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MODELING AND ANALYSIS OF AIRCRAFT OFFLOADING OPERATIONS

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ABSTRACT

This paper describes a successful application of discrete-event simulation techniques to evaluate and improve the plane offloading operations in a central aircargo Hub. The simulation model was built after a thorough analysis of plane offloading procedures, freight flow, and work rules involving the usage of equipment and personnel. Experimentation and extensive statistical analysis were performed to determine the (i) best operating rules, (ii) strategic changes to tug and dolly operations, and (iii) ramp configuration. The final recommendations based on a rigorous analysis to improve the ramp performance and use of models in planning and control are discussed.

1 INTRODUCTION

Application of discrete-event simulation to improve the ramp operations of aircargo companies has been gaining enormous impetus during this decade. A typical aircargo offloading ramp includes (a) runways, (b) gates or park locations, (c) K-loaders, (d) tug and dollies, (e) forklifts, (f) sortline conveyors, (g) belt/roller conveyors, and (h) movement lanes for tugs, planes, etc. The aircargo ramp discussed in this paper is divided into north, south, east and west sides with a capacity to handle 77 planes at any time. During each night, a scheduled number of aircraft arrive at the Hub between 11:00 p.m and 3:00 a.m.

A tailsheet provides the data on the number and types of aircraft, origin, destination, and scheduled arrival and departure times. The gate (park location) for each plane is assigned by the aircraft control tower and it stays at that gate until departure. Containerized freight is transported by 6 different models of aircraft and are offloaded by 14 K-loaders onto a set of dollies linked to a tug. Nearly 40 tugs and 120 dollies are used to offload and move the containers to one of 62 radio-controlled sortline conveyor locations at north and south transfer areas. At each transfer area, 16 forklifts offload the containers from the dollies and transport to breakdown sortline conveyors. The ramp encompasses a centralized park location for all tug and dolly units and two outside conveyors to handle belly freight (see Figure 1).

Essentially, three types of containers are offloaded from the aircraft. These are categorized as (i) *top side huts* (ULDs), (ii) *top side pallets* (PNs), and (iii) *belly freight* transferred to a container for efficient handling. In the existing system, two tugs each connected with 2, 3 or 4 dollies, are assigned to an aircraft to transport the containers. The tugs, once assigned to an aircraft, tend to stay as a team until all the aircraft on the ramp are offloaded. As the tugs approach the Hub building, they are assigned to one of the two transfer areas. Once an aircraft is fully offloaded, the tugs and the crew move as a group to the next nearest plane. Several work rules are followed by tug operators in offloading aircraft. These rules apply to both *top side* and *belly* containers.

The containers from aircraft are transported to one of two locations on the ramp before they are opened, sorted, consolidated, and loaded back into aircraft for delivering to destinations all over the world; (a) huts and PNs are offloaded to sortline conveyors at transfer areas, and (b) loose freight from the aircraft belly is offloaded first to a container and then moved to outside conveyors.

Forklifts at transfer areas take different pickup or dropoff time depending on the number of dollies hooked to a tug. Hence, the total offloading time as well as the congestion levels at the transfer areas vary depending upon the number of dollies hooked to a tug. The more number of dollies per tug tends to increase the dropoff time at the transfer area whereas, a fewer number of dollies per tug tends to cut down the pickup time for the K-loader process at the aircraft.

Huts and PNs are offloaded by forklifts from tug and dollies to any one of 62 sortline conveyors and are moved from the transfer areas to sortation area. The sortline conveyor is an indexing conveyor and has the capacity to accumulate five containers. The conveyor for offloading is decided by a dispatcher based on (i) availability, (ii) proximity, and (iii) the least number waiting on the slat conveyor. A traffic light mounted at the top of each sortline conveyor is used to indicate its availability to forklift operators. The general rule is to load each conveyor with at least one container to ensure uniform loading and minimum delays on the conveyor. The huts and PNs are indexed to the end of the sortline where the freight inside the container is offloaded by forklifts, sortation devices and human operators. Once a container becomes empty, it is removed from the sortline and transported for reuse at one of 16 buildup modules where the sorted freight is consolidated and reloaded to aircraft.

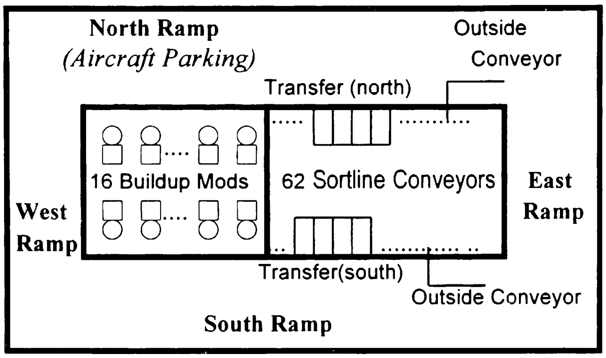

Figure 1: Block Layout of the Central Hub

Two outside conveyors at the north and south end of the Hub building are used to offload the belly containers. In general, the freight in each belly fills up a container. Forklifts are used to move the loaded belly containers from the aircraft. Once these containers are brought to the outside conveyor areas, human operators transfer the belly freight on to the conveyor belt. The freight is conveyed to sortation areas and then to buildup modules.

In this paper, we focus our attention primarily to plane offloading operations at the aircargo Hub in order to accomplish the following objectives;

(a) Build a simulation model to visualize the problems, trouble spots, and changes in behavior of the aircraft offloading operations to the ramp crew as the Hub undergoes changes in the usage of K-loaders, tugs and dollies, and other auxiliary equipment.

(b) Study the impact of varying the number of planes and gates and accordingly find the *best* number of K-loaders and tug and dollies. Identify changes in work rules and communication system to maximize throughput and number of aircraft offloaded and minimize the average time to offload an aircraft.

(c) Study the impact of changing the number of dollies per tug, number of tugs per plane on the average time required to offload a plane. Study the impact of these operation parameters on varying number of planes that arrive at the Hub during a night.

(d) Study the impact of speeding up the K-loader process and changing the number of tugs per plane to five and dollies per tug to three.

(e) Study the impact of assigning a variable number of tugs (instead of two tugs) to aircraft and dispatching tugs by radio on the completion time and average offloading time per aircraft.

2 MODEL DATA

Two types of input data were collected and used in the simulation model. The first type involved the technical specifications associated with the freight, aircraft, gates, tug and dollies, forklifts, sortline conveyors, and outside conveyors along with the assignment rules, work rules, freight flow behavior, control rules for tugs and forklifts, etc. More specifically, the following data were obtained from the Hub; (a) number of gates, (b) ramp maps, (c) technical specifications of conveyors, tugs, dollies, and forklifts, (d) flight profile, (e) aircraft models or types, (f) chronological plane arrival/departure information, (g) number of *topside* containers by plane type, (h) number of *bellies* by plane type, (i) number of containers per belly by plane type, (j) number of dollies per tug, (k) team makeup for offloading containers from a plane, (l) total number of tugs and dollies, (m) number of transfer forklifts, (n) outside conveyor locations/their physical characteristics, (o) aircraft parking/offloading rules, (p) runway characteristics, and so forth.

The second type of information involved a set of input distributions associated with the night-to-night (or hour-to-hour) variations found in the plane offloading operations. These included; (a) plane arrival process at different locations of the ramp, (b) pickup times and dropoff times for tugs and forklifts based on freight type and number of containers, (c) operation times at the slat conveyor, and (d) the plane contents.

3 EXISTING PLANE OFFLOADING MODEL

The model logic was implemented using *Automod II* on an IBM-PC. Ten processes, *P1* to *P10* were developed to represent accurately the behavior of plane offloading operations *(base model)* on the ramp. These include;

P1: Aircraft Arrival at the Hub

P2: Aircraft Parking at the Park Location
- Assign park locations using a rulebase
- Send aircraft directly to next-available gate

P3: Aircraft Arrive at the Gates and Request for Tugs
- Enter the park location for offloading
- Turn off the engine and open cargo doors
- Request tugs/K-loaders/conveyors/crews

P4: Plane Location Specification to Tugs
- Assign two tugs to a plane
- Assign rampid and park location id to the tug

P5: Tug Scheduling, Movement and Control
- Specify the plane park location to begin offloading

- Move the tug to the park location
- Determine the number of huts/PNs picked up
- Transport to container destination
    - North transfer area
    - South transfer area
    - Outside conveyors
- Dropoff the container at its destination
- Move the tug back to the aircraft being offloaded
- Repeat until all containers are offloaded

P6: K-loader Transfer, Tug Pickup and Dropoff

- Specify transfer time based on the K-loader process
- Specify tug pickup time at the aircraft
- Specify tug dropoff time at the transfer area

P7: Transfer Area Selection for Tugs

P8: Pickup and Dropoff by Forklifts at Transfer Areas

- Specify the pickup time based on number of dollies
- Specify the dropoff time per container

P9: Slat Conveyor Selection

- Select the slat conveyor to offload containers
- Selection rules
    - Nearest neighbor rule
    - Next available segment rule
    - Waiting rules if no segment available

P10: Container Movement on a Sortline Conveyor

- Entry station rules
- Exit station rules
- Travelling on segment rules
- Waiting rules on the segment

All ten processes were built with intelligent rules and algorithms, implemented in *Automod II*, to capture the exact behavior of plane offloading operations.

The simulation model was linked with input data files through an efficient interface to perform *"what-if"* scenarios. The aircraft arrival and parking process was implemented with a rulebase to mimic the tower rules used to park the aircraft. The rulebase consists of twenty rules and utilizes the flight profile to obtain all pertinent information on the arriving planes during a night. The rulebase was validated using several flight profiles and arrival times to ensure that all the planes are parked at north, south, east, and west ends of the ramp.

The simulation model was built with a ramp map to incorporate tug and dolly movement lanes, parking locations for planes and tugs, waiting areas for tugs, interaction zones for transfer forklifts to pickup huts and PNs from the tug and dollies, capacity limitations at the intersections to avoid collision between tugs, and control points to keep sufficient space between tugs.

With respect to tug and dolly system, the model was built to depict explicit and accurate representation of its behavior. A smart algorithm was implemented to incorporate the plane assignment rules to tug and dollies (belonging to a team), tugs per plane rules, tug waiting rules, offloading crew rules, collision avoidance rules, right-of-way rules, parking rules, and passing rules. The algorithm uses the tug specification such as acceleration, deceleration, loaded/unloaded speeds, forward, reverse and curve speeds, and ramp map to compute the precise travel times between aircraft and transfer areas.

The processes at the north and south transfer areas were modelled very precisely as well. Eight forklifts on each side of the transfer areas move the containers from the dollies to sortline conveyors. The sortline conveyor selection process was modelled in detail. Another smart algorithm was implemented to ensure uniform container offloading at sortline conveyors such that no single conveyor would be overloaded during a night. Also, the algorithm was built to reroute the tugs to south (or north) transfer areas in case of overloading. At the Hub, this was carried out by a human dispatcher who observed the container movement along the sortlines on a computer screen. Depending upon the overload conditions, the dispatcher communicated with the tug operators using a radio and rerouted the containers.

4 FACTORS AND RESPONSES

Controllable factors and responses were identified to evaluate alternative system configurations based on a list of issues that the Hub management was interested in. For the plane offloading model, the major factors were (a) number of planes (flight profile and plane arrival time distributions), (b) total number of tugs, (c) number of tugs per plane, (d) number of dollies per tug, and (e) number of K-loaders. Likewise, the responses that were of interest include; (a) plane offload capacity in terms of total number of containers offloaded and total number of planes offloaded (b) average time to offload a plane, and (c) completion time for offloading all planes. A report generator and an experimental setup were developed using *AutoStat* and interfaced with the *base model* to conduct *"what-if"* scenarios and statistical analysis.

5 WHAT-IF SCENARIOS

The *base model* was modified to study the impact of alternative ways of (a) assigning tug and dollies to the aircraft, (b) communication, and (c) using equipment, people and facilities. These are described below;

Alternative System I encompasses a change in the existing plane offloading model in which the number of tugs per plane is set to be five, number of dollies per tug is set to be three, and the K-loader process is speeded up to reduce the transfer time from the aircraft to dollies.

Alternative System II encompasses a major change in the existing plane offloading process. The work rules associated with the tug and dolly system are modified to provide more flexibility and independence to tugs. This system is referred as *radio-dispatched tug operations* (RDTO). In RDTO system, once an aircraft arrives, the dispatcher is informed via radio about its park location and number of containers in the plane. The dispatcher determines the number of tugs required (each tug is fitted with three dollies) and then identifies at least one tug that is closest to the plane that can be dispatched and send to that aircraft (similar to dispatching taxi cabs). This means that this tug is currently idle and waiting to be dispatched. The maximum number of tugs dispatched at any time is equal or less than the exact number of tugs required to offload the entire plane. This depends upon the availability of tugs for offloading as well as the fact that there are no other plane is currently requesting for a tug. If there are several planes waiting for tugs at the same time, then the dispatcher sends one or more tugs per plane based on the proximity rules and number of tugs currently idle. Several parking areas are setup on the ramp where the tug and dollies wait for work when they become idle with no planes to offload.

In RDTO system, it is essential that the dispatcher is knowledgeable about two facts; (i) plane information once it is ready for offloading, and (ii) tug-id and its location when a tug completes offloading a container at transfer areas. Based on these facts, the dispatcher can identify the aircraft where there is immediate need for a tug. The next available tug closest to that aircraft is dispatched.

The RDTO system breaks down all the barriers of 2-tug setup found in the existing operation. It offers the flexibility to move K-loaders to the next plane once the last topside container is transferred from the aircraft to the dolly. Further, the belly crews are separated from the top side crews which cuts down the 'waiting for each other to finish offloading' syndrome.

6 EXPERIMENTATION

A simulation experiment was conducted using the *base model* encompassing the current operating procedures and existing levels of aircraft and equipment (59 planes, 40 total tugs, 2 tugs per plane, and 2, 3, or 4 dollies per tug). The purpose was to bench-mark the existing ramp operations in order to provide a basis of comparison for the alternative scenarios investigated.

We made ten replications and computed the mean and standard deviation for the average offloading time for an aircraft using the simulation outputs. The mean and standard deviation were: $y = 31.802$ minutes and $s = 0.8694$ minutes respectively. Hence, any configuration with an average offloading time significantly less than 31.802 minutes would be considered as an improvement over the existing configuration.

The following sets of experiments were conducted to determine the best configuration(s);

(a) Using the *base model*, 37 different configurations were tested for three sets of aircraft (59,68,77) arriving nightly, five levels of total number of tugs operating on the ramp (40,60,80,100,120), four levels of tugs assigned to each plane (2,3,4,5), and three levels of dollies hooked to a tug (2,3,4).

(b) Using the revised *base model* to depict *Alternative System I*, 11 configurations were tested for three sets of aircraft (59,68,77) arriving nightly and five levels of total number of tugs (40,60,80,100,120).

(c) Using the revised *base model* to depict *Alternative System II*, 33 configurations were tested for three sets of aircraft arriving nightly and various levels of tugs (40,60,80,100,120) and K-loaders (8,14,20,26,32).

The first set of experiments (i) establishes a relationship between the overall ramp performance and the resource capacity (tugs, dollies, K-loaders), and (ii) estimates the best configuration even if the total number of aircraft offloaded vary widely (between 59 and 77). The second set of experiments pertains to a configuration in which 5 tugs are assigned to each plane, 3 dollies are assigned to each tug, and modified K-loader process. This series of experiments (i) compares the overall performance with the *base model*, and in particular, to the best equipment configuration without major changes to existing ramp operations; and (ii) determines the total number of tugs required to achieve this best performance. The third set of experiments pertains to the analysis of RDTO system.

In all experiments, the overall system performance was measured in terms of average plane offloading time. Plane offloading time is defined as the amount of time between the arrival of an aircraft at the hub and the completion of the offloading process for that aircraft.

6.1 Existing Plane Offloading (Base Model)

The *base model* to depict the existing plane offloading operation was utilized to accommodate varying number of tugs, tugs per plane, and dollies per tug. The purpose of this experiment was to estimate the best number of tugs to achieve the least offloading time per aircraft. Consider the set of factors shown in Table 1 and their impact on the average plane offloading time (y).

Table 1: Factors for Base Model Experiments

Factor	Description
x_1	Number of aircraft arriving nightly
x_2	Number of tugs
x_3	Number of tugs per plane
x_4	Number of dollies per tug

To assess the impact of varying levels of these factors on the average plane offloading time, we conducted a set of experiments with the *base model* and used the results to fit a linear statistical model of the general form:

$$y = b_o + \Sigma_i b_i x_i + \Sigma_i \Sigma_j b_{ij} x_i x_j + \Sigma_i \Sigma_j \Sigma_k b_{ijk} x_i x_j x_k + \Sigma_i b_{ii} x_i^2 + \Sigma_i b_{iii} x_i^3 + \Sigma_i b_{iiii} x_i^4 + \varepsilon \quad (1)$$
$$i = \{1, 2, \ldots, 4\}, j = \{1, 2, \ldots, 4\}$$
$$k = \{1, 2, \ldots, 4\}, l = \{1, 2, \ldots, 4\}$$

The ranges of experimental factors studied in these experiments are given in Table 2. Coded factor levels were used to estimate expression (1) to minimize the variance of prediction (i.e., in order to obtain the best possible predictions with the least amount of data).

Table 2: Factor Levels for Base Model

Factor	Factor Levels	Coded Factor Levels(ξ_i)
x_1	59, 68, 77	-1.0, 0.0, 1.0
x_2	40, 60, 80, 100, 120	-1.0, - 0.5, 0.0, 0.5,1.0
x_3	2, 3, 4, 5,6	-2.0, -1.0, 0.0, 1.0, 2.0
x_4	2, 3, 4	-1.0, 0.0, 1.0

In order to obtain the best possible fit and to stabilize the error variance, y was transformed by taking the natural log of y. Thus, the form of the fitted equation is:

$$y = \exp(b_o + \Sigma_i b_i \xi_i + \Sigma_i \Sigma_j b_{ij} \xi_i \xi_j + \Sigma_i \Sigma_j \Sigma_k b_{ijk} \xi_i \xi_j \xi_k + \Sigma_i b_{ii} \xi_i^2 + \Sigma_i b_{iii} \xi_i^3 + \Sigma_i b_{iiii} \xi_i^4 + \varepsilon) \quad (2)$$
$$i = \{1, 2, \ldots, 4\}, j = \{1, 2, \ldots, 4\},$$
$$k = \{1, 2, \ldots, 4\}, l = \{1, 2, \ldots, 4\}.$$
$$\xi_1 = (x_1 - 68) / 9, \xi_2 = (x_2 - 80) / 40,$$
$$\xi_3 = (x_3 - 4) / 1, \xi_4 = (x_4 - 3) / 1$$

Multiple regression procedure in *Statistica* software was used to estimate model (2).

Table 3 provides a list of statistically significant coefficients and factors for model (2). The p-value for each model component is the probability that the effect estimated by the analysis procedure is due to chance and not to a systemic behavior. The lower the p-value the more significant (statistically) the component is. All components with p-values greater than 0.1 were selected to be insignificant and excluded from Table 3. The signs of the model coefficients (b's) indicate whether or not the component has a positive or negative effect on the response. The percentage of total variation in the data that is accounted for by the estimated linear model is given by R^2.

Model (2) accounts for 94.42% of all of the variation in the data. High R^2 value generally indicates a comprehensive statistical model as well as a good fit. Subsequent to the estimation, model (2) was used to locate the (near) *optimal* equipment configurations for varying numbers of aircraft arriving nightly at the Hub.

Table 3: Estimated Linear Regression Model
Model (2) (R^2 = .9442)

Component	b	p-value
Intercept	3.485979	0.000000
x_1	0.175055	0.000000
x_2	-0.046504	0.088576
x_3	0.166626	0.000000
x_4	-0.153704	0.000000
x_1x_2	-0.027974	0.000150
x_1x_3	0.030806	0.000002
x_1x_4	-0.054193	0.000000
x_2x_3	-0.069812	0.000000
x_2x_4	-0.038229	0.000001
$x_1x_2x_3$	0.031979	0.000019
$x_2x_3x_4$	-0.054050	0.000000
$x_1x_2x_3x_4$	-0.056447	0.000000
x_2^2	0.163786	0.000000
x_4^2	0.115800	0.000000
x_2^3	-0.088960	0.002268
x_3^3	-0.052137	0.000000

6.2 Alternative System I

In the *base model*, the number of tugs assigned to each plane was increased to five and the K-loader process was modified to speed up the operations at the plane to set up the *Alternative System I* scenario. Further, the dollies were retrofitted with ball tables so that the operator can simply push the container off the K-loader on to a dolly thereby eliminating intermediate operation stages. The purpose of this experiment was (I) to estimate the best number of tugs and K-loaders to be used on the ramp to achieve the least offloading time per plane and (ii) reduction in the overall ramp offloading time for all the planes. Consider the set of factors given in Table 4 used to examine their impact on the average time to complete the plane offloading process.

Table 4 - Factors for Alternative System I Experiments

Factor	Description
x_1	Number of aircraft arriving nightly
x_2	Total number of tugs

To assess the impact of varying levels of tugs on the average offloading time for a given configuration, let us consider the following linear statistical model:

$$y = b_0 + \Sigma_i b_i x_i + \Sigma_j \Sigma_i b_{ij} x_i x_j + \Sigma_i b_{ii} x_i^2 + \Sigma_i b_{iii} x_i^3 + \Sigma_i b_{iiii} x_i^4 + \varepsilon \quad (3)$$
$$i = \{1, 2\}, j = \{1,2\}$$

The ranges and levels of controllable factors investigated in this experiment are provided in Table 5.

Table 5: Factor Levels for Alternative System I

Factor	Factor Levels	Coded Factor Levels(ξ_i)
x_1	59, 68, 77	-1.0, 0.0, 1.0
x_2	40, 60, 80, 100, 120	-1.0, -0.5, 0.0, 0.5, 1.0

In order to obtain the best possible fit y was transformed by taking the natural log of y. Thus, the form of the fitted equation is:

$$y = \exp(b_o + \Sigma_i b_i\xi_i + \Sigma_i\Sigma_j b_{ij}\xi_i\xi_j + \Sigma_i b_{ii}\xi_i^2 + \Sigma_i b_{iii}\xi_i^3 + \Sigma_i b_{iiii}\xi_i^4 + \varepsilon) \quad (4)$$
$$i = \{1, 2, ..., 4\}, j = \{1, 2, ..., 4\}.$$
$$\xi_1 = (x_1 - 68) / 9, \xi_2 = (x_2 - 80) / 40$$

Multiple regression procedure in *Statistica* was used to estimate model (4). Table 6 shows a list of statistically significant coefficients and factors for model (4).

Table 6: Estimated Linear Regression Model Model (4) ($R^2 = 0.9085$)

Component	b	p-value
Intercept	3.432598	0.000000
x_1	0.188586	0.000000
x_1x_2	-0.088700	0.000002
x_2^2	0.217485	0.000000
x_2^3	-0.227007	0.000000

Subsequent to estimation, model (4) was used to locate optimal (or near-optimal) number of tugs for varying number of planes.

6.3 Alternative System II

The RDTO system was modelled to accomplish a greater flexibility. In particular, RDTO dictates that tugs be dispatched individually to arriving aircraft as opposed to twin tug dispatching. The tug operators have more independence and are always directed to move towards the aircraft where the most work load is. The K-loaders are dispatched independently to the next nearest plane (or the critical one) as well.

In RDTO, the existing work rules in assigning tug and dollies were revised to accomplish a major reduction in offloading time per aircraft. The purpose of these experiments was to estimate the best number of tugs and K-loaders to achieve the least offloading time per plane and reduction in overall ramp offloading time for all the planes. Table 7 shows the set of factors selected for this experiment.

Table 7: Factors for RDTO Experiments

Factor	Description
x_1	Number of aircraft arriving nightly
x_2	Total number of tugs
x_3	Number of K-loaders

In RDTO system, the number of dollies per tug is three. The number of tugs per aircraft depends upon the plane type, number of containers to be offloaded, and the availability of tugs at that time. In order to assess the impact of varying numbers of tugs and K-loaders on the ability of the RDTO system to complete offloading a varying number of aircraft (59 to 77) arriving nightly, let us consider the following linear regression model:

$$y = b_0 + \Sigma_i b_i x_i + \Sigma_j\Sigma_i b_{ij}x_ix_j + \Sigma_j\Sigma_i\Sigma_k b_{ijk}x_ix_jx_k\ \Sigma_i b_{ii}x_i^2 + \Sigma_i b_{iii}x_i^3 + \Sigma_i b_{iiii}x_i^4 + \varepsilon \quad (5)$$
$$i = \{1, 2, 3\}, j = \{1,2, 3\}, k = \{1,2,3\}$$

The ranges of the controllable factors studied in these experiments are given in Table 8. Coded factor levels were used to estimate model (5) in order to minimize the variance of prediction (i.e., to obtain the best possible predictions with the least amount of data).

Table 8: Factor Levels for RDTO Experiments

Factor	Factor Levels	Coded Factor Levels(ξ_i)
x_1	59, 68, 77	-1.0, 0.0, 1.0
x_2	40, 60, 80, 100, 120	-1.0, -0.5, 0.0, 0.5, 1.0
x_3	8, 20, 32	-1.0, 0.0, 1.0

In order to obtain the best possible fit y was transformed by taking the natural log of y. Thus, the fitted equation is expressed by:

$$y = \exp(b_o + \Sigma_i b_i\xi_i + \Sigma_i\Sigma_j b_{ij}\xi_i\xi_j + \Sigma_i b_{ii}\xi_i^2 + \Sigma_i b_{iii}\xi_i^3 + \Sigma_i b_{iiii}\xi_i^4 + \varepsilon) \quad (6)$$
$$i = \{1, 2, ..., 4\}, j = \{1, 2, ..., 4\}, \xi_1 = (x_1 - 68) / 9,$$
$$\xi_2 = (x_2 - 80) / 40, \xi_3 = (x_3 - 20) / 12$$

Multiple Regression Procedure in *Statistica* was used to estimate model (6). Table 9 shows a list of statistically significant coefficients and factors for model (6).

Table 9 - Estimated Linear Regression Model Model (6) ($R^2 = .8000$)

Component	b	p-value
Intercept	2.455574	0.000000
x_1	0.116782	0.000000
x_1x_3	-0.143195	0.000000
x_2^2	0.050264	0.005523
x_3^2	0.196400	0.000000
x_3^3	-0.187527	0.000000

Subsequent to estimation, model (6) was used to locate optimal (or near optimal) equipment combinations for varying numbers of planes.

6.4 Selection of Best Configurations

Linear regression models in Sections 6.1 - 6.3 were used to demonstrate the relationships between the factors and accordingly identify the equipment combination that has yielded least (average) offloading time/aircraft. In this section, we discuss the results of the statistical analysis. Table 10 shows the short-listed configuration set chosen from a large number of feasible configurations for fifty nine planes arriving at the Hub per night. These results were obtained using the response surfaces and contour plots generated to show the interrelationships between the number of planes, total number of tugs, and number of dollies per tug. The surface plots were created using the regression equations (models 2, 4 and 6).

Table 10. Short-listed Configurations for Number of Planes/night = 59 (All time units are in minutes)

C	S	N_t	n	d	K	N_k	C_t	X_t
C1	B	40	2	2,3,4	O	-	300	31.8
C2	B	70	3	3	O	-	288	24.9
C3	B	40	3	3	O	-	295	28.0
C4	A1	80	5	3	N	-	299	26.9
C5	A2	40	-	20	N	20	261	11.6
C6	A2	80	-	3	N	17	292	10.2
C7	A1	74	5	3	N	-	307	25.4
C8	B	76	3	4	O	-	269	25.5

In Table 10, S refers to the scenarios evaluated, (where B = *base model*, A1 = *Alternative System I*, A2 = *Alternative System II*), N_t corresponds to the number of tugs on the ramp, n refers to the number of tugs assigned to a plane, d denotes the number of dollies hooked to a tug, K denotes the K-loader process (O refers to existing and N refers to the modified process), N_k corresponds to the number of K-loaders, C_t denotes the completion time (or time window for plane offloading) in minutes, and X_t refers to the mean of average offloading time in minutes per aircraft.

Eight short-listed configurations (as denoted by C) are provided in Table 10. C1 configuration corresponds to the current plane offloading process at the Hub. C2 and C3 refer to *"what-if"* scenarios performed with the current system except (i) tugs were fitted with 3 and 4 dollies respectively, (ii) 3 tugs were assigned to a plane instead of 2, and (iii) total number of tugs on the ramp were 70 and 40 respectively.

C4 and C7 refer to *Alternative System I* in which (i) all tugs were fitted with 3 dollies, (ii) 5 tugs were assigned to a plane, (iii) number of tugs was 80 and 74 respectively, and (iv) K-loader process was speeded up.

C5 and C6 refer to *Alternative System II* with an exception that the number of tugs and K-loaders varied. C8 refers to the scenario in which the total number of tugs was 76 with the number of tugs per plane was 3 and the number of dollies per tug was 4.

Analogous to the analysis conducted for 59 planes per night, best-feasible configurations were identified for 68 and 77 planes arriving each night at the Hub. The short-listed configurations were examined carefully and a list of final recommendations were identified.

7 RECOMMENDATIONS

Three recommendations were made to the management of the Hub based on our interactions with simulation/ animation models and extensive statistical analysis. Each recommendation improved the performance of the ramp and any one, if implemented, would bring in reduction in X_t and C_t. The recommendations in Table 11 were ranked based on the tradeoffs between the anticipated performance improvement, changes needed in operation procedures, and capital investment.

Table 11. Final Recommendations

Rank	Recommended Operation Setup	C_t	X_t
I	Radio Dispatched Tug Operation (40 Tugs, 20 K-loaders)	261	11.6
II	Existing System (76 tugs, 3 Tugs/Plane, 4 Dollies/Tug)	269	25.5
III	Existing System (70 Tugs, 3 Tugs/Plane, 3 Dollies/Tug)	288	24.9

Recommendation I was highly ranked as it reduced immensely the average offloading time per aircraft when compared to existing plane offloading operations. This behavior was found to be consistent even when the total number of planes arriving each night at the Hub was increased. In addition, this recommendation required major changes in work rules for assigning tugs to the aircraft, flexibility and independence to tugs, as well as dispatching by the radio.

Recommendation II was the second choice as it involved no changes to work rules and K-loader process while offloading containers from the aircraft to dollies; however, the number of dollies hooked to each tug was increased to 4.

Recommendation III involved no changes to K-loader process, work rules, and tug setup. Overall, these recommendations showed a significant improvement in the ramp performance at the least cost.

8 CONCLUSIONS

In summary, the benefits of the ramp simulation study in the aircargo company are two-fold;

(a) Pinpoint both strategic and operation improvements on the current plane offloading processes, equipment usage, and facility layouts due to changes in the behavior of freight handled at the Hub. This helps the decision maker to continuously improve productivity and throughput.

(b) Estimate the appropriate levels of equipment and suitable facility layouts *a priori,* due to an increase in the number of planes offloaded. This helps the decision maker to better utilize the top dollars before it is being spent on new equipment purchases.

Further, the ramp model along with experimental setups are useful in conducting operations planning and control on a nightly basis at the Hub. For a given plane arrival process during a night, the Hub management can estimate (a) completion time to offload all the planes, (b) peak hours and lean hours and accordingly plan for the operation crew, equipment, and service requirements, (c) number of gates required at the ramp, (d) number of tugs and forklifts needed to finish offloading all the planes within a specified time window, and (e) number of containers expected to be offloaded by the hour and the anticipated work loads.

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