	0.606	0.606	0.606	0.606	0.48	0.606	0.606	0.606	0.606	0.606
32	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
33	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141
34	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141	0.141
35	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
36	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186
37	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186	0.186
38	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
39	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
40	1	1.042	1.042	1	1.042	1	1	1	1	1	1	1
41	0.424	0.467	0.467	0.424	0.467	0.424	0.424	0.424	0.424	0.424	0.424	0.424
42	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576
43	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576
44	0.671	0.496	0.496	0.671	0.496	0.496	0.496	0.496	0.496	0.496	0.496	0.496
45	0.289	0.114	0.114	0.289	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114
46	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504
47	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504	0.504
48	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344
49	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382	0.382
50	0.541	0.541	0.541	0.541	0.541	0.541	0.541	0.541	0.541	0.541	0.541	0.541
51	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
52	1	1	1	1	1	1	1	1	1	1	1	1
53	1	1	0.929	1	1	1	1	1	1	1	1	1
54	0.222	0.151	0.151	0.222	0.209	0.222	0.222	0.151	0.151	0.151	0.151	0.151
55	0.65	0.579	0.579	0.65	0.579	0.65	0.65	0.579	0.579	0.579	0.579	0.579
56	0.65	0.579	0.579	0.65	0.579	0.65	0.65	0.579	0.579	0.579	0.579	0.579
57	0.275	0.275	0.275	0.275	0.217	0.275	0.275	0.275	0.275	0.275	0.275	0.275
58	0.428	0.428	0.428	0.428	0.37	0.428	0.428	0.428	0.428	0.428	0.428	0.428
59	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217
60	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217
61	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574	0.574
62	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204
63	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
64	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804
65	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804
66	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196
67	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
68	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
69	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
70	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385	0.385

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
71	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532	0.532
72	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
73	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
74	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
75	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
76	0.217	0.217	0.165	0.165	0.165	0.165	0.165	0.165	0.165	0.165	0.165	0.165
77	0.298	0.298	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246
78	0.298	0.298	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246	0.246
79	0.589	0.589	0.536	0.536	0.536	0.536	0.536	0.536	0.536	0.536	0.536	0.536
80	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545	0.545
81	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373
82	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
83	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
84	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
85	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
86	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172	0.172
87	0.455	0.455	1	1	1	1	1	1	1	1	1	1
88	0.455	0.455	1	1	1	1	1	1	1	1	1	1
89	0.161	0.161	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
90	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
91	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
92	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
93	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.408
94	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322
95	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322	0.322
96	1	0.533	1	1	1	1	1	1	1	1	1	1
97	1	0.533	1	1	1	1	1	1	1	1	1	1
98	0.633	1	1	1	1	1	1	1	1	1	1	1
99	0.633	1	1	1	1	1	1	1	1	1	1	1
100	1	0.456	1	1	1	1	1	1	1	1	1	1
101	0.47	0.665	0.665	0.47	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665
102	0.805	1	1	0.805	1	1	1	1	1	1	1	1
103	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
104	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
105	0.5	0.5	0.5	0.334	0.5	0.334	0.334	0.334	0.334	0.334	0.334	0.334

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
106	0.5	0.5	0.5	0.334	0.5	0.334	0.334	0.334	0.334	0.334	0.334	0.334
107	0.967	0.967	0.967	0.801	0.967	0.801	0.801	0.801	0.801	0.801	0.801	0.801
108	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467	0.467
109	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
110	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
111	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
112	1	1	1	0.637	0.637	1	0.637	1	1	1	1	1
113	1	1	1	0.637	0.637	1	0.637	1	1	1	1	1
114	0.184	0.184	0.184	0.184	0.184	0.469	0.184	0.184	0.184	0.184	0.184	0.184
115	0.465	0.465	0.465	0.465	0.465	0.75	0.465	0.465	0.465	0.465	0.465	0.465
116	0.465	0.465	0.465	0.465	0.465	0.75	0.465	0.465	0.465	0.465	0.465	0.465
117	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535
118	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535	0.535
119	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281
120	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281	0.281
121	0.898	0.898	0.898	1	1	1	1	1	1	1	1	1
122	0.637	0.336	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
123	0.637	0.336	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
124	0.637	0.336	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
125	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
126	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
127	0.049	0.049	1	0.049	1	1	0.049	1	1	1	1	1
128	0.879	1	1	0.879	1	1	0.879	1	1	1	1	1
129	0.879	1	1	0.879	1	1	0.879	1	1	1	1	1
130	0.506	0.506	0.506	0.506	0.506	0.298	0.506	0.506	0.506	0.506	0.506	0.506
131	0.423	0.423	0.423	0.423	0.423	0.214	0.423	0.423	0.423	0.423	0.423	0.423
132	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084
133	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
134	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
135	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
136	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208	0.208
137	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
138	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286	0.286
139	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136
140	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136	0.136

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
141	0.449	0.449	0.449	0.449	0.424	0.449	0.424	0.449	0.449	0.449	0.449	0.449
142	0.259	0.259	0.259	0.259	0.234	0.259	0.234	0.259	0.259	0.259	0.259	0.259
143	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191
144	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644	0.644
145	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374
146	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374	0.374
147	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
148	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277	0.277
149	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
150	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
151	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
152	0.445	0.95	0.95	0.95	0.95	0.95	0.445	0.95	0.95	0.95	0.95	0.95
153	0.445	0.95	0.95	0.95	0.95	0.95	0.445	0.95	0.95	0.95	0.95	0.95
154	0.495	1	1	1	1	1	0.495	1	1	1	1	1
155	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
156	1	1	1	1	1	1	1	1	1	1	1	1
157	0.335	0.292	0.335	0.292	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
158	0.54	0.497	0.54	0.497	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
159	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665
160	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
161	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205
162	0.916	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716	0.716
163	0.417	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217	0.217
164	0.882	0.682	0.682	0.682	0.682	0.682	0.682	0.682	0.682	0.682	0.682	0.682
165	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284	0.284
166	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499	0.499
167	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318	0.318
168	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182	0.182
169	0.694	0.393	0.694	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393
170	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607
171	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607	0.607
172	0.432	0.432	0.432	0.432	0.432	0.403	0.432	0.432	0.432	0.432	0.432	0.432
173	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568
174	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568	0.568
175	0.349	0.349	0.358	0.349	0.358	0.358	0.349	0.349	0.349	0.349	0.349	0.349

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
176	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651
177	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651
178	1	1	0.56	0.56	1	1	0.56	1	1	1	1	1
179	0.804	1	1	1	1	1	1	1	1	1	1	1
180	0.804	1	1	1	1	1	1	1	1	1	1	1
181	0.544	0.544	0.544	0.544	0.39	0.544	0.544	0.544	0.544	0.544	0.544	0.544
182	0.819	0.819	0.819	0.819	0.665	0.819	0.819	0.819	0.819	0.819	0.819	0.819
183	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
184	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
185	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
186	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
187	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
188	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
189	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181	0.181
190	0.107	0.107	1	1	1	1	1	1	1	1	1	1
191	0.637	0.637	0.637	0.637	0.493	0.637	0.637	0.637	0.637	0.637	0.637	0.637
192	1	1	1	1	0.855	1	1	1	1	1	1	1
193	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
194	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363	0.363
195	0.661	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342
196	0.275	0	0	0	0	0	0	0	0	0	0	0
197	1.115	0.796	0.796	0.796	0.796	0.796	0.796	0.796	0.796	0.796	0.796	0.796
198	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204
199	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204
200	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204	0.204
201	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.454
202	0.387	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342
203	0.387	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342
204	0.355	0.355	0.355	0.355	0.355	0.279	0.355	0.355	0.355	0.355	0.355	0.355
205	0.355	0.355	0.355	0.355	0.355	0.279	0.355	0.355	0.355	0.355	0.355	0.355
206	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645
207	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645	0.645
208	0.695	0.659	0.659	0.659	0.695	0.659	0.659	0.659	0.659	0.659	0.659	0.659
209	0.695	0.659	0.659	0.659	0.695	0.659	0.659	0.659	0.659	0.659	0.659	0.659
210	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
211	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
212	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341
213	1	0.283	0.283	1	1	1	1	1	1	1	1	1
214	0.39	0.454	0.454	0.454	0.39	0.454	0.39	0.39	0.39	0.39	0.39	0.39
215	0.39	0.454	0.454	0.454	0.39	0.454	0.39	0.39	0.39	0.39	0.39	0.39
216	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388	0.388
217	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
218	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222
219	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222
220	0.226	0.226	0.096	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226
221	0.226	0.226	0.096	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226
222	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401
223	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143
224	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143
225	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373
226	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
227	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
228	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258
229	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258
230	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
231	0.15	0.35	0.15	0.15	0.15	0.35	0.15	0.15	0.15	0.15	0.15	0.15
232	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
233	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
234	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393
235	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393	0.393
236	0.561	0.561	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624
237	0.561	0.561	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.624
238	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376
239	0.817	1	1	0.817	1	1	1	1	1	1	1	1
240	0.561	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
241	0.561	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
242	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
243	0.96	0.96	1	1	0.96	1	1	1	1	1	1	1
244	1	0.699	1	1	1	1	1	1	1	1	1	1
245	0.398	0.565	0.565	0.398	0.398	0.565	0.398	0.565	0.565	0.565	0.565	0.565

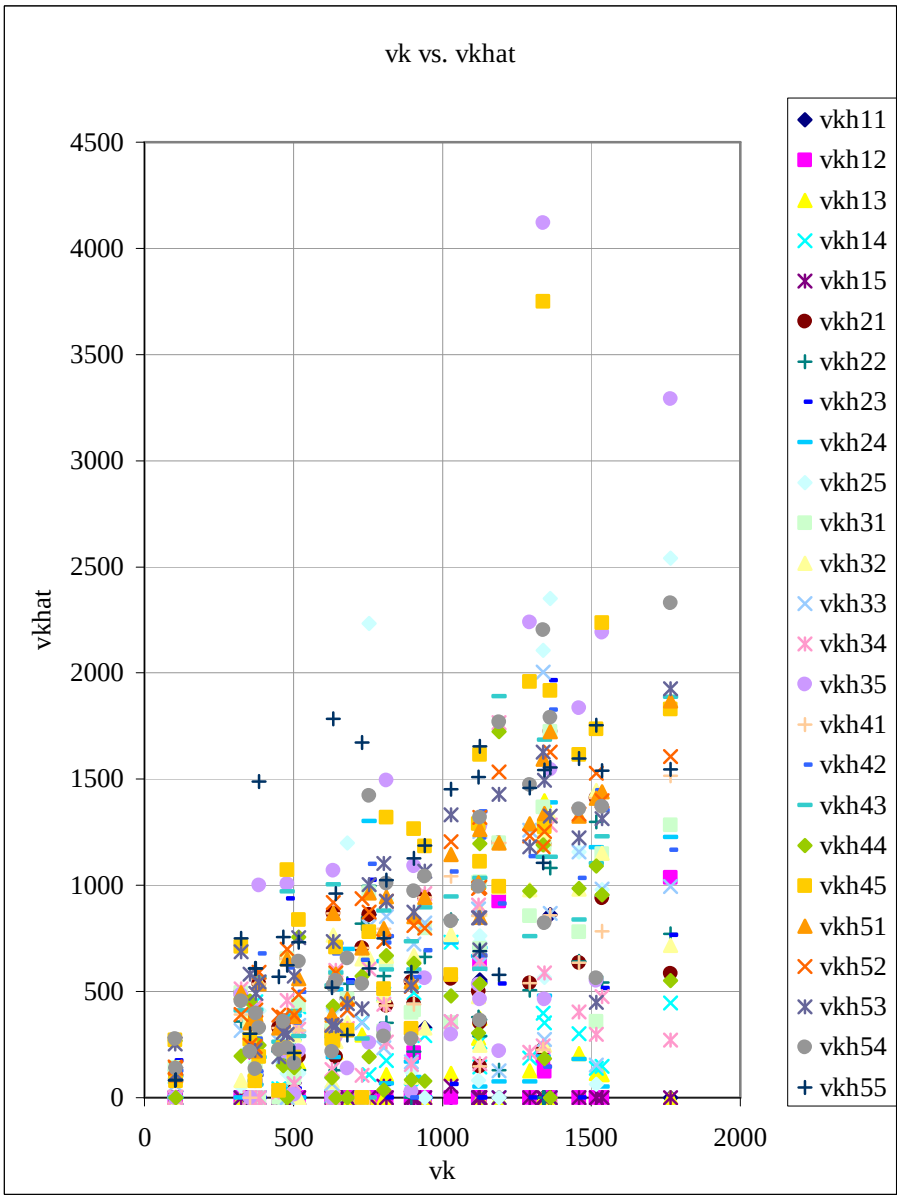
n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
246	0.047	0.213	0.213	0.047	0.047	0.213	0.047	0.213	0.213	0.213	0.213	0.213
247	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351	0.351
248	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463	0.463
249	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435	0.435
250	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
251	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
252	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
253	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323
254	0.31	0.443	0.443	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
255	0.099	0.231	0.231	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.099
256	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
257	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
258	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198	0.198
259	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211	0.211
260	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703	0.703
261	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157	0.157
262	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492
263	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
264	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335	0.335
265	0.609	0.698	0.698	0.609	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698
266	0.609	0.698	0.698	0.609	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698
267	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
268	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
269	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
270	0.401	0.161	0.401	0.161	0.401	0.401	0.401	0.401	0.401	0.401	0.401	0.401
271	0.731	0.491	0.731	0.491	0.731	0.731	0.731	0.731	0.731	0.731	0.731	0.731
272	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345
273	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269	0.269
274	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
275	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254
276	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254
277	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
278	0.786	0.987	0.786	0.786	0.786	0.786	0.786	0.786	0.786	0.786	0.786	0.786
279	0.421	0.623	0.421	0.421	0.421	0.421	0.421	0.421	0.421	0.421	0.421	0.421
280	0.291	0.492	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
281	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345	0.345
282	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
283	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
284	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364
285	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205	0.205
286	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
287	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
288	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
289	0.776	0.776	0.718	0.776	0.718	0.776	0.718	0.718	0.718	0.718	0.718	0.718
290	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282
291	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282	0.282
292	1	1	1	1	0.92	1	1	1	1	1	1	1
293	0.935	0.935	0.935	0.377	0.935	0.377	0.935	0.935	0.935	0.935	0.935	0.935
294	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
295	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
296	1.155	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.584
297	0.621	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
298	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534
299	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534	0.534
300	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
301	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
302	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416	0.416
303	0.691	0.711	0.711	0.691	0.711	0.711	0.691	0.711	0.711	0.711	0.711	0.711
304	0.238	0.258	0.258	0.238	0.258	0.258	0.238	0.258	0.258	0.258	0.258	0.258
305	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289
306	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289	0.289
307	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472	0.472
308	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
309	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
310	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183
311	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183	0.183
312	0.521	0.683	0.683	0.683	0.683	0.683	0.521	0.683	0.683	0.683	0.683	0.683
313	0.521	0.683	0.683	0.683	0.683	0.683	0.521	0.683	0.683	0.683	0.683	0.683
314	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317
315	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
316	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317	0.317
317	0.905	1	1	1	1	0.905	1	1	1	1	1	1
318	0.271	0.329	0.271	0.329	0.329	0.329	0.329	0.329	0.329	0.329	0.329	0.329
319	0.674	0.733	0.674	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733	0.733
320	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402	0.402
321	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188
322	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188	0.188
323	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
324	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268
325	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268
326	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
327	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
328	0.916	0.916	0.916	0.916	0.916	0.715	0.916	0.916	0.916	0.916	0.916	0.916
329	0.744	0.744	0.744	0.744	0.744	0.543	0.744	0.744	0.744	0.744	0.744	0.744
330	0.514	0.514	0.514	0.514	0.514	0.313	0.514	0.514	0.514	0.514	0.514	0.514
331	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173
332	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256	0.256
333	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285	0.285
334	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
335	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
336	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084	0.084
337	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
338	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
339	0.361	0.361	0.361	0.251	0.361	0.361	0.361	0.361	0.361	0.361	0.361	0.361
340	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
341	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
342	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
343	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
344	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403
345	0.988	0.988	0.988	1	1	1	1	1	1	1	1	1
346	0.794	0.777	0.794	0.794	0.777	0.794	0.777	0.794	0.794	0.794	0.794	0.794
347	0.195	0.177	0.195	0.195	0.177	0.195	0.177	0.195	0.195	0.195	0.195	0.195
348	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206	0.206
349	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572
350	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366	0.366

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
351	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
352	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
353	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233	0.233
354	0.067	0.067	0.067	0.067	0.067	0.067	0.4	0.067	0.067	0.067	0.067	0.067
355	0.067	0.067	0.067	0.067	0.067	0.067	0.4	0.067	0.067	0.067	0.067	0.067
356	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933	0.933
357	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375
358	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557
359	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557	0.557
360	0.523	0.523	0.369	0.523	0.523	0.523	0.523	0.523	0.523	0.523	0.523	0.523
361	0.523	0.523	0.369	0.523	0.523	0.523	0.523	0.523	0.523	0.523	0.523	0.523
362	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477
363	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477	0.477
364	1	0.952	1	1	1	0.952	1	1	1	1	1	1
365	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617
366	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617	0.617
367	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
368	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
369	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
370	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
371	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
372	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
373	0.123	0.584	0.584	0.584	0.123	0.123	0.584	0.123	0.123	0.123	0.123	0.123
374	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877
375	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877	0.877
376	0.703	0.703	0.703	0.703	0.799	0.703	0.703	0.703	0.703	0.703	0.703	0.703
377	0.281	0.281	0.281	0.281	0.377	0.281	0.281	0.281	0.281	0.281	0.281	0.281
378	0.578	0.578	0.578	0.578	0.674	0.578	0.578	0.578	0.578	0.578	0.578	0.578
379	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422
380	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422	0.422
381	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297	0.297
382	0.803	0.803	1	1	0.803	1	1	1	1	1	1	1
383	1	0.814	1	1	1	0.814	1	1	1	1	1	1
384	0.562	1	1	1	1	1	1	1	1	1	1	1
385	0.562	1	1	1	1	1	1	1	1	1	1	1

n	yh34	yh35	yh41	yh42	yh43	yh44	yh45	yh51	yh52	yh53	yh54	yh55
386	0.54	0.54	1	1	1	1	1	1	1	1	1	1
387	0.54	0.54	1	1	1	1	1	1	1	1	1	1
388	1	1	1	1	1	1	1	1	1	1	1	1
389	1	1	1	1	1	1	1	1	1	1	1	1
390	0.208	0.208	0.264	0.208	0.264	0.264	0.208	0.208	0.208	0.208	0.208	0.208
391	0.208	0.208	0.264	0.208	0.264	0.264	0.208	0.208	0.208	0.208	0.208	0.208
392	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294
393	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294
394	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792	0.792
395	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291	0.291
396	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497	0.497
397	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
398	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207	0.207
399	1	0.77	1	1	1	1	1	1	1	1	1	1
400	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728
401	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272
402	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272	0.272
403	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
404	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
405	1	1	1	1	1	1	1	1	1	1	1	1
406	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
407	0.877	1	1	1	1	1	1	1	1	1	1	1
408	1	0.238	0.238	1	0.238	1	1	1	1	1	1	1
409	1	0.238	0.238	1	0.238	1	1	1	1	1	1	1
410	0.131	0.131	0.131	0.416	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131
411	0.131	0.131	0.131	0.416	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131
412	0.56	0.56	0.56	0.846	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
413	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
414	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
415	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
416	1	0.952	1	1	0.952	1	1	1	1	1	1	1
417	1	0.952	1	1	0.952	1	1	1	1	1	1	1


vk vs. vkhat
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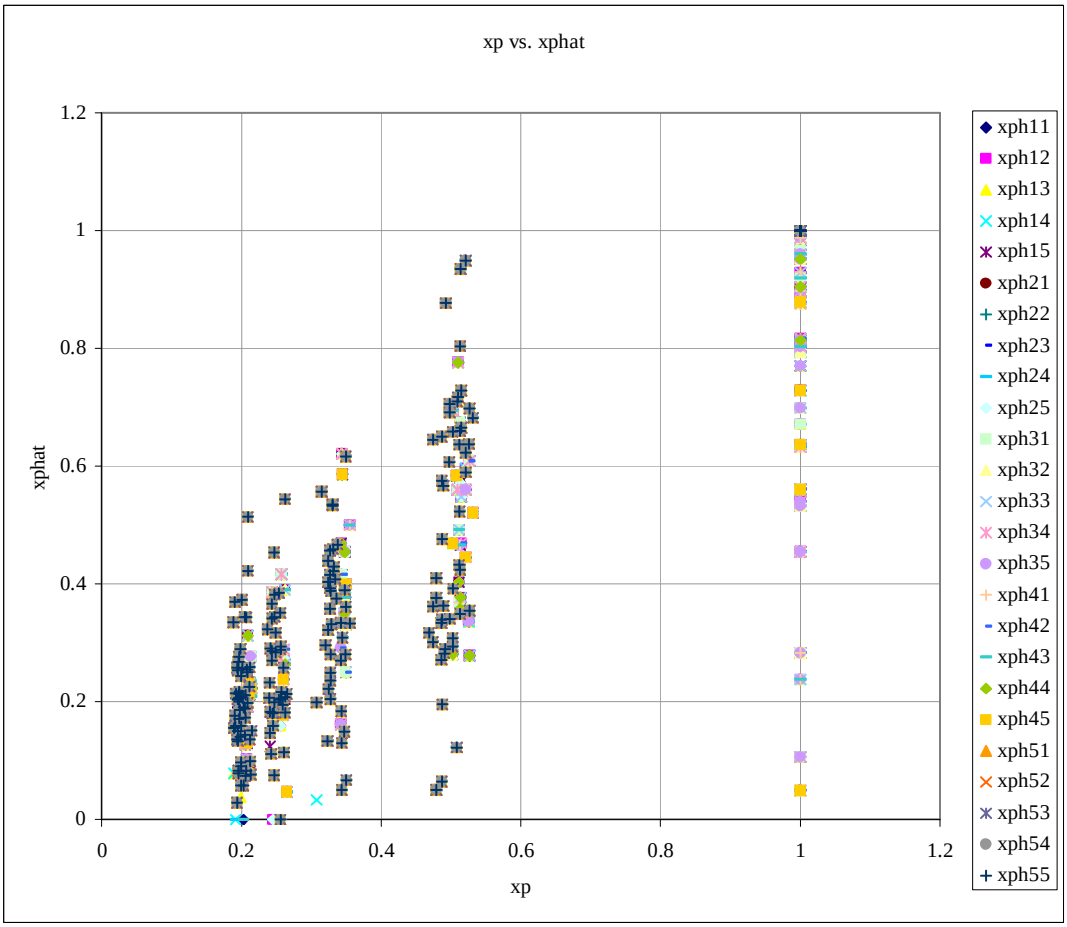
xp vs. xphat
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