ABSTRACT

KULSHRESTHA, PREETIKA. An Intelligent Energy Management System for Charging of Plug-in Hybrid Electric Vehicles at a Municipal Parking Deck. (Under the direction of Dr. Mo-Yuen Chow.)

There is a need to address potential problems due to the emergence of technologies that will affect the utility industry in a time horizon of less than 20 years. One such technology is the plug-in hybrid electric vehicle (PHEV); the emergence of these vehicles in the marketplace poses a potential threat to the existing power grid. With a large number of these vehicles 'plugged-in' for charging, in the absence of control over the power drawn, the additional load can result in grid instabilities and disruptions. As a solution to alleviate such a situation and to allow for smooth integration of PHEVs into the grid, an "intelligent energy management system" (iEMS) is proposed in this thesis. The iEMS intelligently allocates power to the vehicle battery chargers through real time monitoring and control, to ensure optimal usage of available power, charging time and grid stability.

The research presented here provides the conceptualization of the system architecture and the definition of its components, their attributes and interactions. A Simulink based simulator incorporating the dynamics of the real world scenario at a municipal parking deck with random plug-in/out times and varying initial states of charge is presented. A mathematical framework is provided for developing the iEMS algorithm for the optimal power allocation strategy under utility power constraints; taking into consideration the vehicle battery parameters and user preferences. The formulation and solution of the optimization is also proposed for a chosen objective function followed by the presentation of simulation results. The thesis concludes with the description of an experimental setup consisting of a Labview based GUI along with a ZigBee communication nodes which is a first step towards validating the system performance in a real-world deployment.

An Intelligent Energy Management System for Charging of Plug-in Hybrid Electric Vehicles at a Municipal Parking Deck

by
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BIOGRAPHY

Preetika Kulshrestha was born in Germany on the 26th of October, 1985. She received her Bachelor of Engineering degree in Electronics and Telecommunication Engineering in 2007 from Ramarao Adik Institute of Technology, University of Mumbai, India. In fall of 2007, she joined North Carolina State University as a graduate student. She has been working under the guidance of Dr. Mo-Yuen Chow at the Advanced Diagnosis Automation and Control (ADAC) lab since Spring 2007.

Her primary research interests lie in control, optimization and computational intelligence. Currently she is working on a project involving power allocation strategies to plug in hybrid electric vehicles at the Future Renewable Electric Energy Delivery and Management Systems Centre, NCSU. With the defense of this thesis, she is receiving the degree of Master of Science in Electrical Engineering from NCSU.

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I am grateful to Dr. Srdjan Lukic and Dr. Hao Ma for their insightful remarks during weekly group meetings which resulted in interesting and valuable discussions that have contributed greatly to this thesis. I also extend my acknowledgement to Dr. James. J. Brickley and Dr. Hamid Krim for kindly agreeing to be on my thesis committee.

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None of this would have been possible without my family. They have been a source of tremendous strength and inspiration.

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CHAPTER I - Introduction

There has been a renewed interest in the revival of the electric power grid in order to incorporate greater efficiency, reliability, self healing property etc. This has resulted in a vision for the power delivery system of the future [1], also termed as the “Smart Grid”. One thrust of the smart grid lies in decentralization of the control in the grid [2]. This distribution of intelligence in the smart grid and the concept of incorporating the consumer constraints and preferences for power delivery have opened up interesting avenues of research in control.

Alongside the transformation in the power system, there has also been a significant increase in research and technological development to develop vehicles that utilize electricity for their operation [3]. Plug-in Hybrid electric vehicles are very promising in this respect due to reduced emissions and greater economy. Their emergence will result in the interactions of these vehicles for charging purposes with the electric power grid, this will not be without potential problems; for instance, if the power drawn is uncontrolled, it could lead to grid instabilities and blackouts. There is a need of an underlying framework that will describe the system architecture for enabling the integration of these vehicles with the grid and also to propose solutions to potential problems that could emerge due to their interactions. The goal of this thesis is the development of this framework by the proposal of a system architecture and the modeling and simulation of the real world scenario. Here the scenario of a Municipal Parking Deck is considered, where a large number of PHEVs are parked for charging. The problem addressed is the management of the power consumption of the vehicles during the charging process in order to limit the over all power within utility constraints. An intelligent energy management system (iEMS) is proposed as a solution to the problem along with a description of its operation and a proposed algorithm for allocation of the power.

This thesis is a compilation of three papers that outline the problem definition, proposed solution and obtained results with each paper organized as a chapter (II, III and IV). Firstly, in Chapter II, the conceptualization of the system architecture that will enable the charging of PHEVs at a parking deck is presented. The real world description is then abstracted in the form of a model with details on the state transitions of its entities, their functions and behavior. With this model as the foundation, a Matlab/Simulink based simulator that attempts to closely mimic the real world scenario is developed. Features incorporated are the randomized plug-in/out times, different battery capacities in the battery model, times of availability of the users etc. The simulator is modular, with each module representing a system entity (agent), thus we have three types of modules – the utility, the iEMS and the vehicles. The goal of developing the Simulink based simulator is to have a software test-bed that can be used for representing myriad real-world scenarios at the parking deck for comprehensive testing of the iEMS algorithm.

After the theoretical system description and a software test-bed, in Chapter III, the mathematical framework for formulating the optimization problem for dynamic power allocation is described. The formulation on a particular objective is presented along with the simulation results. The results compare two proposed schemes and a heuristic scheme for allocating power.

The final validation of the allocation strategy will be when it is optimal in the real world deployment, involving actual vehicles and the communication network. In Chapter IV, communication architecture is proposed with ZigBee [4] as the chosen communication platform. As a beginning step towards validation of the iEMS algorithm in the real world deployment, a system setup with ZigBee nodes in the local and remote network with the monitoring and control done by a Labview GUI is discussed. Chapter V discusses the conclusion and results and ideas for future work.

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CHAPTER II - Intelligent Energy Management System Simulator for PHEVs at Municipal Parking Deck in a Smart Grid Environment

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Intelligent Energy Management System Simulator for PHEVs at Municipal Parking Deck in a Smart Grid Environment

***Abstract* -** There is a need for in-depth study of technologies that will affect the utility industry in a time horizon of less than 20 years. One such technology is the plug-in vehicle (PHEV); there is a need for energy management when a large number of plug-in hybrid vehicles penetrate the market. In this paper, we propose an "intelligent energy management system (iEMS)" that intelligently allocates power to the vehicle battery chargers through real time monitoring and control, to ensure optimal usage of available power, charging time and grid stability. We begin by conceptualization of the system architecture and description of its operation and provide a theoretical framework for system modeling. A detailed PHEV battery model and state of charge estimation algorithm are also being developed to simulate different PHEVs to be recharged at a municipal parking deck. We will present the simulator we have developed for representing the iEMS using Matlab/Simulink and discuss obtained results and future directions.

***Index Terms* -** batteries, battery chargers, discrete event simulation, energy conservation, energy management, intelligent control, modeling, power distribution control, power systems, SCADA systems

I. INTRODUCTION

Plug-in hybrid electrical vehicles (PHEVs) are drawing significant attention due to increasing oil prices, depleting resources and the environmental pollution issues. The Electric

Power Research Institute (EPRI) projects that by 2050, 62% of the entire US vehicle fleet would consist of PHEVs (moderate PHEV penetration scenario) [1]. PHEVs are similar to hybrid electric vehicles, in that the vehicle combines electrical power and gasoline to propel the vehicle. The PHEV has the additional feature that the vehicle battery can be recharged from standard electric wall outlets while the conventional hybrid vehicles can only be charged from the internal combustion engines. The California Cars Initiatives estimates that cost of driving for Plug-in Hybrids is at an equivalent cost of $1 per gallon [2], which is significantly lower than the current gas price. In addition to the capability of utilizing grid power, PHEVs also have the potential to transfer power to the grid to alleviate peak power demand and provide ancillary services to the grid [3]. Since PHEV technology is promising for automotive applications due to fuel economy and green house gas emission reduction and possible utility applications, various aspects of PHEV technology like battery storage, battery state monitoring etc. are an active area of research in automotive industry [4], [5].

At 2.2 percent of the automobile market share, 350,000 hybrid vehicles were sold in 2007 in United States [6]. If PHEVs were to attain the same market share, with an average battery capacity of 4kWh, a fleet of 500 PHEVs citywide would potentially add an extra two megawatt load to the power grid (assuming simultaneous charge of all 500 vehicles at one-hour charge rate). Voltage instability and blackouts can occur when these PHEVs are plugged-in at peak hours. To avoid the worst scenarios, an intelligent energy management system (iEMS) that controls the load power consumption is needed. Presently, commercial systems have been developed that have the capability to remotely control the charging of pilot plug-in vehicle fleets [7]. However, there is a need for a more in-depth study into this problem. In addition there needs to be a method to evaluate worst case scenarios and system failures via simulation.

Section II of this paper will present the system architecture that will enable effective energy management of multiple plug-in hybrid electric vehicles parked at a municipal parking deck. The functions, attributes and interactions of the system entities (iEMS, load, utility) will be described. The system consists of a controller that will dynamically sample the power consumption from the load and make a real-time decision on power allocation. Section III will describe how the system is modeled and implemented in Matlab/Simulink and present simulation results on a test case. Section IV will summarize the paper and suggest future work.

II. SYSTEM ARCHITECTURE

We are considering the scenario of charging the vehicles at a parking deck, in which case, each vehicle has an expected time of availability as a load. This charge time window may be input by the user at the time of parking along with user preferences such as pricing and type of charge etc. Each vehicle can also be characterized by its battery parameters such as the battery chemistry, capacity, state of charge, open circuit voltage level, temperature etc. The system will allocate power to each vehicle depending on the battery properties and the user preferences. Thus to sum up, the system involves the dynamic power management of loads while taking into consideration customer preferences and load attributes in order to optimize energy utilization. The smart grid incorporates technology that aims at advanced demand side management and control strategies and greater say of the customers' preferences in utility services. We see that the system described represents an element of the smart grid in the respect that it aims to achieve similar objectives.

Fig. 1 illustrates the basic architecture of the whole system. The system consists of: the power grid, energy management systems and the loads (charger and the battery/vehicles). Each parking deck comprises of multiple loads (PHEVs) and is controlled by an iEMS. Note that we can also use distributed iEMS approach, which will be one of our future project tasks. Many such iEMSs may be connected to the utility, acting as an interface between the grid and loads.

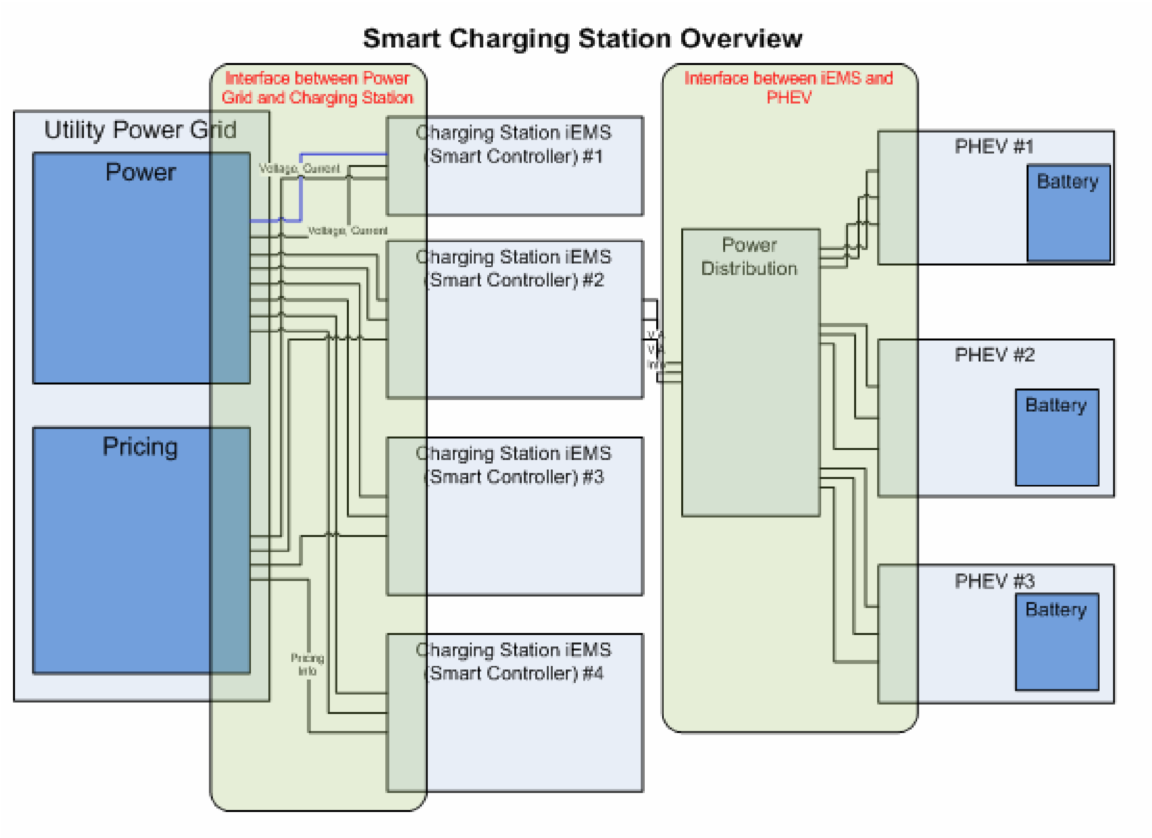


Figure 1: The Smart Charging Station Architecture

On the utility side, information about available power and pricing is periodically updated to the iEMS; multiple chargers are then simultaneously monitored and controlled according to the real time decisions made by the iEMS. The communication between the iEMS and the chargers may be facilitated by wireless technology; evaluation of Zigbee is currently underway for this project. The power from the utility is routed to the chargers (topologies for

power routing and details on the communication interface, power-electronics etc. are out of the scope of this paper). Each user will have access to an interface for providing information on charge time window, rate of charge (slow, medium, fast) and other preferences.

iEMS: Fig. 2 shows the flow of operations in the system, which is designed based on SCADA with the iEMS as the master controller and the chargers as slaves. Whenever a vehicle is plugged-in at the charging deck, data regarding the time of availability, battery parameters like initial state of charge (SOC), capacity etc. and other user specific details is acquired and communicated to the controller. Based on the data from all the vehicles currently plugged-in and the information on the available power and pricing from the utility, the controller makes a decision regarding the power to be allocated to each vehicle and communicates this information to the chargers. The optimization is recomputed periodically and also triggered by specific events in the system (every time a new car plugs in or change in power from the grid or request of update from vehicle).

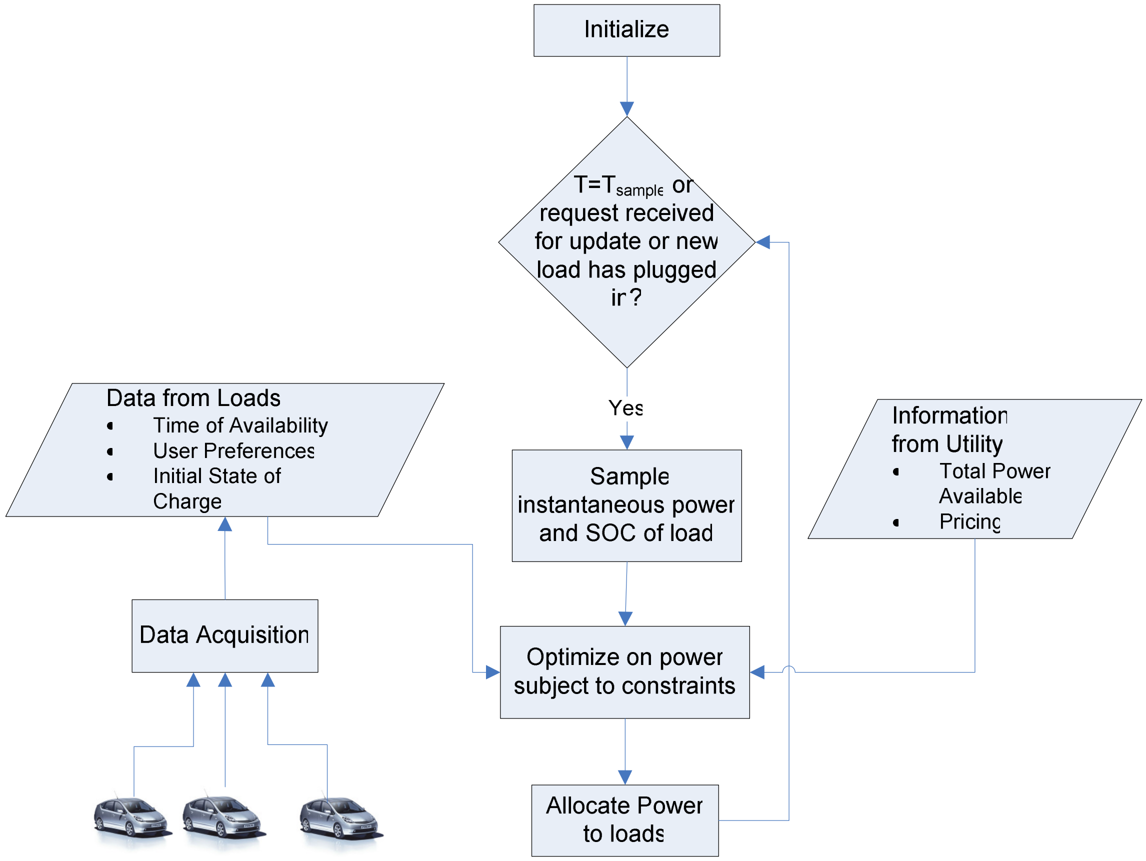


Figure 2: Flow chart of the iEMS operation

III. SYSTEM MODELING AND SIMULATION

A. Modeling

Our aim has been to develop a simulator and virtual test-bed for evaluating different scenarios and algorithms (with respect to number of loads, load behavior, utility power etc.) in order to come up with the optimal allocation strategy. The given system comprises of utility, iEMS and the load. The load is defined as the vehicle battery/charger system. The system is characterized as hybrid as it consists of entities with continuous states (battery dynamics) and discrete events (plug-in, start of charging process, plug-out etc.) [8]. The theoretical modeling of the system was inspired from Agents Based Approach [9], [10]. The three primary entities of the system - utility, iEMS and load – may be classified into three types of agents. The attributes and functions of each of these agents are described in this section. The main thrust of our research in this case is to develop an algorithm for optimal power allocation scheme for the iEMS and thus some subtleties and details of the utility and load agent are not being considered at the current stage.

1) Utility Agent:

Attributes: The attributes of an agent are its properties that influence the system behavior. The attributes from the power grid affecting the system are the power and the pricing. Whenever there is a change in the power available, the system power allocation will have to be triggered or recomputed.

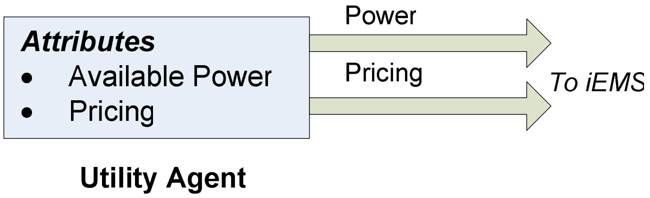


Figure 3: Utility agent

Functions: The function of the utility agent is to periodically inform the iEMS about the power available and the pricing information.

Simulation: The utility has been currently modeled as a simple block containing power and pricing information. Further studies on the actual nature of power availability will be performed in order to enhance the details in the utility model.

2) Load (Charger and Battery) Agent:

Attributes: The attributes of the load are: state of charge of the battery (%), charging time window (h), battery capacity (Ah) and instantaneous power drawn by the battery (kW) (more attributes for user preferences like type of charge or pricing may be added).

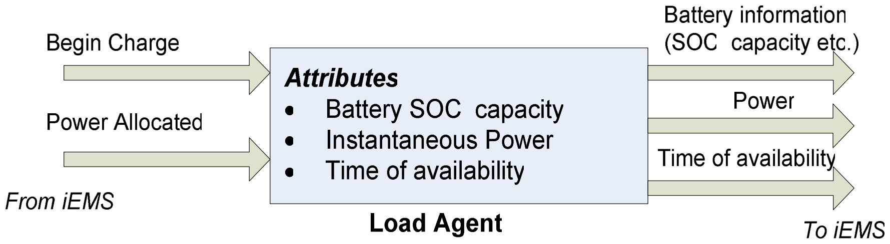
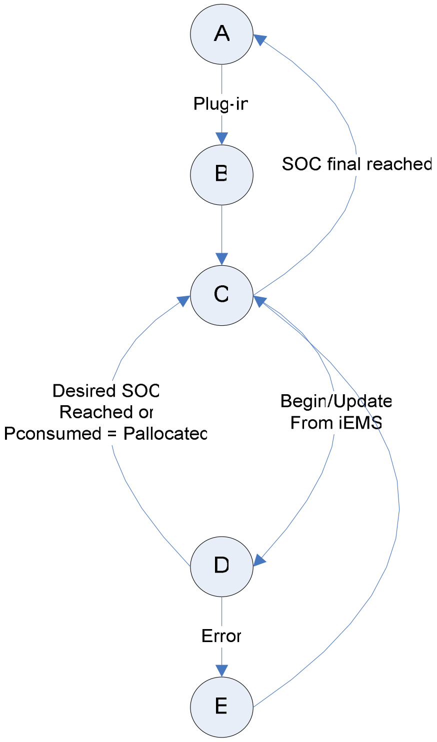


Figure 4: Load agent

Functions: The functions of the load are described in terms of a state transition diagram (Fig. 5), which involves the following states:

- Idle: There is no activity, the load may be waiting for a control action or it may have completed charging the battery.
- Data Acquisition: The data is acquired from the battery and the user.
- Communication: Data is communicated to controller.
- Charging: Battery charging is in progress.
- Error: There is an error in the system and system operation is halted until error is resolved.

Fig. 5 illustrates the state transition diagram. Initially the load agent is in the idle state. When the vehicle is plugged-in to the grid for charging, there is a transition to the data acquisition state. In this state, battery information (state of charge, capacity etc.) and user specific information like time of availability and user preferences is acquired. The next state is communication of this information to the controller (iEMS). The load transitions from this state to the charging state when it receives the ‘begin charge’ command from the controller along with information relating to the allocated power. The load remains in the charging state until one of the two events happen: a) the instantaneous power consumed by the load has reached allocated power – it transitions to the communication state, requesting the controller for additional power, b) the charging process is completed – the load then transitions to the communication state, informing the controller about end of charge and then goes into idle state. The load will remain in this state until it is plugged-out. During the charging process if there is an error condition (malfunction of charger, battery etc.), the load immediately stops the charging process and informs the controller about the error condition.



- A - Idle
- B – Data Acquisition
- C - Communication
- D - Charging
- E - Stop

Figure 5: State transition diagram of the load

Simulink implementation: Within the load agent, primarily, three components are embedded:

The stateflow chart: It coordinates the state transitions of the load depending on the events.

Data acquisition subsystem: The vehicle data is acquired in this subsystem. Charging time information is obtained from a random source with appropriate limits (0.5-10 hours). States of charge and capacity values are acquired from the battery model.

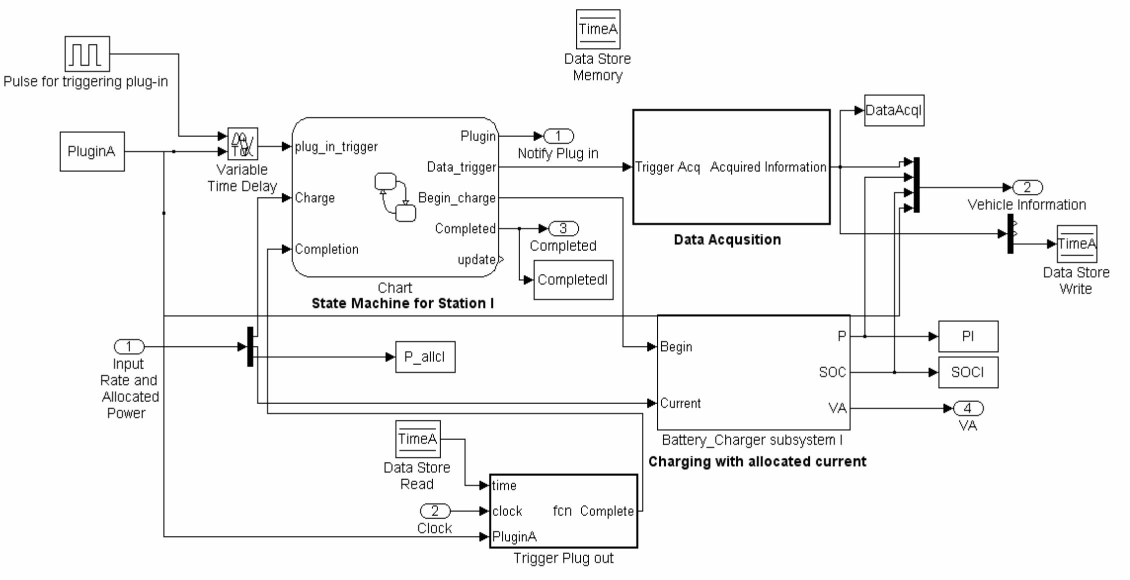


Figure 6: Components of the load agent

Battery and the charger subsystem: This block represents the battery and charger subsystems. The simulator contains the battery and charger models as separate modules which enables the incorporation of any battery model or charging algorithm into it. Currently a simple equivalent circuit model is used to simulate the battery behavior [11]. Fig. 7 shows the Simulink implementation of a single battery cell. For simulating a full vehicle battery, we are simulating the series connection of 80 such cells and connection of 7 such cells in parallel. For the charger, we are currently using a constant current – constant voltage charging algorithm, as shown in Fig. 8.

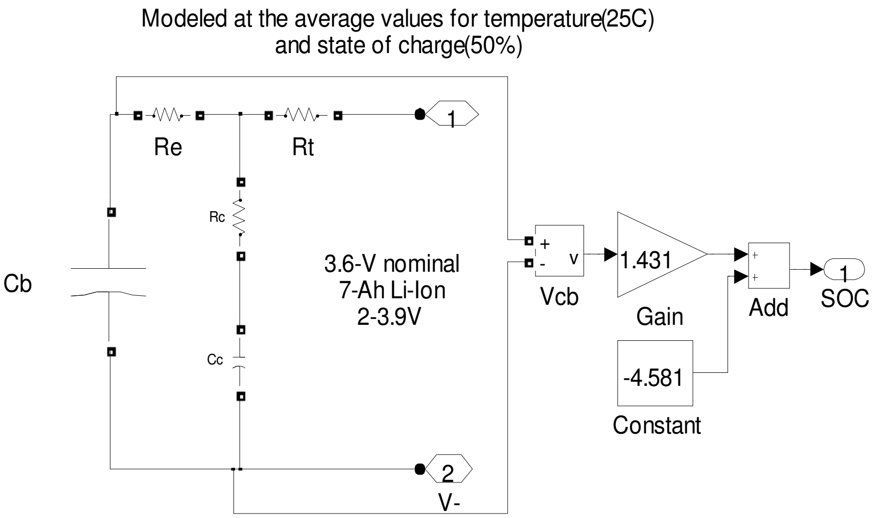


Figure 7: Battery implementation in Simulink

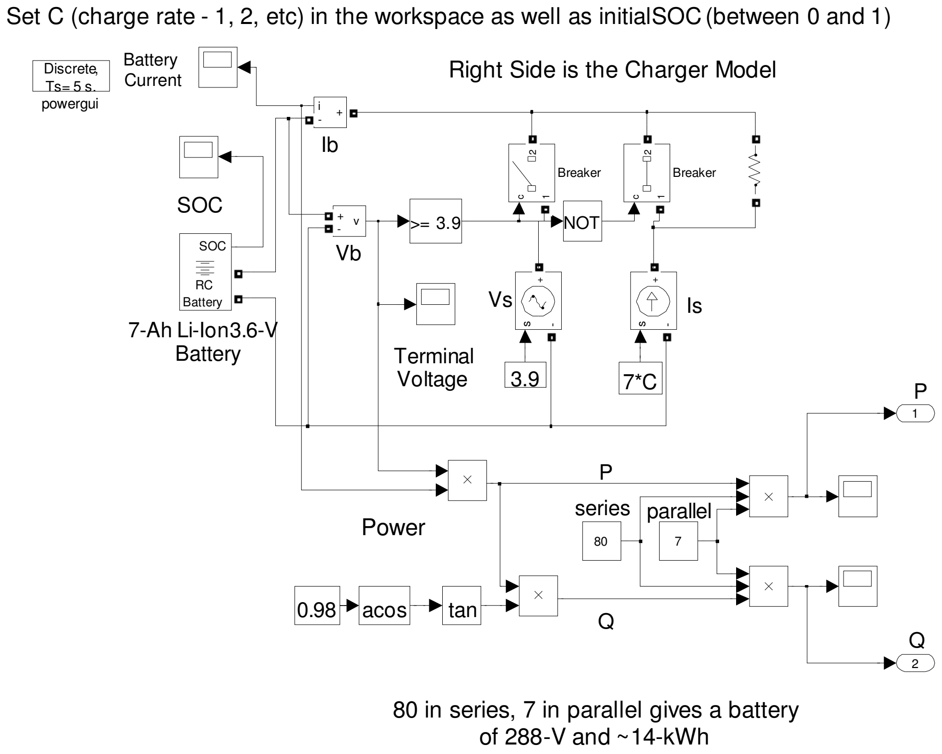


Figure 8: Constant current charger

We are also developing a more detailed battery model that will allow us to incorporate other battery states beyond the state-of-charge [12] into the iEMS optimization. Our goal is to incorporate factors like the aging effect, internal resistance, charge acceptance in the

battery modeling process so as to formulate charging algorithms that dynamically adapt to the battery 'state of health' [13] described by these factors. Thus far we have adopted the approach detailed in [14] as the starting point for precise state-of-charge modeling. We are modeling high power lithium ion ANR26650ml battery cells from A123 Systems [15] as these cells are used in the after-market plug-in vehicle conversion kits.

3) iEMS Agent

Attributes: For the iEMS, the attributes are: total number of active loads at any instant, allocated power to each load agent and the time interval used for sampling instantaneous power of load.

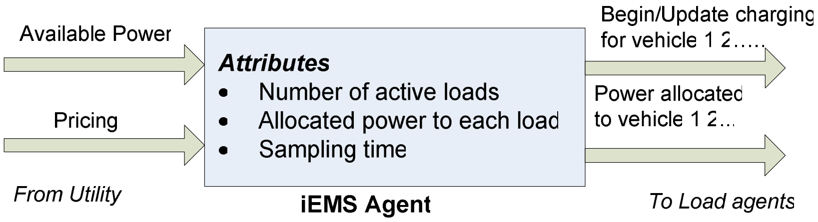


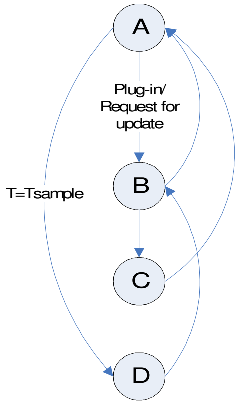
Figure 9: iEMS agent

Functions: The functions of the iEMS are described in terms of the following states:

- Idle: There is no activity.
- Optimize: Calculation of power allocation when:

    - There is a change in utility power.
    - A new load has plugged-in.
    - Periodically, after sampling the instantaneous power consumed by loads.
- Communication: Inform the loads of power allocated.
- Sample: Sample power consumed by the load to recalculate power allocation.

Fig. 10 illustrates the state transition diagram of the iEMS. Initially the iEMS agent is in the idle state. It transitions to optimize state when: i) a new vehicle plugs in, ii) a request for updating allocated power is received, iii) there is a change in power available from utility. After optimization, it transitions to communication state, in which it informs all the load agents of the updated power allocation. It then goes back to idle state. In this state, it periodically switches to the sample state to sample the instantaneous power consumption of the load agents and then recalculates the power allocation (optimize state), communicates this information and resumes the idle state. The frequency of sampling is a function of the system parameters such as the battery charging rate and is subject to bandwidth limitations. Determining the optimal sampling rate will be a topic of further research.



- A - Idle
- B – Optimize
- C - Communicate
- D – Sample instantaneous power

Figure 10: State transition diagram of the iEMS

Simulation: For the iEMS, the state transitions are translated into a Stateflow chart and the optimization engine is a triggered subsystem with an embedded Matlab function. Currently, our simulator describes the interaction among these three agents with a nominal optimization algorithm to allocate power.

B. Sample System Simulation

Numerous examples exist in literature for simulation of event triggered systems with discrete and continuous components. Simulink provides an excellent platform for complex modeling and real time simulation [16], [17]. Advanced techniques (Artificial Neural Networks, Fuzzy logic etc.) have been used for solving power system issues like reliability and fault identification [18], [19]. Such examples from existing literature will help us in performing advanced studies for the proposed system in the future. With the theoretical framework that has been described and guidance from existing tools and literature, a simulator representing the system was developed in Simulink.

Fig. 11 shows a snapshot of the simulator for two vehicles. Each agent (vehicle/load) is modeled as a subsystem. Within this subsystem, a stateflow [20] chart coordinates the flow of operations for that agent (as mentioned before). Communication between agents is facilitated by event triggers using the stateflow charts, the communication signals may also be delayed by the approximate time of delay in the network (effect on system performance with delay in the communication channel is to be evaluated later).

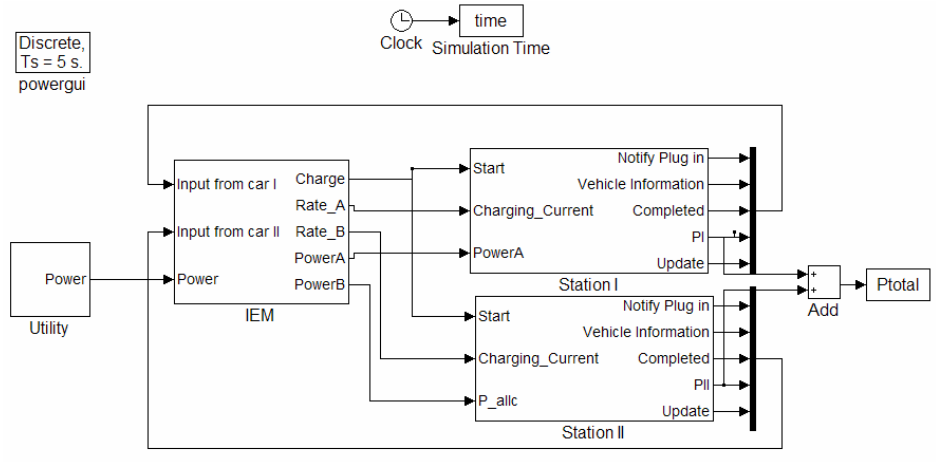


Figure 11: Simulink implementation

The simulation is event driven. Following shows the simulation of the system for the following scenario:

The two blocks (Station I, Station II in Fig. 11) represent the loads. Each load plugs-in at the station at a random time. For example, if simulation begins at t=0 s, car A may plug-in at t=2340 s and car B may plug-in at t=100s. In the test case, car A plugs-in at t=3000s, and car B plugs in at t=0s.

Once a load plugs-in, it will go through the states as described previously. In our simulation, data acquired from the loads is:

CarA: Time of availability = 2.764h (9950s), Capacity=7Ah, initial SOC=0.4, CarB: Time of availability = 2.72h (9792s), Capacity=7Ah, initial SOC=0. We have currently chosen a small battery for the simulation process; however, a battery model that more closely approximates a PHEV battery can be incorporated later, as the results are scalable.

In the implemented algorithm, the controller allocates power in steps of 150 W to each car after it plugs-in, the starting value of allocated power depends on the initial terminal voltage and the rate of current. With this strategy; the iEMS updates the power allocation in approximately 16.67 minutes, this interval of update was observed when the graph of the pulses representing iEMS and load communication were plotted for the sample simulation. Fig. 12 and Fig. 13 show the plot of actual power consumption and allocated power for each vehicle:

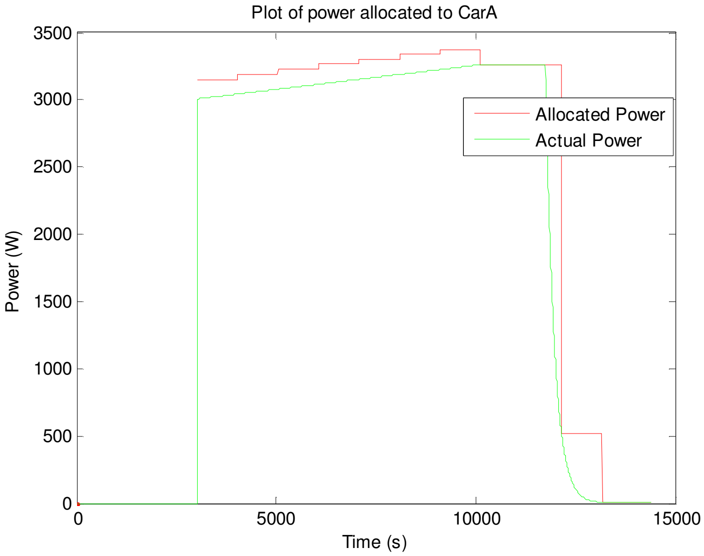


Figure 12: Plot of power consumed and power allocated (CarA)

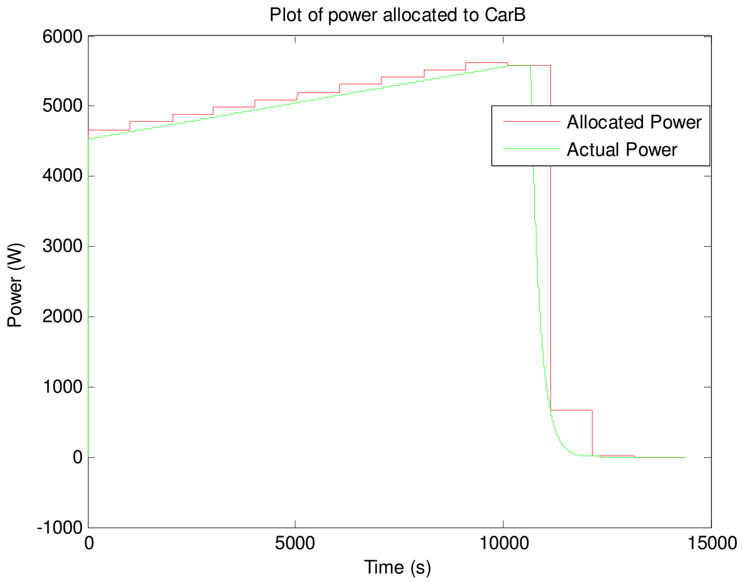


Figure 13: Plot of power consumed and power allocated (CarB)

The overall power consumption is shown in Fig. 14. This is without any energy management; we observe that there is an overshoot above 8 kW (available power). A basic management scheme is implemented when the total available power is lesser than the sum of the power required by the two vehicles. The vehicle which is available for lesser time is given priority over the other vehicle i.e. its power requirements are satisfied and the other vehicle is allocated the remaining power. With this scheme, improved results are obtained as

illustrated in Fig. 15. We see that the constraint on total power is satisfied, but the time of completion of charge is more than that specified. A more sophisticated algorithm will be implemented in order to resolve this.

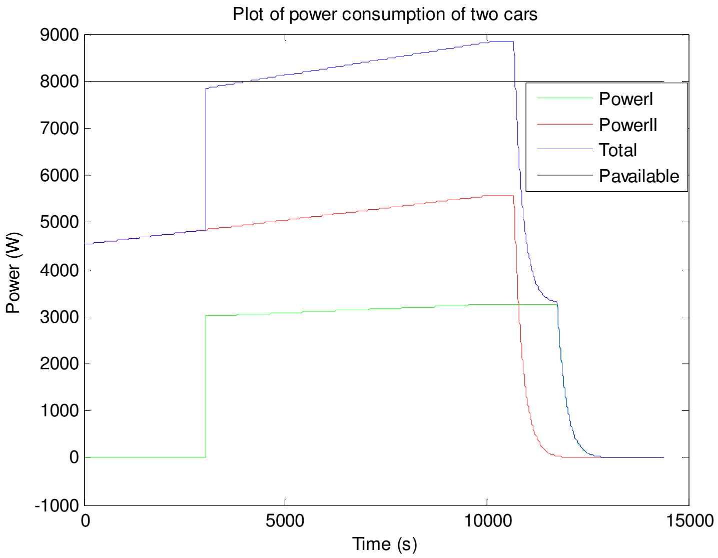


Figure 14: Power consumption without management

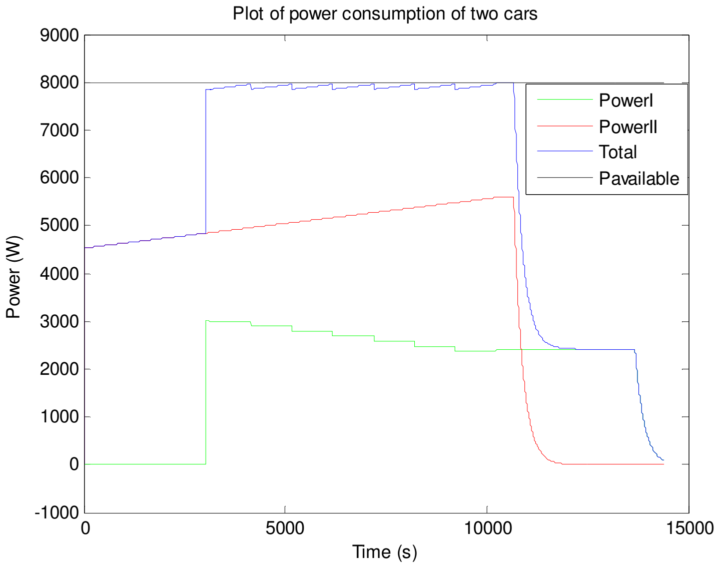


Figure 15: Power consumption with management

C. Development of GUI

To conceptualize the system operation, a Graphical user interface was developed in Labview [21]. The GUI reflects the information available to the controller/iEMS. This GUI will be an integral part of the SCADA system, representing information in consolidated form for real time data monitoring and control. Details such as overall power utilization, vehicle charging status, log of historical power consumption, communication link status etc. have been included in the GUI. The given figures show some of the snapshots of the GUI implemented. The simulator will act as a backbone and feed information into this GUI.

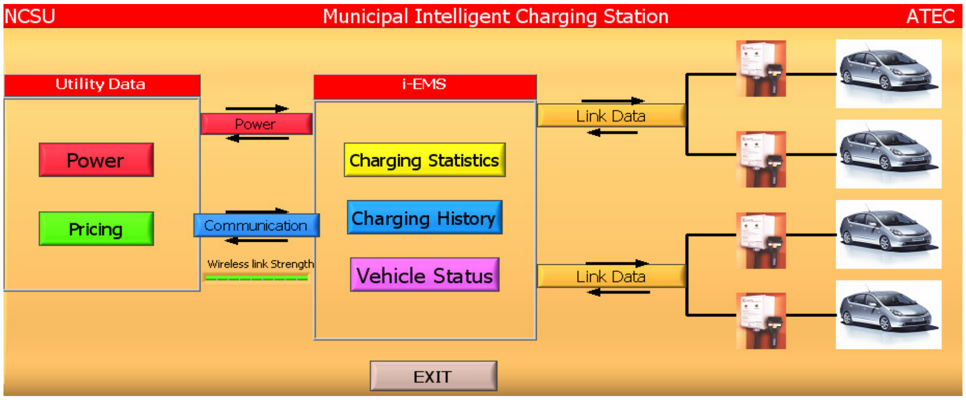
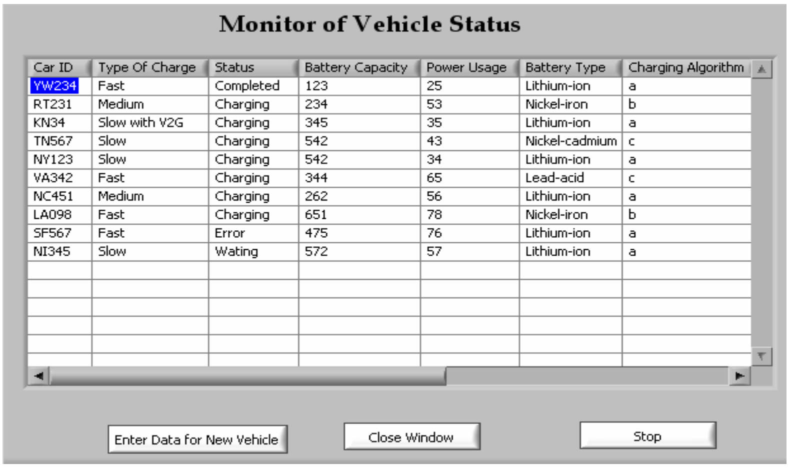


Figure 16: Labview GUI (main console)



Car ID	Type Of Charge	Status	Battery Capacity	Power Usage	Battery Type	Charging Algorithm
YW234	Fast	Completed	123	25	Lithium-ion	a
RT231	Medium	Charging	234	53	Nickel-iron	b
KN34	Slow with V2G	Charging	345	35	Lithium-ion	a
TN567	Slow	Charging	542	43	Nickel-cadmium	c
NY123	Slow	Charging	542	34	Lithium-ion	a
VA342	Fast	Charging	344	65	Lead-acid	c
NC451	Medium	Charging	262	56	Lithium-ion	a
LA098	Fast	Charging	651	78	Nickel-iron	b
SF567	Fast	Error	475	76	Lithium-ion	a
NI345	Slow	Wating	572	57	Lithium-ion	a

Figure 17: Status monitoring

IV. CONCLUSION

In this paper, we have described an intelligent energy management system (iEMS) for controlling the power consumption of large number of PHEVs plugged into the grid. The conceptualization of the system as a SCADA system was discussed and the graphical user interface for system monitoring and control have been included. We presented system modeling and described a simulation environment that will allow for the evaluation of the iEMS. The iEMS will intelligently allocate power to the vehicle battery chargers through real time monitoring and control, to ensure optimal usage of available power, minimize charging time and improve grid stability. We have also presented some test results for our simulation. Our long term aim is to develop a real-time test bed for evaluating different scenarios and iEMS algorithms in order to come up with the optimal allocation strategy for defined optimization criteria.

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CHAPTER III - Dynamic Power Allocation for Energy Management at Municipal Parking Deck for Charging of Plug-in Hybrid Electric Vehicles

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Dynamic Power Allocation for Energy Management at Municipal Parking Deck for Charging of Plug-in Hybrid Electric Vehicles

Abstract

The emergence of plug-in hybrid electric vehicles will influence the operation of the power grid as the penetration of these vehicles in large numbers will amount to a sizable additional load. This paper proposes an algorithm for an intelligent energy management system (iEMS) to allocate limited power available from the utility to a large number of PHEVs parked at a municipal parking deck while also taking the vehicle battery characteristics and user preferences into consideration. We begin with a detailed description of the system operation and components followed by the proposal of a mathematical framework for optimization of power allocation. We then propose the formulation and solution for achieving the optimal allocation strategy taking state of charge maximization at plug out time as the objective. We conclude with the presentation of simulation results and their comparisons with two other approaches and future work.

I. INTRODUCTION

There has been an increase in the technological advances for developing greener vehicles due to renewed interest in green energy, resource conservation and need for reduced vehicular emissions. Plug-in Hybrid electric vehicles are emerging as a promising solution to the green energy problem. Studies project that by 2050, 62% of the entire US vehicle fleet would consist of PHEVs (moderate PHEV penetration scenario) [1]. The emergence of these vehicles will lead to interactions between the automobile sector and the electric power grid, opening up avenues for potential mutually beneficial relations between the two. Not only do the PHEVs utilize grid power for charging, they also have the potential to transfer power back to the grid to alleviate peak power demand and provide ancillary services to the grid [2]. However, the PHEVs will add a sizable additional load to the existing grid thereby resulting in potential problems that need to be addressed in order to develop the infrastructure required for their integration with the grid.

With the commercialization of PHEV technology, the vehicles would be parked at the office and business parking decks, residential parking spaces, malls etc. Considering the fact that currently, very fast charge algorithms [3] (~ 5-10 minutes charging time) are not always considered safe for the battery and that an average vehicle is idle 90-95% of the time (parked in a parking lot) [4]. Instead of customers waiting at the charging stations (like existing gas stations) for charging their vehicles, an ideal solution would be to transform the existing large parking decks into charging decks, with the vehicles plugged into the grid during their idle time. While this would give the grid greater flexibility in dealing with the additional load, it is not without potential problems.

If we assume that in a parking lot of a capacity of 3000, even if only 1/3rd of the vehicles are PHEVs, in the absence of any control on the power drawn, assuming that all the vehicles (Average capacity = 4kWh, at one hour charge rate) are charged simultaneously, there will be a surge of 4 MW in the overall load to the grid. Thus, unsupervised charging of these vehicles can lead to unpredictable and potentially large loads in the system, resulting in grid instabilities and blackouts. In order to prevent such a scenario, there is a need of intelligence at the distribution end in order to manage the power consumption for smooth operation of the grid. In this paper, we discuss the concept of an intelligent energy management system that would intelligently allocate power to these distributed loads through real time monitoring and control, to ensure optimal usage of available power and charging time and grid stability.

The concept of smart grid has introduced the distribution of intelligence in the power system; which enables making local decisions with an easier access to the user's preferences and optimizing the power delivery with both the utility and consumer's interest under consideration. The problem we have described is also addressed in the smart grid environment, wherein the iEMS makes a decision on power allocation in order to manage the energy by taking the user preferences on pricing, time of charge, type of charge, vehicle to grid operation etc. [2] as well as the grid requirements on available power, pricing etc into consideration. Solution for this problem will provide an effective way to integrate the plug-in hybrid electric vehicles in to the smart grid and open up an interesting research area for two way transactions between these entities for satisfaction of individual and global objectives.

In [5], the architecture for the overall system that would enable intelligent energy management was proposed along with the description of system components and functions. Here, we provide a more detailed analysis on the system and conclude with a proposed scheme for performing the power allocation. The paper is organized as follows: Section II describes the system architecture and components with an introduction to the optimization objectives and constraints. In section III, we propose a general mathematical framework for power allocation, followed by a specific example. Section IV presents simulation results and analysis and comparison of the proposed algorithms. We conclude the paper with a discussion of future scope in the Section V.

II. SYSTEM ARCHITECTURE

The three primary components of the system are: PHEVs, energy management systems and the power grid (utility). We consider vehicles clustered in parking decks, with each parking deck under the control of an iEMS. Essentially, a cluster of vehicles controlled by an iEMS is a controllable load for the grid. The iEMS acts as an interface between the vehicles and the utility. Information about available power and pricing is periodically updated to the iEMS; multiple chargers at a parking deck are then simultaneously monitored and controlled according to the real time decisions made by it. Fig. 18 illustrates the flow of information in the system.

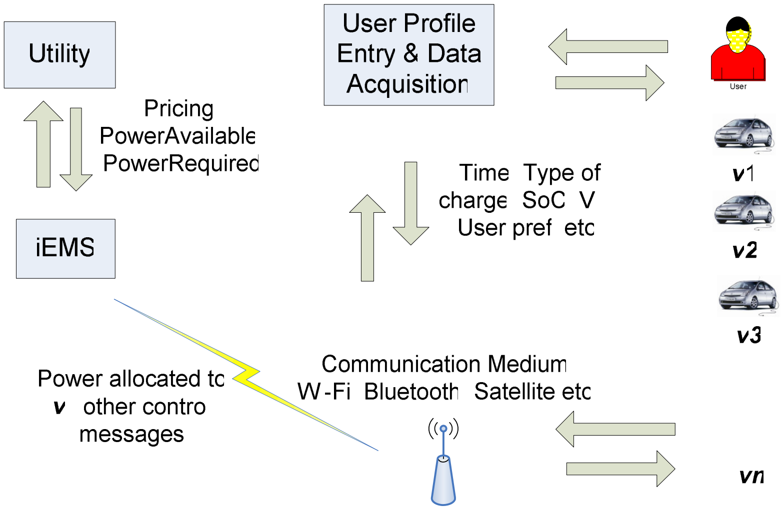

Figure 18: Information flow in the system

At the time of plug-in, the customer will specify their preferences on the type of charge desired, estimated time of availability, willingness to participate in V2G, price they are willing to pay for charging etc. This information may be entered via an interface within the vehicle itself or an external user GUI available at the parking deck or from an internet profile maintained by the user for that vehicle [6]. The parking deck can be equipped with an intelligent charger at each vehicle parking space, capable of acquiring the vehicle battery state and relaying it to the iEMS via a communication medium, alternately, each PHEV could be communication enabled, capable of sending its battery data via a wireless medium to the iEMS (a common communication protocol across all vehicles could be established for enabling this). For our study, the ZigBee protocol [7] is under current consideration, thus we shall assume that the user enters his/her preferences at the charging post and this, along with the data acquired by the intelligent charger is then communicated wirelessly to the iEMS via ZigBee nodes. In a large parking deck, data could be aggregated at the routers and sent to the controller. Other communication options like: power line communication, Wi-Fi, Bluetooth, Satellite etc. can also be explored.

The electric load that can be sustained by the utility from a parking lot will change during the course of the day as the system load varies. For vehicles willing to provide electricity back to the grid, opportunities could also arise for V2G operation depending on the grid requirements. Thus the varying price of electricity can also be incorporated in the system information for better decision making. Using the information from the utility and the vehicles, the iEMS will make a real-time decision on power allocation to each vehicle and communicate this to the intelligent chargers.

Since the state of the system is constantly changing with the arrival and departure of vehicles and changing power requirements from the utility, the system states are sampled at regular time intervals as the power allocation needs to be recomputed each time a vehicle plugs in/out or there is a change in power availability.

The system is hybrid in nature; its event based character arises from the plug-in, plug-out activity and sampling time steps used by the iEMS for making its decisions. Also, the vehicle charging process is continuous with a dynamically varying non-linear power consumption curve. The randomness of the initial states of charge, plug-in and out times and varying power curves introduce dynamicity in the system which makes the optimization for power allocation a large scale, nonlinear, time varying multi-objective problem with multiple constraints. In the ensuing sections, we provide a framework for system modeling and operation, addressing system goals and constraints along with optimization on a chosen objective.

A. System Modeling

The interactions in the system occur between the iEMS and the utility on one hand and the loads (vehicles) and the iEMS on the other. The iEMS acts as broker agent, taking information about the power availability from the utility on one hand (can also be the transformer rating at the parking deck), and the vehicle battery states and user preferences on the other hand. It makes a decision on power allocation which is optimal in terms of satisfying both the parties. The system components can be modeled on ‘Agents Based

Approach' [8], in which each entity has a set of attributes, states and functions and the entities interact with each other in order to achieve individual and system goals. This section briefly describes the system components. Fig. 19 shows the interactions between the agents in the system.

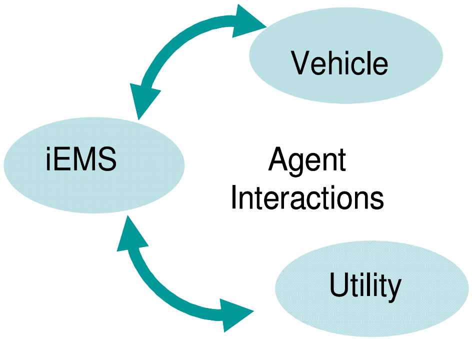

Figure 19: Interactions between the agents

1) Vehicle (Load)

Each vehicle is modeled as an entity with various attributes that are significant for system operation. These attributes are: User preferences - expected time of availability, pricing, type of charge (slow, medium, fast) etc., and Battery parameters - initial state of charge, capacity, battery state of health, battery temperature etc. These factors will influence the control decision from the iEMS, the charging algorithm implemented by the intelligent charger, as well as the nature of data being exchanged over the communication channel.

2) iEMS

The iEMS at the parking deck should be able to intelligently make decisions based on the dynamic characteristics of the charging deck like: different arrival times of cars, initial state of charge of the batteries and time of availability in the parking deck. For the iEMS, the relevant attributes are: total number of active loads at any instant, allocated power to each load agent and the time interval used for sampling instantaneous power of load.

3) Utility

The utility provides bounds on the maximum acceptable power consumption at a parking deck, it also informs the iEMS periodically about the real time electricity prices and power required for ancillary services.

The system operation and components defined above provide a framework for developing an iEMS algorithm to allocate power to the vehicles. Here, we discuss the possible objectives and constraints for optimization.

B. Optimization objectives

A number of objectives are possible for the problem. Many objectives can be formulated around the user preferences. For example, minimization of the time taken to charge the vehicle battery for all the users in accordance with the price they are willing to pay. For users that do not mind compromising on the time and would like to charge at lowest prices, the objective could be to only charge when the electricity cost is below a threshold. If vehicle to grid is also activated then the power flow could be facilitated such that profit to each user is maximized [9]. Another objective could be to minimize the overall power consumption (if desired by utility) while trying to guarantee a minimum threshold SoC (say, 60%) for each vehicle. The objective considered in this paper is the maximization of the state of charge at plug-out for each vehicle with the utility power and time of availability of each user as constraints.

C. System Constraints

The primary constraint considered here is the power availability from utility. Type of charge (slow, medium, fast), time of availability in the parking lot, minimum desired state of charge at plug-out, maximum price the user is willing to pay for charging, maximum power that can be absorbed by a vehicle battery, other battery requirements etc. are other possible constraints. The user could also specify the number of miles he/she plans to drive after plug-out, in which case, the SoC for achieving this will be guaranteed at plug-out. Another constraint for the iEMS could be in terms of the layout of the parking deck, the sizing and capacity of the cables will place a limit on the power that can be channeled to each vehicle(s). For a more robust system, we could consider the abrupt plug-out by a user before stated time, and in this case, the aim would be have some fairness in the SoC distribution at every time step so as to have a reasonable SoC even before plug-out. Additional constraints in the system could be in terms of the bandwidth availability of the communication channel for sampling the states of the vehicles, which would limit the sampling time. System performance with packet delays and drops could also be evaluated.

The final goal of the iEMS is to be flexible in terms of accommodating multiple objectives for different users. It also opens up the possibility of dividing the station into clusters, grouping vehicles/users with common objectives and assigning the responsibility of optimizing on each cluster to a sub-iEMS thereby translating the problem into the arena of distributed control. The decision on how much power to allocate to each sub-iEMS will be made by the central iEMS or could also result from bidding actions by the sub-iEMSs (game theory).

D. System Simulator

A detailed description of the Simulink based simulator developed for the system and the modeling and operation of system components is available in [5] (previous chapter). The figure below illustrates the simulator for five vehicles which has been used for testing and analysis of the proposed algorithm.

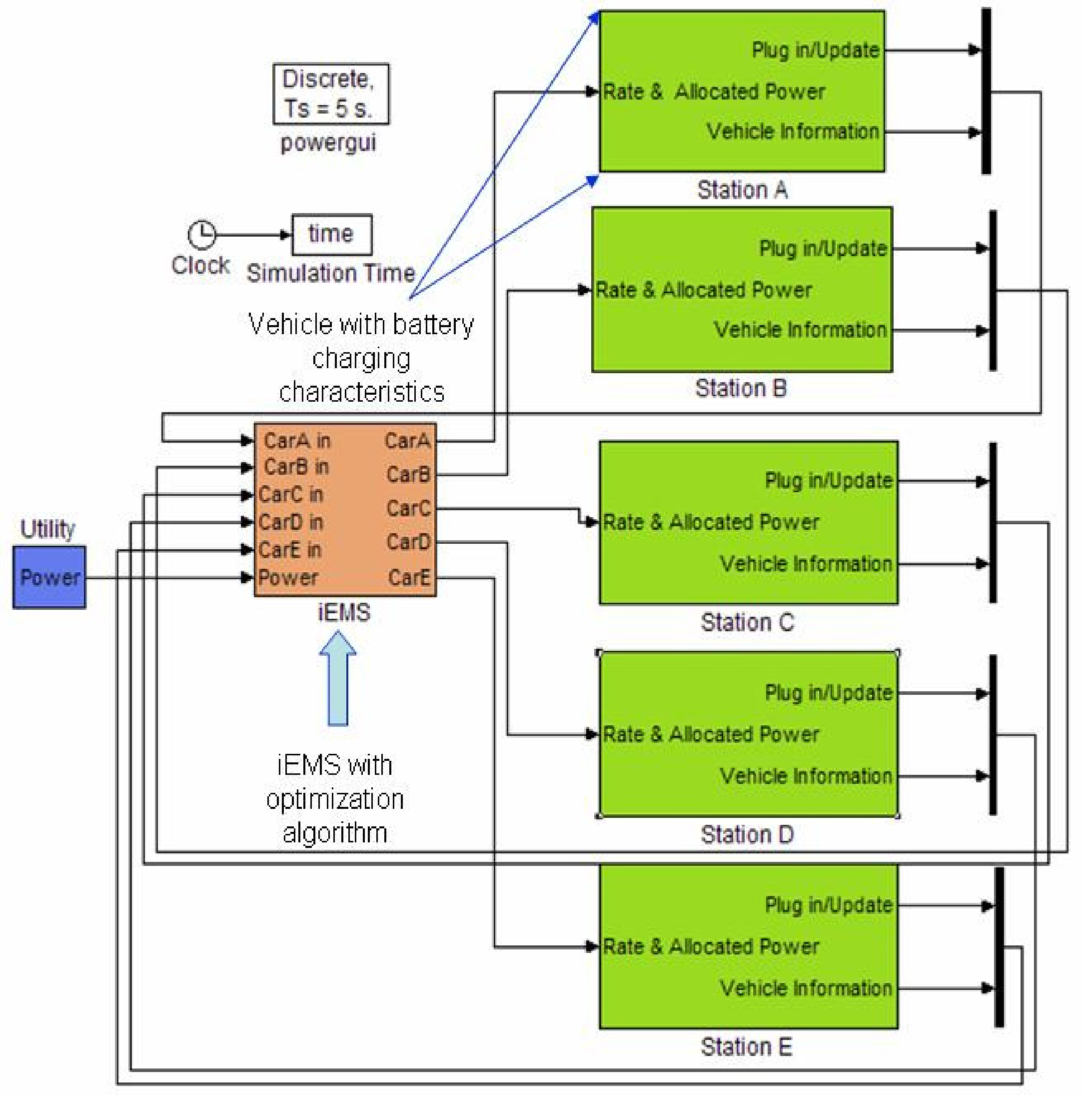

Figure 20: System simulator for 5 vehicles at the parking deck

III. GENERAL MATHEMATICAL FORMULATION

Two examples of relevance here are: unit commitment and economic dispatch [10], [11]. While unit commitment involves ON/OFF decision on operation of a generating unit, economic dispatch involves the decision on amount of power to be provided by each unit, the cost function for both being nonlinear (typically). The problem we address is similar in the respect that it involves an optimization decision to satisfy the load and minimize costs however; it also has lot of scope for setting a variety of objectives or cost functions and is applied at the distribution end.

Let $\boldsymbol{v}$ represent an n dimensional attribute vector (tuple) representing the vehicle. This can incorporate: vehicle ID, GPS location, driving distance after plug-out, time of plug-out, rated vehicle capacity, maximum power that can be absorbed during charging, battery state of health, pricing preference of the user, participation in V2G (binary) - *static attributes*; rate of charge, terminal voltage, current state of charge, current power consumption - *dynamic attributes*.

Since the decision made is recalculated by the iEMS at regular intervals, let the system time be descretized into time steps. Size of each time step can be constant or variable and decided with consideration of the communication channel delays, effectiveness of the control action etc. Let k be the index of the current time step.

Let C be the set containing the attribute vectors corresponding to the vehicles in the system present at time step k. $C(k) = [\boldsymbol{v}_1, \boldsymbol{v}_2, \boldsymbol{v}_{3 \ldots\ldots} \boldsymbol{v}_n]$.

Let $\boldsymbol{u}$ be the n dimensional attribute vector of the iEMS. It can contain elements such as: Number of vehicles currently plugged in (**N**), vector of power allocated to each vehicle, weight/priority assigned to each vehicle for optimization (for our algorithm), time interval used for sampling and optimization, set of objectives for which optimization can be made etc.

Let the attribute vector of utility for the parking deck be represented by ***d***: power available, pricing at current time, power required from V2G etc.

The objective stated in terms of a cost function is:

$$\min_{\mathbf{u}} J(\cdot)$$

subject to $\mathbf{f}(t) = \mathbf{0}$

and $\mathbf{g}(t) \leq \mathbf{0}$

J can be a function(al) of:

$P_s(k)$: Power available from the utility at time step k

$P_r(k)$: Power required by the utility from V2G at time step k

$prc(k)$: Price of electricity in \$/kW

$N(\mathrm{k})$: Network condition, e.g., network delay

$p_i(k)$: Power allocated by the iEMS to the i-th vehicle at time step k

Δt: Time interval for sampling by the iEMS

$T_{in,i}$: Time in for the i-th vehicle

$T_{a,i}$: Available time for charging for the i-th vehicle

$T_{l,i}$: Time at which i-th vehicle will leave

$pref_i$: User charging preference for the i-th vehicle e.g.

$c_i(k)$: price per kWhr customer i is willing to pay

$V2G_i$: participation in vehicle to grid (0 or 1)

$\mathbf{x}_{b,i}$(k): Current battery state for vehicle i e.g.

$C_{r,i}(k)$: Capacity required to be filled for vehicle i in time step k

$T_{r,i}(k)$: Time remaining for charging the vehicle at time step k.

$SoC_i(k)$: vehicle state of charge at beginning of time step k

$V_i(k)$: Terminal voltage of the battery at time step k

$I_i(k)$: Rate of current for charging vehicle i in time step k (assumed constant over a time interval)

C_i: Rated Capacity of vehicle i

P_{iMAX}: Maximum power that can be absorbed by vehicle i

$\boldsymbol{v} = [P_{iMAX}, \mathbf{x}_{b,i}(\mathrm{k}), C_i, pref_i, T_{l,i}, T_{in,i}]$

$\boldsymbol{u} = [p_i(k), \Delta t, \mathbf{N}]$

$\boldsymbol{d} = [P_s(k), P_r(k), N(\mathrm{k}), prc(k)]$

Some preliminary considerations of these functions are:

f:

$$\mathbf{x}_{b,i}(k+1) = \mathbf{f}_b\left(\mathbf{x}_{b,i}(k), \mathrm{p}_i(k), \mathbf{q}_{b,i}(k)\right)$$

$$SoC_i(k+1) = f_{SoC}\left(\mathbf{x}_i(k), \mathbf{q}_i(k)\right)$$

$$SoH_i(k+1) = f_{SoH}\left(\mathbf{x}_i(k), \mathbf{q}_i(k)\right)$$

$$SoF_i(k+1) = f_{SoF}\left(\mathbf{x}_i(k), \mathbf{q}_i(k)\right)$$

…

where:

$\mathbf{x}_{b,i}$: state variable of the i-th battery

$\mathbf{p}_i$(k): power allocated to the *i*-th battery

$\mathbf{q}_{b,i}$: *i*-th battery parameters

SoC_{i}: State of charge of the *i*-th battery

SoH_{i}: State of health of the *i*-th battery

SoF_{i}: State of function of the *i*-th battery [12]

g:

$$\sum_i p_i(k) \le P(k)$$

$$p_i(k) \le p_{iMAX}(k)$$

…

J:

$J_1(k) = \sum_k \sum_i T_{c,i}$ - minimize the charging time

$J_2(k) = -\sum_k \sum_i pref_i(\cdot)$ - maximize the user preference

…

u:

$p_i(k)$: power allocated to the *i*-th vehicle

e.g., $p_i(\mathrm{k}) \in [p_{\min}, p_{\max}]$

$$\text{if p is} \begin{cases} +ve \text{ battery is being charged (G2V)} \\ 0 \text{ no dis/charging activities} \\ -ve \text{ battery is putting power back to the grid (V2G)} \end{cases}$$

Specific Example:

We present here the preliminary formulation with the objective of maximizing the average state of charge at every time step, the future goal is to solve the problem for n time steps. As mentioned earlier, our constraints will be the power available from the utility, state of charge of each battery, user preferences (we are considering the time of availability for the current formulation), the maximum power that can be absorbed by a vehicle and those imposed by the vehicle charging dynamics.

Thus, in summary, our basic objective is:

max $J(k) = \sum_{j} \sum_{i} SoC_i(k+j)$ (j=1 for the current stage)

Let the states of charge of the vehicles be weighted by a variable say ***w***. Since all the vehicles are different in their attributes (time of leaving and current state of charge, in consideration here), maximizing the SoC of a vehicle will give a reward proportional to its attributes (vehicle with less time remaining should get more power and thus will give higher reward upon maximization of its SoC). Let the measure of this reward be denoted by the term '*priority*'. A vehicle with higher priority will yield a greater reward and vice versa. Let $w_i(k)$ be the priority assigned to vehicle *i* at time step *k* where,

$w_i(k) = f(C_{r,i}(k), T_{r,i}(k))$

$C_{r,i}(k) =$ Capacity required to be filled for vehicle *i* in time step *k*

$C_{r,i}(k) = (1 - SoC_i(k)) * C_i$. Assumption: $SoC_i \in [0,1]$

$T_{r,i}(k) =$ Time remaining for charging the vehicle at time step *k*, $T_{r,i}(k) = T_{l,i} - T_{cur}(k)$, ($T_{cur}(k)$ = time at current time step). A vehicle with higher remaining capacity and less time remaining has higher priority over the other vehicles in the current iteration. Thus the objective function changes to:

$$\max_{u} J(k) = \sum_{i} w_i(k) * SoC_i(k+1)$$

Now, the priority, $w_i(k)\alpha C_{r,i}(k)$ and $w_i(k)\alpha \frac{1}{T_{r,i}(k)}$ i.e. the priority of a vehicle is high if it has less time remaining and also, it is high if it has high capacity requirement. We have currently used a simple formula for priority assignment, $w_i(k) = C_{r,i}(k) + \frac{1}{T_{r,i}(k)}$

Since the second term can be very small (as it is a reciprocal), in order to give equal importance to the two terms, $C_{r,i}(k)$ and $\frac{1}{T_{r,i}(k)}$ have been scaled by factors α_1 and α_2 so that they have equal contribution to the priority term.

$$w_i(k) = \alpha_1 C_{r,i}(k) + \alpha_2 \frac{1}{T_{r,i}(k)}$$

SoC term in the objective function: For a battery with a capacity of C_i, coulombic efficiency η_i, being charged with a current $I_i(k)$ over a period of time Δt, and current state of charge $SoC_i(k)$, the SoC at the next time step is given by:

$$SoC_i(k+1) = SoC_i(k) + \frac{\eta_i I_i(k)\Delta t}{C_i}$$ (For simplicity we assume $\eta_i = 1$)

Since the decision variable is power, let $P_i(k)$ be the power allocated to vehicle *i* in the k^{th} time step, replacing $I_i(k)$ with power: $I_i(k) = \frac{p_i(k)}{V_i^{'}(k)}$

Assumption: Rate of charge $I_i(k)$ remains constant during one time step. Thus if the allocated power is $p_i(k)$, then it is assumed that the rate for charging is such that the power consumed by the vehicle just reaches $p_i(k)$ at the end of the current time step. This will not lead to the most efficient utilization of the allocated power, but will simplify the formulation process.

For the iEMS, we assume that the battery model is a capacitor circuit obeying the equation: $C\frac{dV}{dt} = I$, in time Δt , the voltage will rise by, say ΔV . $\frac{1}{C} I \Delta t = \Delta V$,

$$V_{next} = V_{current} + \frac{1}{C} I \Delta t$$

That is we can approximate the rise of voltage to be linear over a small time for capacitor charging (until it saturates).

$V_{next} = V_{current} + \frac{p}{V_{next} C} \Delta t$, ($I = \frac{p}{V_{next}}$), substituting the values, V becomes the solution to the equation:

$$V_{next}^2 - V_{next} V_{current} - \frac{p \Delta t}{C} = 0 \text{, } V_{next} = \frac{V_{current} + \sqrt{V_{current}^2 + 4 p \Delta t / C}}{2}$$

Thus, the objective function is:

$$\max_p J(k) = \sum_i w_i(k) \left[SoC_i(k) + \frac{p_i(k) \Delta t}{V_i(k+1) C_i} \right],$$

where, $V_i(k+1) = \dfrac{V_i(k) + \sqrt{V_i^2(k) + 4p_i(k)\Delta t / C_i}}{2}$, the decision variable is $p_i(k)$. Upon simplification we get: $\max\limits_{p} J(k) = \sum\limits_{i} \alpha_i(k) p_i(k)$, where, $\alpha_i(k) = w_i(k) * K_i$, $K_i = \dfrac{\Delta t}{C_i}$ (K_i = constant)

Thus final formulation is: $\max\limits_{p} J(k) = \sum\limits_{i} \alpha_i(k) p_i(k)$

subject to:

- $\sum\limits_{i} p_i(k) \le P(k)$
- $\alpha_i(k) = w_i(k) \dfrac{\Delta t}{C_i}$
- $SoC_i(k+1) = SoC_i(k) + \dfrac{p_i(k)\Delta t}{V_i(k+1) C_i}$
- $w_i(k) = \alpha_1 C_{r,i}(k) + \alpha_2 \dfrac{1}{T_{r,i}(k)}$
- $C_{r,i}(k) = (1 - SoC_i(k)) * C_i$
- $T_{r,i}(k) = T_{l,i} - T_{cur}(k)$
- $V_{next} = V_{current} + \dfrac{1}{C} I \Delta t$
- $I_i(k) = \dfrac{p_i(k)}{V_{next}}$
- $p_i(k) <= p_{i,max}(k)$

Solution to the problem:

$\sum_i \alpha_i(k)p_i(k) \leq \alpha_{iMAX}(k)\sum_i p_i(k)$, $\alpha_{iMAX}(k)$ = upper bound, maximum priority

$\sum_i \alpha_i(k)p_i(k) \leq \alpha_{iMAX}(k)P_s(k)$, thus one possible optimal solution to the problem is to allocate all the power to the vehicle with the highest priority (in the current time step). This is surely limited by the maximum power that can be absorbed by the vehicle. Thus, once we have allocated the maximum possible power to the vehicle that will give highest rewards, the problem can recursively allocate power to second best and following candidates until the total power has been exhausted. In this case, for a problem that is otherwise formidable in terms of its solution because of the multi-variable nature (power to each vehicle) and multiple constraints, we have been successful in finding an optimal solution which is fairly simplified, under the stated assumptions.

It is also observed that the goal of obtaining the optimal scheme for power allocation in our system is fraught with contradicting requirements. Firstly, we want to avoid complexity in our model in terms of inclusion of detailed battery charging equations for two reasons: we are able to communicate a limited amount of data between the iEMS and the vehicles, secondly, we would like our algorithm to work with any type of charging algorithms and battery types on the vehicle side, by making some assumptions that hold true for all vehicle/charger types. On the other hand, more detailed information from each vehicle would greatly contribute to computing the optimal solution (albeit resulting in much higher computational complexity in the process).

IV. SIMULATION RESULTS AND ANALYSIS

We present here the results from comparisons between two proposed approaches. The first one is as described before, the other derived from within its mathematical formulation process in which we just halt at the formation of the priority function and use the normalized priorities for allocating power at each step i.e.

$$p_i(k) = w_i(k) * P_s(k)$$

s.t.

$$\sum_{i=1}^{N} w_i(k) = 1$$

Let this scheme be denoted by "*Dynamic Priority Allocation*". We also compare another heuristic, in which equal power is allocated to all the vehicles for which,

$p_i(k) = \dfrac{P_s(k)}{\mathrm{N}}$ is the allocation scheme. (N = number of vehicles in the system)

The index chosen for comparing the algorithms is the SOC (State of Charge) at plug-out. We first discuss a test case for system simulation with five vehicles. The generalized results are later deduced by randomizing the inputs and testing under multiple conditions. The initial state of the system for the test case is given as:

***v* =** [P_{iMAX}, SoCi, $C_{i,}$, $T_{in,i}$, $T_{l,i}$]

***u* = [** Δt **, N]**

***d* = [**$P_s(k)$]

$$C=\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{bmatrix}=\begin{bmatrix} 14\text{kW} & 0.7 & 7\text{Ah} & 8:00\text{am} & 10:40\text{am} \\ 14\text{kW} & 0.1 & 7\text{Ah} & 8:00\text{am} & 11:22\text{am} \\ 14\text{kW} & 0 & 7\text{Ah} & 8:20\text{am} & 10:17\text{am} \\ 14\text{kW} & 0.4 & 7\text{Ah} & 8:50\text{am} & 11:36\text{am} \\ 14\text{kW} & 0.5 & 7\text{Ah} & 9:06\text{am} & 1:04\text{pm} \end{bmatrix}$$

u=[1000s, 5]

***d*=[**10kW**]**

The following three figures represent the power consumption curves of the vehicles for the three algorithms during the simulation process.

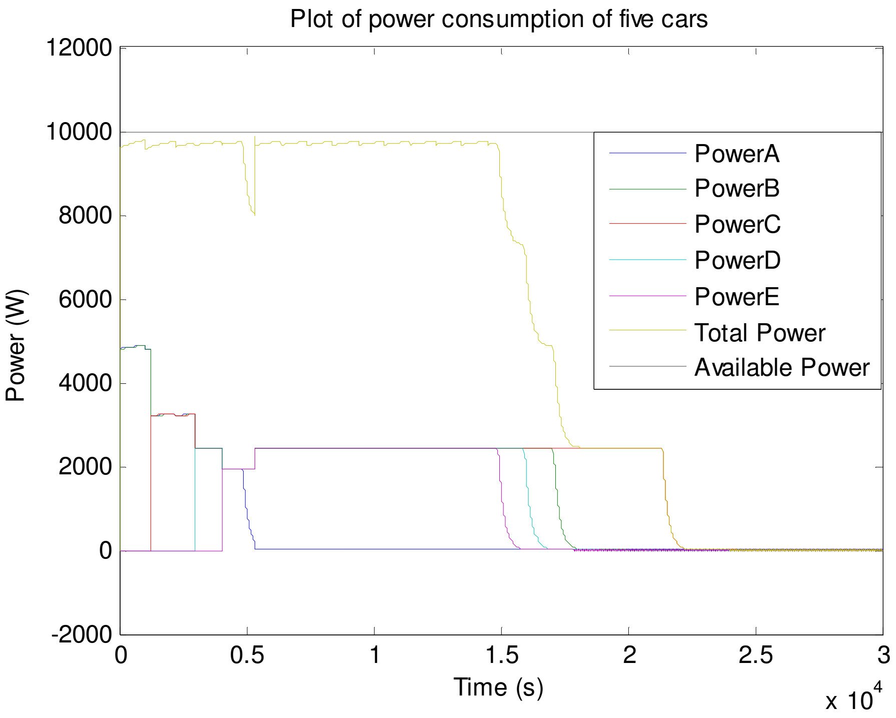

Figure 21: Equal priority allocation

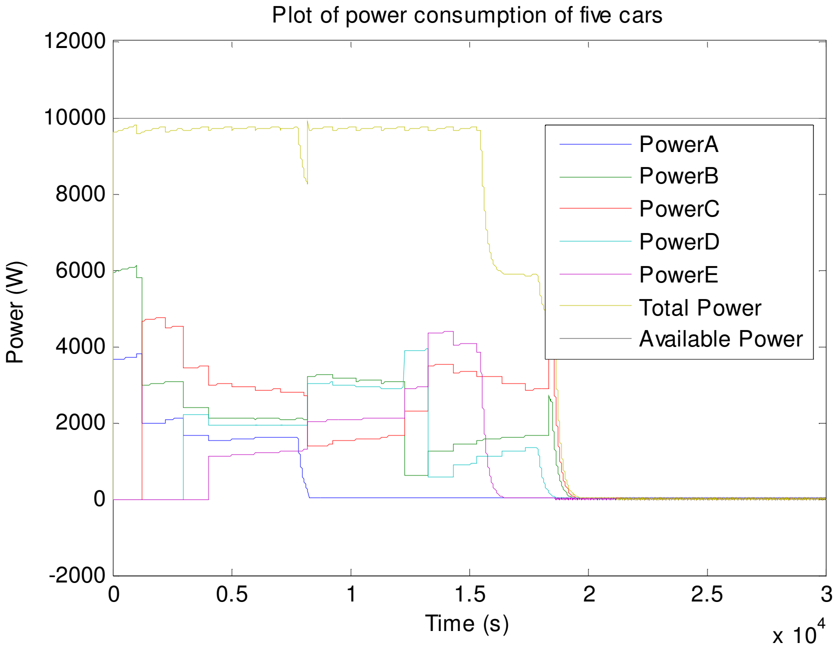

Figure 22: Dynamic Priority Assignment

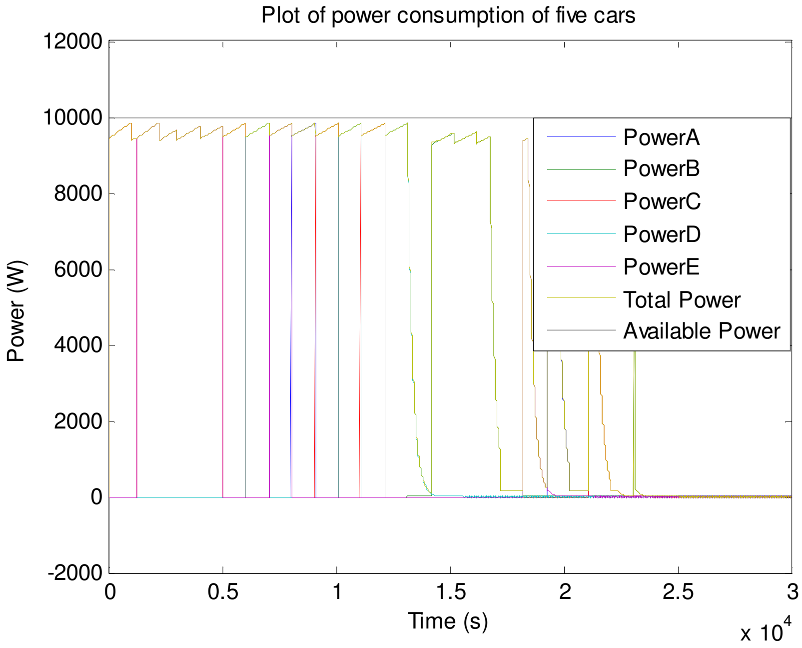

Figure 23: Optimal Allocation for SoC Maximization

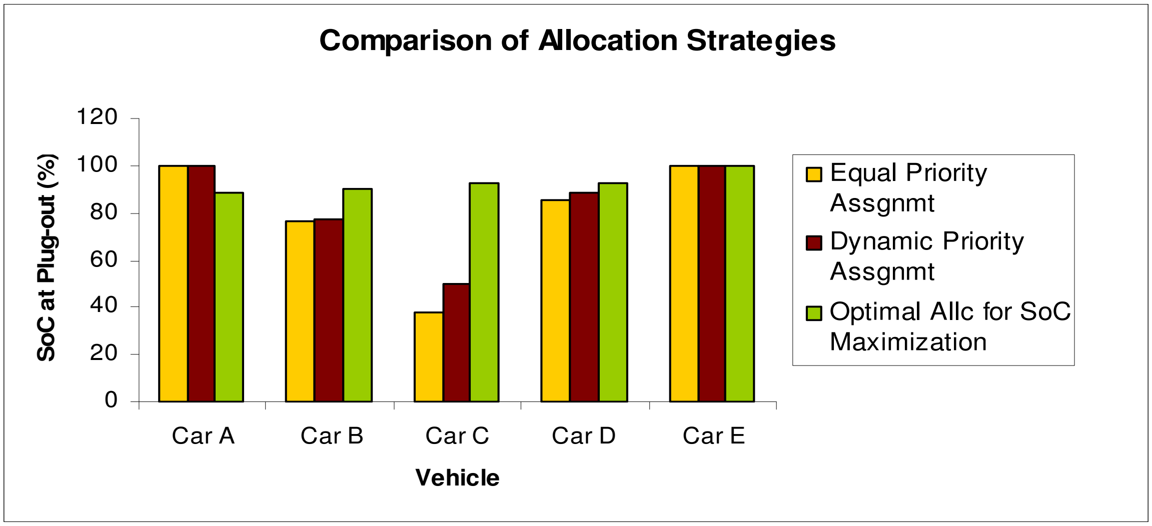

Figure 24: Comparison of allocation strategies

As observed in Fig. 24, for the given test case, the optimal allocation scheme performs much better than the other two schemes. However, in order to test and compare the proposed algorithm under all possible conditions, the algorithms were subjected to vigorous testing under different conditions with randomized inputs were. The parameter values and obtained results are discussed as under:

A. Simulation parameters

State of Charge at plug-in: Uniform Random Number between 10% and 75%

Time of Availability: Uniform Random Number between 0.5 and 2 hours

Time of Plug-in: Uniform Random Number between 0 and 2 hours

Simulation Run Time: 4 hours

Battery Capacity: Uniformly distributed between 6 Ah and 15 Ah

Number of times the simulation was run for each algorithm: 100

The following figures and tables show the distribution of the state of charge of the vehicles at plug-out over the 100 simulations run. Thus, the information represented is the distribution over 500 (100 runs * 5 vehicles) test cases simulated under the randomized parameter values as specified above.

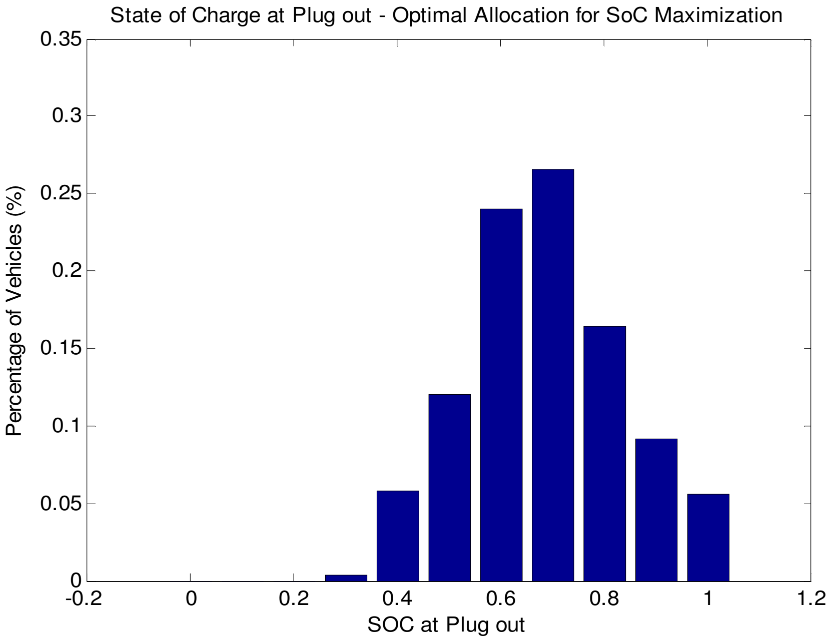

Figure 25: Distribution of vehicles vs. SoC at plug out for Optimal allocation for SoC maximization

Table 1: Range of SOC with the percentage and number of vehicles for Optimal Allocation for SOC Maximization

SOC Range	**Percentage**	**Number of Vehicles**
0 - 5%	0%	0
5-15%	0%	0

Table 1 Continued

15-25%	0%	0
25-35%	0.4%	2
35-45%	5.8%	29
45-55%	12%	60
55-65%	24%	120
65-75%	26.6%	133
75-85%	16.4%	82
85-95%	9.2%	46
95-100%	5.6%	28

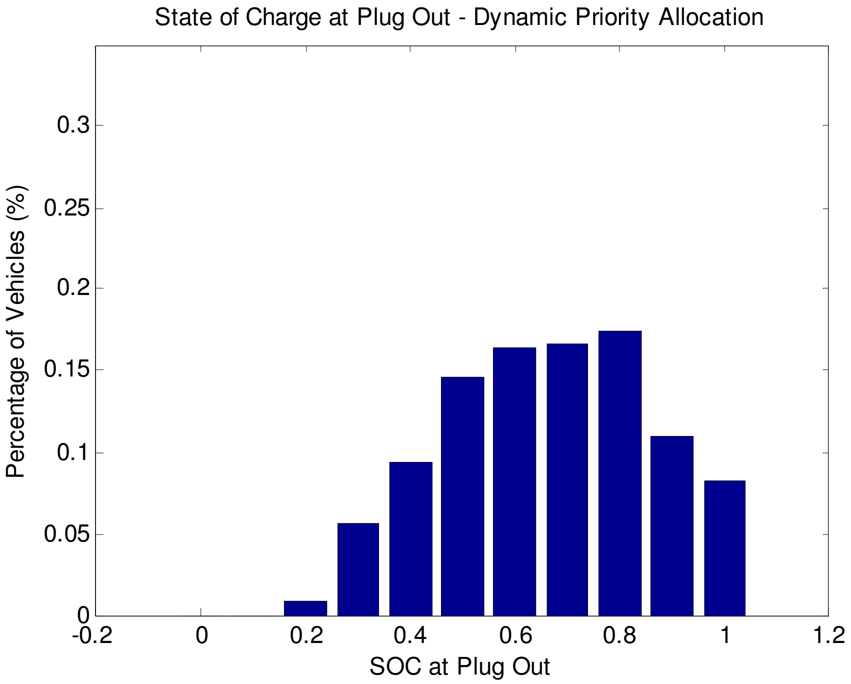
State of Charge at Plug Out - Dynamic Priority Allocation

Figure 26: Distribution of vehicles vs. SOC at plug out for dynamic priority allocation

Table 2: SOC range at plug out and percentage and number of vehicles for Dynamic Priority Allocation

SOC Range	**Percentage**	**Number of Vehicles**
0 - 5%	0%	0
5-15%	0%	0
15-25%	0.8%	4
25-35%	5.6%	28
35-45%	9.4%	47
45-55%	14.6%	73
55-65%	16.4%	82
65-75%	16.6%	83
75-85%	17.4%	87
85-95%	11%	55
95-100%	8.2%	41

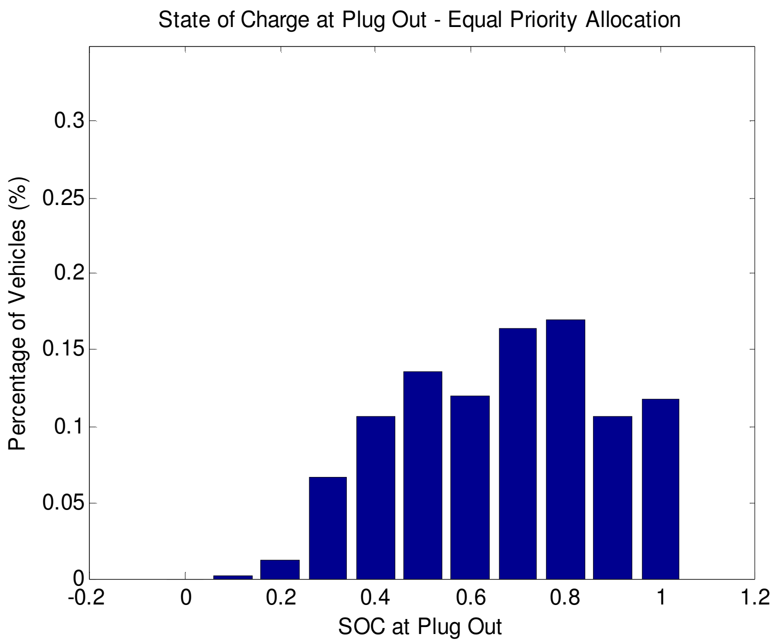

Figure 27: Distribution of vehicles vs. SOC at plug out for Equal priority allocation

Table 3: SOC range at plug out and percentage and number of vehicles for Equal Priority Allocation

SOC Range	**Percentage**	**Number of Vehicles**
0 - 5%	0%	0
5-15%	0.2%	1
15-25%	1.2%	6
25-35%	6.6%	33
35-45%	10.6%	53
45-55%	13.6%	68
55-65%	12%	60
65-75%	16.4%	82

Table 3 Continued

75-85%	17%	85
85-95%	10.6%	53
95- 100%	11.8%	59

B. Analysis

In Optimal allocation for SOC Maximization algorithm results, 81.8% (409) of the vehicles leave with an SOC of 55% and above, however, in Dynamic Priority Allocation, the percentage is 69.6% (348) and in equal priority allocation it is 67.8% (339). From the graphs, it is observed that the distribution of the percentage of vehicles vs. the state of charge at plug out is somewhat Gaussian in the case of the optimal allocation scheme, with the center at around 60-70% SOC. Thus, most vehicle SOCs are concentrated in this region at plug out.

Comparing the optimal scheme with the other two schemes, there are comparatively lesser vehicles which leave at 80-100% SOC. However, number of vehicles leaving with lower SOC is also reduced. In optimal allocation, there are no vehicles leaving with a SOC of 25% or lower and only 2 vehicles in a total of 500 cases that leave with a SOC of 25-35%. While in Dynamic allocation, 4 vehicles leave with 15-25% SOC and 28 with 25-35% SOC (total of 32 vehicles leaving at 35% and below). In equal priority allocation, there are 40 vehicles that leave with 30% SOC or lower (1 at 10%, 6 at 20% and 28 at 30%). Thus, if the index of comparison is used as the number of vehicles leaving at 35% SOC or lower, then the optimal allocation scheme performs 93.75% better than Dynamic Allocation and 95% better than Equal Priority Allocation.

We can see that higher SOC at plug-out for some vehicles is sacrificed in order to provide a high average SOC for all vehicles in the case of the optimal allocation for SOC maximization scheme. This is a result in agreement with the intuition and intention with which the problem was formulated. We had started with the goal of maximizing the *average* state of charge of the vehicles at the end of each iteration; the solution deduced being to give maximum power (that can be absorbed) to the vehicle with highest priority. Once this power would have been allocated to the vehicle, its priority would drop drastically in the next iteration (capacity required will drop), thus another vehicle will be then assigned the maximum power, thereby bringing a balancing effect in the SOCs of the vehicles.

V. CONCLUSION AND FUTURE WORK

The problem addressed in this paper provides a large scope for exciting future research in the area of smart grid interactions with distributed loads. The future goal for this research is to model the problem closer to a real world scenario by incorporating variable utility power availability, performance evaluation with communication delay, packet drop, and signal strength (Network in the Loop iEMS), more user preferences etc. Exploration of distributed control, optimization on predicted system states, demonstration on a real world test-bed etc. are also areas of future research.

In this paper, we proposed a system to enable the integration of plug-in hybrid electric vehicles into the power grid. We discussed the concept of an intelligent energy management system for managing PHEV charging at a municipal parking deck, providing a description of system operation and components. We also presented a mathematical framework for system description and formulation of the optimization problem for power allocation. The framework proposed was extended to a specific example with a chosen objective and constraints and the solution provided under stated assumptions. We then compared the proposed algorithm with two other approaches in the simulation results and concluded with potential future directions.

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CHAPTER IV - Labview Based Demonstration Test-Bed for Intelligent Energy Management of PHEVs at a Municipal parking deck

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Labview Based Demonstration Test-Bed for Intelligent Energy Management of PHEVs at a Municipal parking deck

Abstract - Large penetration of Plug in Hybrid Electric Vehicles (PHEV) poses a potential threat to grid stability if PHEV battery charging is not managed. The management of the PHEV charging process is facilitated by an intelligent energy management system (iEMS) which communicates with the vehicle to sample the vehicle states and makes a decision on power allocation. In this paper, a demonstration test-bed is presented in which the monitor and control of simulated vehicles in a local and remote network is enabled with a Labview based GUI and the communication is facilitated by ZigBee nodes.

I. INTRODUCTION

With the emergence of advanced vehicular technologies, research efforts have been directed towards advanced batteries and storage systems, engine and powertrain control, HEV optimization etc. Until lately, research was only focused on the subsystems within a vehicle and methods of optimizing their design and operation. With the vehicular technologies progressing towards PHEVs and the requirement of a smart grid, such vehicles will play an important role of a component in the power system and no longer remain an isolated entity.

The Electric Power Research Institute (EPRI) projects that by 2050, 62% of the entire US vehicle fleet would consist of PHEV (moderate PHEV penetration scenario) [1]. The penetration of these vehicles in the market would add a sizable excess load to the grid which can result in voltage instabilities and blackouts. To avoid the worst scenarios, an intelligent energy management system (iEMS) that controls the load power consumption is needed.

In [2] and chapter III, the system architecture, modeling and mathematical framework has been discussed for intelligent energy management of PHEV charging at a municipal parking deck. The system is similar to a supervisory control and data acquisition system, with the difference that the controller is equipped with more sophisticated decision making logic. The data reflecting the state of the system – vehicle battery states, communication signal strength, user inputs etc. is aggregated at the control station and processed by the iEMS for power allocation. In this paper, a Labview based demonstration test-bed is described to monitor and control the vehicle charging process.

The municipal parking considered will be instrumented with intelligent charging posts enabled with a communication platform that can communicate details about the charging process of the attached PHEV to a central controller or iEMS. So far, the iEMS algorithm has been implemented in a software Simulink based test-bed, an important consideration is the performance of the algorithm in a real world deployment. Its performance will be influenced by the communication network characteristics (delay, throughput, packet loss etc.) as well as other considerations regarding the vehicle batteries. The demonstration presented here is a first step towards developing a system that more closely resembles the real world scenario with the communication being facilitated by ZigBee nodes. Labview provides the advantage of being an intuitive graphical programming language with a large number of I/O libraries for data acquisition and interactive displays and thus has been chosen as the platform for demonstration [3]. In the Labview demonstration, a GUI is used for representing system data and it contains an embedded file containing the iEMS algorithm. The decisions made by the algorithm are sent via Labview to the ZigBee node connected to the host computer and then transmitted wirelessly to the receiving nodes.

This paper is organized as follows:s I discusses the system components used for the demonstration, section II describes the experimental setup for communication and control of the vehicles by the iEMS. Section III describes the Labview program used for developing the GUI and monitor and control followed by graphical results and conclusion.

II. SYSTEM DESCRIPTION

The system components are described as under:

A. Vehicle

The vehicle battery information and user preferences are relevant for system operation. For the experiment, a battery model mentioned in [4] is deployed on the Texas instruments MSP430F2274 microcontroller [5] to represent a plug in hybrid battery. The user preferences are also coded into the MSP430.

B. iEMS

With growing power requirements for various sectors of economy like industrial, residential, manufacturing etc. grow, there is a need for a more intelligent energy management system that is enabled for advanced demand side management and real-time control. In the case of the parking deck, where a large number of PHEVs will be plugged in simultaneously, there is need for such an intelligent energy management which will help prevent possible grid instability due to surge in power consumption.

The iEMS is designed based on SCADA with the iEMS as the master controller and the chargers as slaves. Whenever a vehicle is plugged-in at the charging deck, data regarding the time of availability, battery parameters like initial state of charge (SOC), capacity etc. and other user specific details is acquired and communicated to the controller. Based on the data from all the vehicles currently plugged-in and the information on the available power and pricing from the utility, the controller makes an optimization decision regarding the power to be allocated to each vehicle and communicates this information to the chargers. The optimization is recomputed periodically and also triggered by specific events in the system (every time a new car plugs in or change in power from the grid or request of update from vehicle). The information exchange between the vehicle and the controller is realized using ZigBee communication [6]. The effectiveness of the power allocation by the iEMS is dependent on faster communication between the nodes. Some interesting research challenges lie in the evaluation of system performance with varying network characteristics. With the changing power consumption profiles of the vehicles and varying power availability from the utility, another challenge is to decide the optimal sampling interval for each vehicle given the constraints of the underlying communication network. Resolution of these and related issues will lead to an allocation scheme that is optimal in every sense. Here, a demonstration test bed is presented which enables the iEMS interaction with vehicles (simulated at current stage) in the presence of the ZigBee communication network. Currently, the system consists of two local and one remote node, however a future goal is to scale it to larger number of nodes and observe the system performance. In the experimental system, the iEMS resides inside a Labview based GUI for monitoring and control of system.

C. Utility

The utility provides bounds on the maximum acceptable power consumption at a parking deck, real time electricity prices can also be provided so that users that wish to charge their cars when rates are below a threshold can do so. The information from the utility currently incorporated is the power availability, residing on the iEMS computer. The iEMS internally acquires utility information for its decision on energy management.

D. Communication Platform

Various possible communication options that were considered for the parking deck were: Bluetooth, Wi-fi (802.11), Power line communication, ZigBee etc. While evaluating the various wireless communication protocols with respect to cost and low power consumption, ZigBee emerges as the ideal communication platform. ZigBee is a suite of high level communication protocols based on the IEEE802.15.4 that provides for data rates of up to 250Kbps over a range of over 10 to 100 meters. It is a standard maintained by the ZigBee Alliance [6] which is actively involved in energy management and efficiency systems. ZigBee is designed for low power consumption and complexity allowing a variety of network topologies. Thus the communication architecture was designed with ZigBee as the platform. The maximum application payload data that is available per ZigBee frame according to revised IEEE 802.15.4 standard, IEEE 802.15.4-2006 is 102 octets [7]. This is largely sufficient enough to communicate the various parameters like state of charge of the battery, instantaneous power consumption, time of availability of car, user preferences like type of charge from the vehicle to the iEMS as well as parameters like pricing, allocated power, and status information from the iEMS to the vehicle.

ZigBee is a wireless communication protocol using small, low power digital radios based on the IEEE 802.15.4 standard for wireless personal area networks. ZigBee devices can be categorized into RFD (Reduced function device), FFD (Full function device) and ZC (ZigBee coordinator) [6]. The ZigBee Coordinator is responsible for maintaining the whole ZigBee network. It acts as a root node which lets newer ZigBee nodes to join or leave the network. The FFDs behave as end devices that can communicate with the ZigBee Coordinator as well as other FFD/RFDs in the network and also as an intermediate router in the ZigBee network. The least complex devices are the RFDs which can only communicate with a router or the coordinator. They can't relay any data from other nodes in the network. The RFDs can wake up whenever they want to send their data and go back to sleep thus reducing the power consumption.

Fig. 28 shows the proposed communication architecture. The charging deck is categorized into different zones (4 below – Zone A, B, C, and D). The zones are created based on visibility range of ZigBee, the layout of the power lines, and the physical structure of the deck. Each of the ZigBee nodes at the charging post is configured as an FFD or RFD and is responsible for communicating vehicle related information like the state of charge of the battery, the availability time of the car etc. from the PHEV parked at the charging post to the central controller or iEMS either directly or through other FFDs in the neighboring charging posts. The iEMS after obtaining these values calculates the power allocation and sends this information over the ZigBee link back to the vehicle. The FFDs periodically send the updated state of charge of the batteries until full charge. If the iEMS is located remotely, local communication is enabled using ZigBee and the data is routed through the internet to the iEMS.

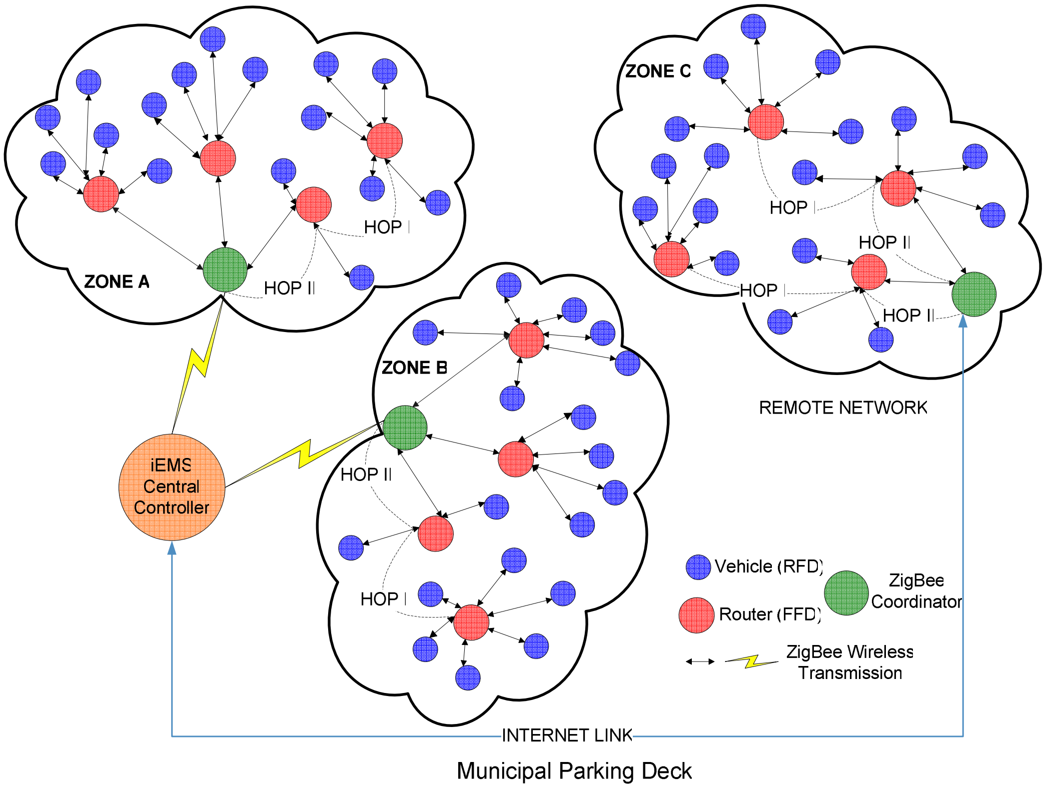


Figure 28: Communication architecture

III. EXPERIMENTAL SETUP

In this section, the integration of the system (vehicle, iEMS and the communication link) is described. Fig. 29 shows the setup used for demonstration. We are using the ez430-RF2480 Zaccel kit manufactured by Texas Instruments [8] for the experiment. The messages are exchanged locally using ZigBee on two sites (I and II). Site I is connected to Site II via the internet; this has been incorporated to consider the scenario in which one iEMS manages an area too large to be covered by one ZigBee network. An example would be a multi-level parking deck.

To simulate the PHEV battery, a battery model representing the vehicle is deployed on the Texas instruments MSP430F2274 microcontroller. The MSP430 is a micro processor platform of ultra low power 16-bit RISC processors from Texas Instruments [5]. Two of these modules communicate with the iEMS (ZigBee coordinator) locally. The iEMS also remotely controls the charging process on the third vehicle model through the internet.

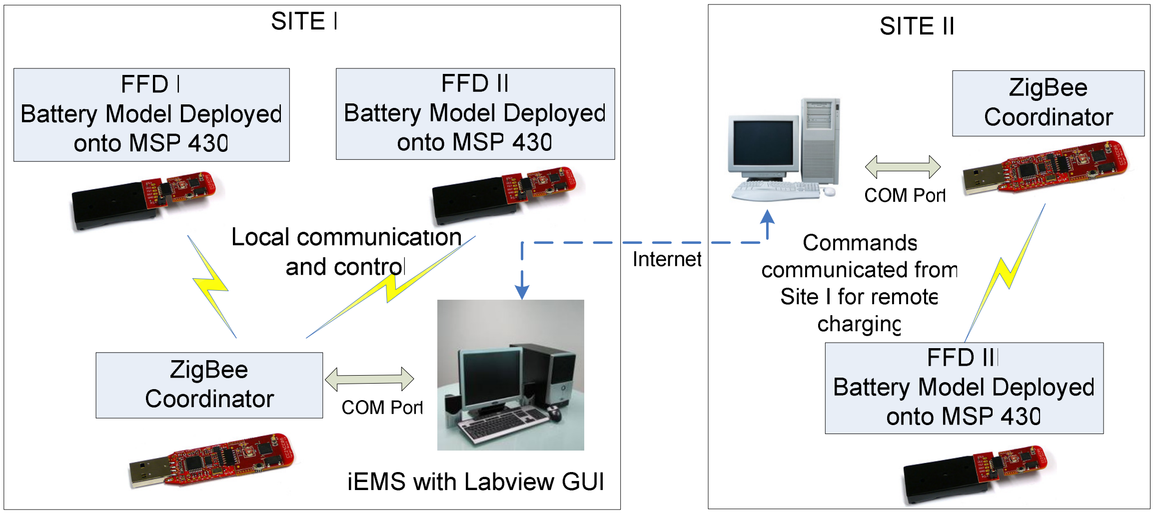


Figure 29: System setup

IV. LABVIEW CODE

This section describes the details of Labview program that is used for developing the GUI.

A. Reading and writing information from the ZigBee node

The ZigBee node is connected to the COM port of the PC using a USB connector. In Labview, the VISA (Virtual Instrument Software Architecture) vi is used for reading the COM port data. The following two figures show the VISA Open and VISA read functions used for opening a session with the COM port device (ZigBee coordinator) and reading the information.

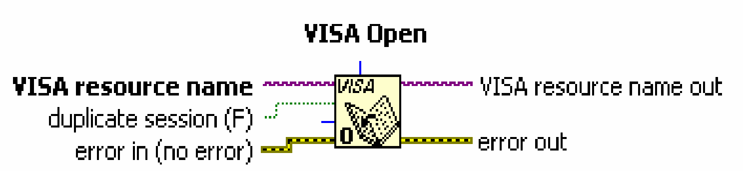


Figure 30: Open VISA session with COM port

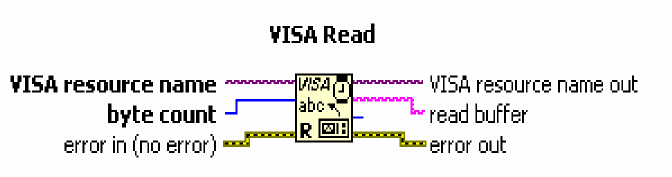


Figure 31: Read data from COM port

The ZigBee node periodically reports the following parameters of the simulated battery model and the user:

Status: ‘01’= Plug in, ‘02’= Charging, ‘03’= Update, ‘04’=Completed

State of Charge: 0 to 100

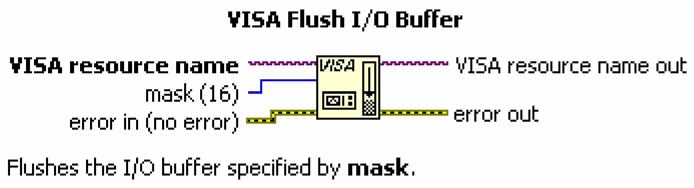
Power Consumed: upto 10kW (5 digits)

Time of Availability: 0 to 10 hours

Node ID: 4 digits

Mode: 1 digit – Constant Voltage =1, Constant Current =0

This data is received by the ZigBee coordinator and sent over the COM port of the PC. The I/O buffer is flushed after the VISA read operation in order to prevent the same data from persisting at the COM port over a long interval. Fig. 32shows the Labview function used for achieving this.


VISA Flush I/O Buffer

Flushes the I/O buffer specified by **mask**.

Figure 32: VISA flush I/O Buffer

The string subset function is used in order to extract the data from the input string.

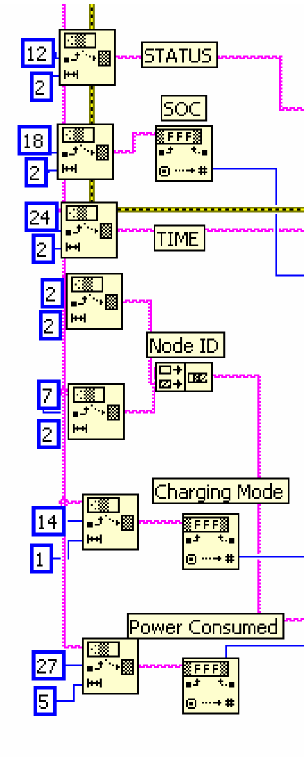


Figure 33: Extraction of data

A case selector is used to execute the functions based on the node ID. The Labview program is setup to listen continuously at the COM port for incoming data, once new data arrives, the relevant fields are extracted. The data is provided to the subvi responsible for optimization (iEMS subvi). The output of the algorithm is a power allocation and corresponding rate of current. This is communicated back to the coordinator via the VISA write function. The coordinator then transmits the message wirelessly to the node. The write operation is only performed if the status is ‘01’ or ‘03. The iEMS embedded in Labview computes the optimization when the status is ‘01’ or ‘03’, in other cases; it reports/displays the state of charge and power consumption of the battery. Figure 34 shows the write operation.

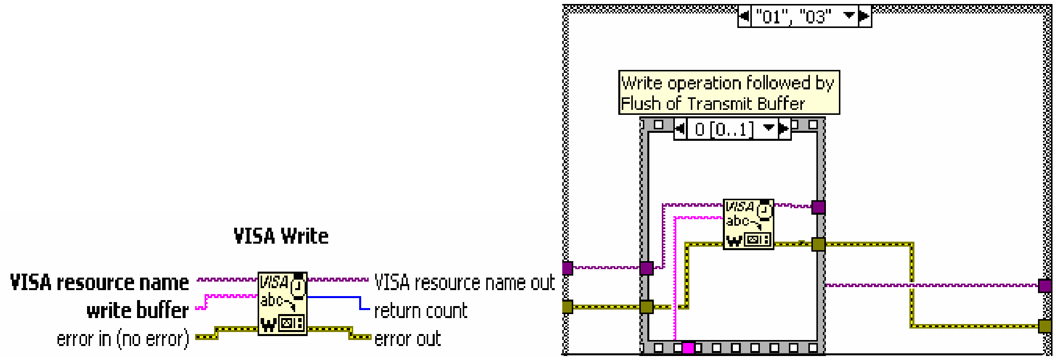


Figure 34: VISA write operation

B. iEMS Operation

The iEMS subvi takes the following inputs in order to make the decision on power allocation:

- Current State of charge of each vehicle
- Time of availability of each vehicle
- Power being consumed by each vehicle

- Charging mode of the vehicle (Constant current or Constant Voltage)
- The capacity of each vehicle is assumed to be 7 Ah.

This information is made available to the subvi by the ZigBee nodes at the following reporting intervals:

- Local Node A: every 13 s
- Local Node B: every 10s
- Remote Node C: every 10s

This in turn interprets to the sampling interval of each node. With the given information about the system state, the iEMS makes a decision on the power to be allocated to the requesting node.

iEMS Algorithm used:

Dynamic priority based allocation has been used for computing the rate of current and power allocation. In this, a priority is assigned dynamically to each vehicle in accordance with its attributes and the power is allocated in proportion to the priorities. Let $p_i(k)$ be the power allocated to vehicle *i* and $w_i(k)$ be the priority allocated to it in the time step *k*. Then,

$$p_i(k) = w_i(k) * P_s(k)$$

s.t. $\sum_{i=1}^{N} w_i(k) = 1$

The priority function is given as: $w_i(k) = f(C_{r,i}(k), T_{a,i})$, where

$C_{r,i}(k) =$ Capacity required to be filled for vehicle *i* in time step *k*

$C_{r,i}(k) = (1 - SoC_i(k)) * C_i$. Assumption: $SoC_i \in [0,1]$

$T_{a,i}$ = Time of availability for vehicle i

A vehicle with higher remaining capacity and less time of availability has higher priority over the other vehicles in the current iteration. The priority, $w_i(k)\alpha C_{r,i}(k)$ and $w_i(k)\alpha\frac{1}{T_{a,i}}$.

Currently used the following formula has been used for priority assignment:

$w_i(k)=\alpha_1 C_{r,i}(k)+\alpha_2\frac{1}{T_{r,i}(k)}$, where α_1 and α_2 are scaling factors.

Fig. 35 shows the connections to the iEMS subvi:

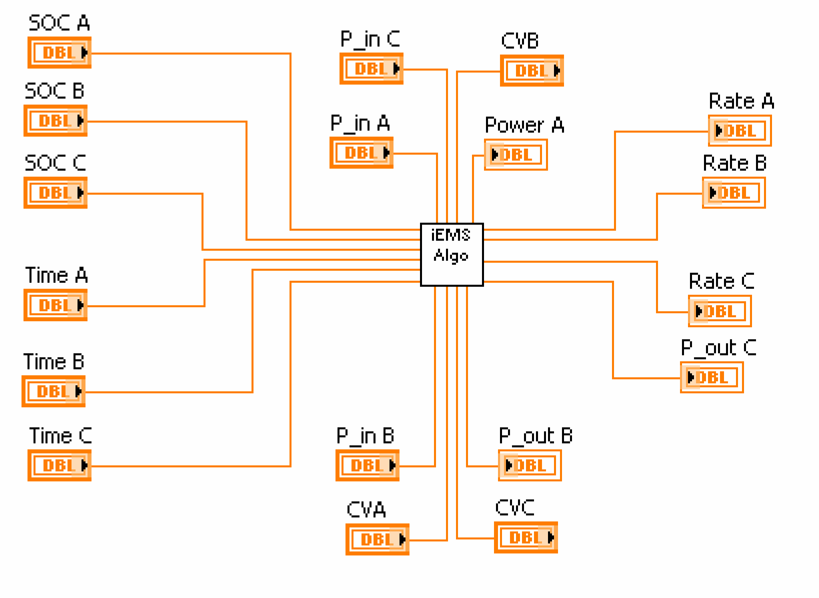


Figure 35: iEMS subvi

P_in: Power currently consumed

CVA: Whether the charging is in constant voltage mode or not

The battery model deployed on the nodes is charged with a CC-CV charger. During the CV mode, the power consumption of the vehicle drops down drastically, thus information about the mode enables the iEMS to reduce the priority of that vehicle as its current drops exponentially. The vehicle in CV mode is given a power only slightly more than current consumption (thus the requirement of input of current power consumption) as its power consumption will drop exponentially, while the other vehicles are allocated power in accordance with their current priorities. Fig. 36 shows the connections of the iEMS subvi in the Labview GUI block diagram.

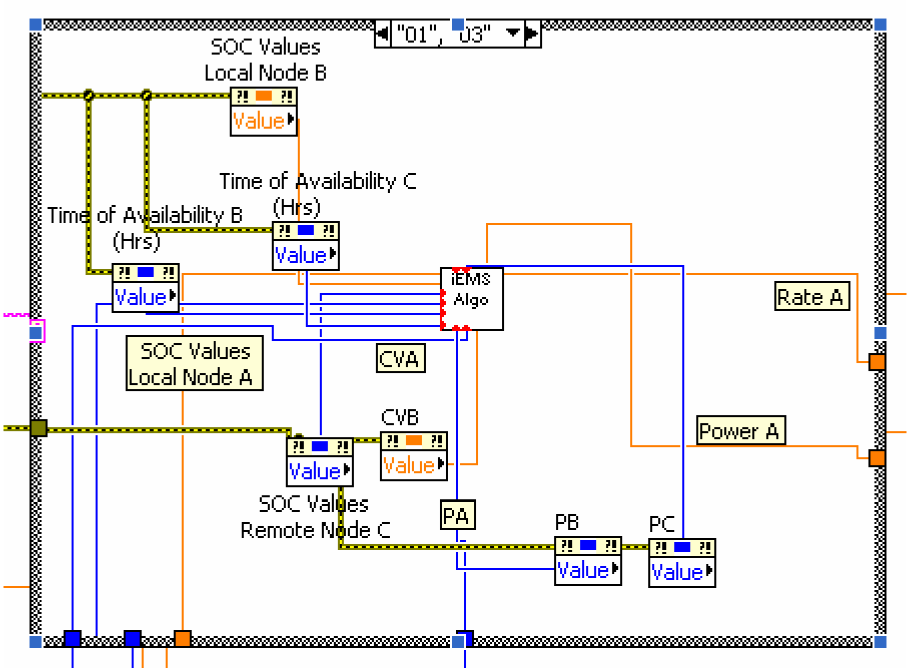


Figure 36: iEMS subvi data inputs in the Labview GUI

C. Communication with the Remote Node

The remote node reports the same parameters to the iEMS, in addition it reports the address/name of the remote site.

TCP Connection

The data from the remote node is sent via the internet. The Labview program listens continuously on the TCP port 2055 for this data using the TCP listen vi as shown in the figure below.

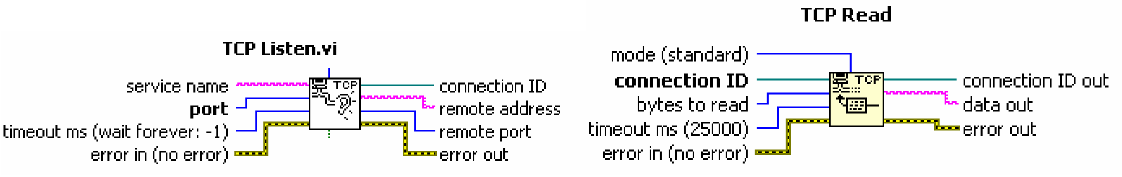


Figure 37: TCP listen and read vi

The TCP read vi is used for reading data at the TCP port. The data is then routed to the iEMS subvi for making power allocation decision. Thus the subvi is called every time a local/remote sends data to the coordinator. For the COM port read and TCP read operation to function continuously and independent from each other, two separate while loops have been used. In order to make the optimization decision for any node, the states of all other nodes need to be sampled. Thus the iEMS subvi in each while loop will need to have access to the information from the other loop. To facilitate this, a property node of the parameters of each of the other node was included and the error input of this node was taken from the TCP block to synchronize the data. The output (power allocation and rate) is then sent over the TCP link to the remote network using the TCP write block.

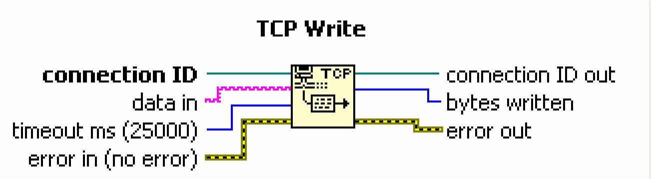
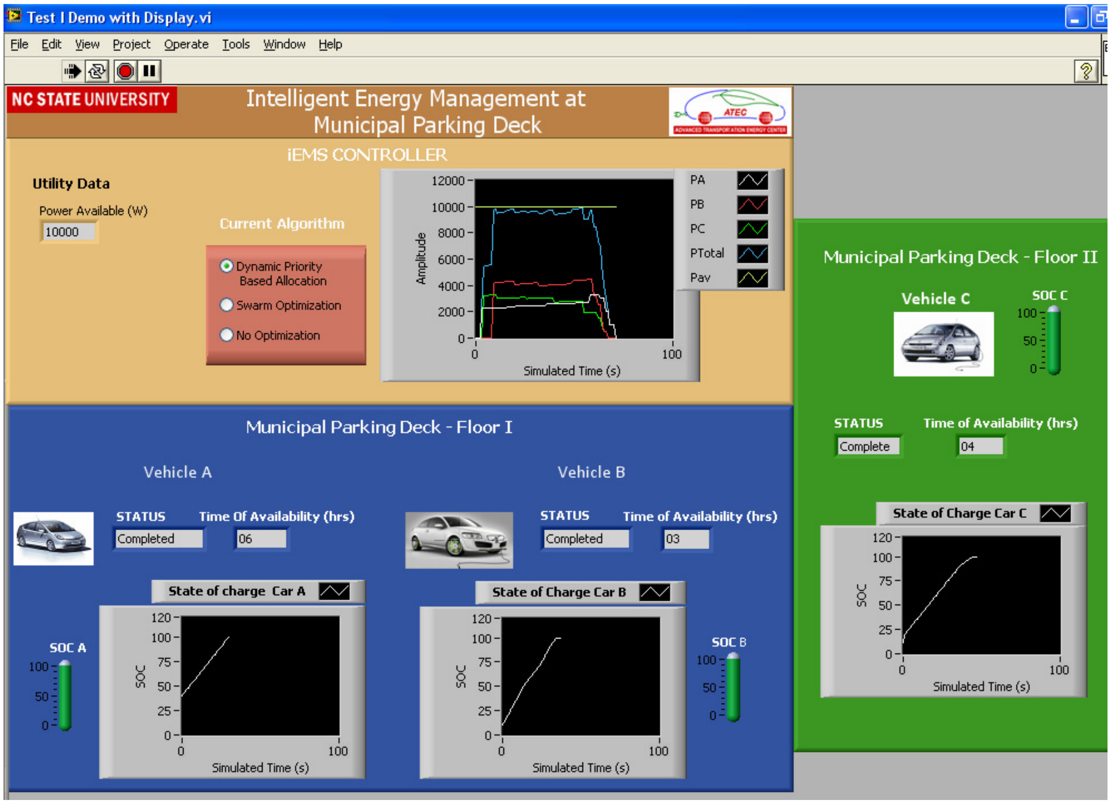


Figure 38: TCP write vi

Fig. 39 shows the results of an experiment run with the following initial parameters as shown in Table 4:

Table 4: Initial values for the simulated batteries

	Local Node A	Local Node B	Remote Node C
Initial State of Charge	40	10	20
Time of Availability	6	3	4



Power Available (W): 10000

Current Algorithm:
- ● Dynamic Priority Based Allocation
- ○ Swarm Optimization
- ○ No Optimization

Vehicle A — STATUS: Completed; Time Of Availability (hrs): 06

Vehicle B — STATUS: Completed; Time of Availability (hrs): 03

Vehicle C — STATUS: Complete; Time of Availability (hrs): 04

Figure 39: Labview Snapshot of the experimental run

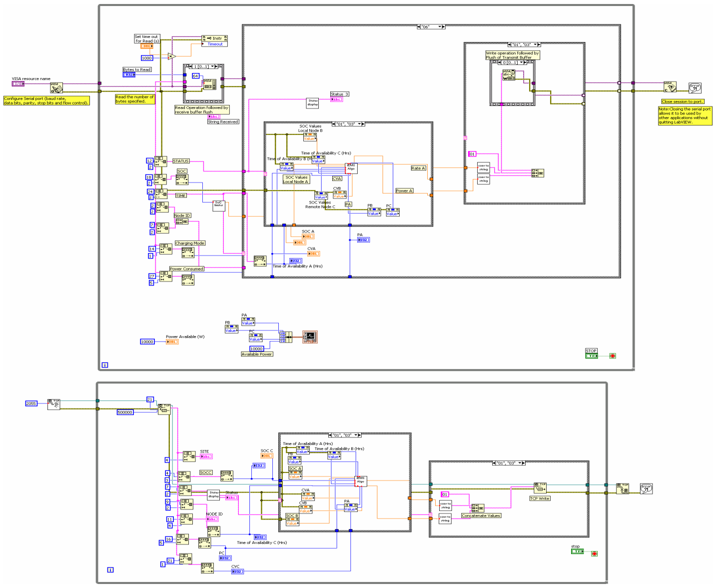


Figure 40: Labview GUI block diagram

V. CONCLUSION AND FUTURE WORK

In order to validate the performance of an iEMS allocation strategy, the future task will be to use actual PHEV batteries along with ZigBee nodes to interact with the iEMS. Also, there is a need to evaluate the communication channel parameters like delay, throughput and received signal strength in order to determine the effect of these on system performance. Incorporation of more detailed information at the GUI like: type of charge, charging algorithm being used, charging history, vehicle to grid preference, communication signal strength, number of vehicles currently active, previous day/week/month charging logs, pricing etc. is another area of future work.

In this paper, a Labview based demonstration setup for enabling monitor and control of Plug-in Hybrid vehicles at a municipal parking deck has been described. The communication structure with ZigBee as the enabling communication technology for the system has also been discussed. An experimental setup with the plug in hybrid vehicle batteries simulated on the ZigBee nodes and interaction of the iEMS with the local and remote network has been presented followed by the Labview program logic and graphical results.

VI. REFERENCES

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CONCLUSION

This thesis proposes an intelligent energy management system to dynamically allocate power to plug-in hybrid electric vehicles at a municipal parking deck. The primary system components are identified as: Utility, iEMS and the vehicles. The attributes significant to system operation include (and are not limited to) the power availability, pricing for the utility, sampling time, number of loads, optimization criteria for the iEMS, the battery dynamic and static parameters and user preferences for the vehicle. The functions and interactions of the entities are described in the form of state transitions. The theoretical system operation is implemented into a simulator to aptly reflect the system operation, with each simulation implementing dynamic power allocation to five vehicles that arrive at random time intervals at the parking deck. A mathematical framework is provided to perform the allocation and an algorithm – "*Optimal Allocation for SoC Maximization*" is proposed for the iEMS and its performance is compared with two other proposed strategies. A Labview based demonstration test bed has also been presented for the system.

There many interesting avenues for future work in this topic. For the optimization, a variety of objectives can be set; the iEMS could also be made to operate on different objectives for each vehicle and the utility simultaneously in order to optimize energy utilization. Additional constraints/considerations can also be incorporated in the system operation e.g.: vehicle to grid operation, communication channel throughput and bandwidth, abrupt user plug out, pricing, decision based on advanced battery properties like SOH, SOF etc. Another focus of future work is to demonstrate the performance of the iEMS algorithm with real vehicle batteries and its evaluation as the system scales up.