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Minimizing residential distribution system operating costs through intelligently scheduled plug-in hybrid electric vehicle charging

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MINIMIZING RESIDENTIAL DISTRIBUTION SYSTEM OPERATING COSTS THROUGH INTELLIGENTLY SCHEDULED PLUG-IN HYBRID ELECTRIC VEHICLE CHARGING

By

Nathan Steven Fettinger

A THESIS

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This thesis, "Minimizing Residential Distribution System Operating Costs through Intelligently Scheduled Plug-in Hybrid Electric Vehicle Charging," is hereby approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE IN COMPUTER ENGINEERING.

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Dedication

To my teachers, family, and friends! Thank you all who have helped me to learn and grow.

Contents

List of Figures

List of Tables

Abstract

Rising fuel prices and environmental concerns are threatening the stability of current electrical grid systems. These factors are pushing the automobile industry towards more efficient, hybrid vehicles. Current trends show petroleum is being edged out in favor of electricity as the main vehicular motive force. The proposed methods create an optimized charging control schedule for all participating Plug-in Hybrid Electric Vehicles in a distribution grid. The optimization will minimize daily operating costs, reduce system losses, and improve power quality. This requires participation from Vehicle-to-Grid capable vehicles, load forecasting, and Locational Marginal Pricing market predictions. Vehicles equipped with bidirectional chargers further improve the optimization results by lowering peak demand and improving power quality.

Chapter 1

Introduction

1.1 Motivation for Hybrid Vehicles

Several factors are driving the automobile industry towards hybrid powered vehicles. These automobiles can reduce the country's dependence on increasingly expensive fossil fuels, reduce carbon emissions, and lower driving costs through increased fuel efficiencies [1]. To further persuade consumers, legislation has been passed in many countries providing incentives for purchasing and owning a hybrid vehicle [2, 3, 4]. These benefits are making it more economically feasible to drive hybrid vehicles. Compared to fully electric or hydrogen powered vehicles, electric hybrids are safer, more reliable, and retain longer driving ranges due to limitations in today's energy storage technologies. This is pushing the automobile industry towards researching new storage technologies as well as designing new types of vehicles using this technology.

1.1.1 Motivation for Hybrid Electric Vehicles

Hybrid Electric Vehicles (HEVs) use the same petroleum fuel as traditional Internal Combustion Engine (ICE) vehicles. However, regenerative breaking and assistance from an electric motor improve the output efficiency of these vehicles [5]. By reducing gasoline usage and utilizing electricity for primary propulsion, Plug-in Hybrid Electric Vehicles (PHEVs) further improve the efficiency. A typical vehicular ICE is about 20 percent efficient [6]. The majority of the energy from petroleum is lost as heat, requiring a portion of the captured energy to cool the ICE. Power plants can propel multiple stage turbines using this excess heat, allowing a portion of the energy to be captured. The entire process of generating and transmitting electricity to households is about 33 percent efficient; it is constantly being improved through advances in technology [7]. On average, the electric motor drives used in vehicles are only about 70 percent efficient at generating propulsion, depending on the size and speed of operation [5]. Converting and storing the energy also induces losses; proposed chargers vary in the range of 85 to 97 percent [8, 9, 10, 11, 12, 13]. When all of this is considered, the PHEV all electric mode is about 20 to 24 percent efficient; a small gain in efficiency. Therefore, current benefits include the ability to produce the energy from renewable resources. These sources are also environmentally friendly, releasing little to no atmospheric pollutants [14]. These benefits alone make the PHEV an ideal replacement for traditional ICE vehicles.

The PHEVs can recharge its battery bank through external electricity sources. The maximum distance the vehicle can be propelled using only the electric engine is called the all electric range [15]. This is directly dependent on the type and capacity of the battery. Typically, Lithium-ion batteries are used since they have longer lifetimes than traditional batteries, and they do not suffer from usage issues such as memory defects. PHEV are designed to improve efficiencies without requiring a trade off for usability and driving range[16].According to the US Department of Transportation (DOT), the average daily commute is about 29 miles [17]. Using this as a design attribute, car manufacturers are targeting their PHEVs with a 20 to 40 mile all electric range [16]. The ICE is still present in the vehicle for extended ranges and dynamic power output.

1.1.2 Types of Hybrid Electric Vehicles

Hybrid vehicles combine two or more types of energy storage systems to provide propulsion for the vehicle [18], most commonly electricity and petroleum. There are several types of HEVs. This is determined by configuration of the drivetrain system. In a parallel hybrid system, the vehicle is propelled though the Internal Combustion Engine (ICE) as well as a separate motor which can also supply power directly to the drivetrain.

In a series hybrid system, the vehicle can only be propelled an electric motor and a battery. The battery can be charged through regenerative braking, the ICE, or by external sources. The ICE is used with a generator to produce electricity to recharge the battery when other sources are not available, making the car in essence a Range Extended Electric Vehicle (REEV). In a combination or series-parallel hybrid the vehicle is propelled like the parallel hybrid, but the ICE can be also utilized to recharge the battery in addition to providing strictly propulsion. These vehicles can be further characterized into full hybrids and mild hybrids, dependent on the maximum propulsion each system can generate. A mild hybrid is much like a conventional vehicle with an electric motor to provide additional torque when needed. The electric motor allows the ICE to be turned off while idling, keeping the motor running at the same RPMs but without any fuel. The electricity needed to perform this is captured solely through regenerative braking. Full hybrids can be completely operated and propelled through the electric motor, while the ICE is off. HEVs that can recharge the battery bank through external electricity sources are also known as PHEVs. The control over the power output combination of these two systems determines the fuel economy and performance of these vehicles, which is still an active area of research.

The electric engine and battery bank in PHEVs is much larger than standard HEVs, allowing the vehicle to be completely propelled by the electric engine for extended periods of time. The maximum period the vehicle can be propelled utilizing only the electric engine is called the all electric range. This is dependent on the capacity of the battery bank. Once the battery is depleted of usable energy, the ICE is utilized, providing an extended range mode. In this mode, regenerative braking and excess power from the ICE generator is still utilized to recharge the battery bank. However, the power captured by these sources is relatively low, and is only used to support the ICE when additional torque is required. To return to the all electric mode, large amount of energy is required to restore the battery to capacity which requires external sources not available while driving. This is the key distinction between HEVs and PHEVs.

The automobile industry wants to design these higher efficiency vehicles without requiring the drivers to make a tradeoff for usability. According to the US Department of Transportation (DOT), the average daily commute is about 29 miles [17]. Using this as a design attribute, car manufacturers are targeting their PHEVs with a 20 to 40 mile all electric range. With the current technology, this corresponds to a usable battery capacity of 10 to 20 KWh. While this correspondence depends heavily on driving conditions and the driving habits, it encompasses the characteristics of current production vehicles [16]. This allows the daily commute to be driven as if in an all electric vehicle. The hybrid ICE is present for longer trips, making the vehicle very versatile. This is giving the driver all of the benefits without the tradeoffs that previous electric hybrids were prone to.

1.2 Motivation for Vehicular Charge Scheduling

With advances in communication technology, the US electricity grid is becoming networked and remotely controllable. This modernization of the grid is more commonly referred to as the Smart Grid. With the addition of Advanced Metering Infrastructure (AMI), the distribution system can collect data in real time [19]. This allows for analysis and control programs to improve grid reliability while minimizing operating costs and downtime. This fine grained data can also be archived and used to improve future usage and pricing predictions in the Locational Marginal pricing (LMP) market [20]. This would allow utilities to provide tiered or real time pricing options, as well as compensating the consumer for the use of smart appliances and vehicles.

With real time data collection and control, a centralized entity could autonomously manage the distribution grid. Other research articles have referenced such a device by many names; most commonly it is called an intelligent Energy Management System (iEMS) [21]. Devices such as in line switches, voltage and frequency regulators, capacitor banks, DG, and even Vehicle-to-Grid (V2G) capable PHEVs can be utilized and remotely controlled to improve the power quality [22]. Through the use of throttled and scheduled PHEV charging, the base load would be increased, allowing for more efficient and renewable generators to be used in the creation of the electricity [23].

Given the average commuting distance, vehicles would arrive home with nearly depleted batteries and require energy corresponding to their usable battery capacity. In a typical household, a vehicle is used daily for commuting and errands. This formulates to at least a 30 percent increase in daily electricity demand per household per PHEV [24]. This is much larger than the average annual electricity demand increase over the last few years. Electrical utilities should start investing immediately in capacity upgrades if the charging of PHEVs is not controlled. This is because most utilities are running near peak capacity during the evening hours, which directly corresponds to the peak in uncontrolled charging demand for PHEVs. The use of controlled and optimized scheduling can alleviate the need for capacity upgrades by deriving the energy required for charging during off peak times. Also, by filling in the demand valleys, the base load is increased allowing the larger and more efficient generators to create the electricity.

Chapter 2

Scheduling Techniques

2.1 Delayed Charging

Delayed charging is currently the widely available option for the early adopters of PHEVs [16]. With no grid communication architecture adopted, there is little to no room for scheduling. With delayed charging, the owner decides a starting time and maximum charging rate. The vehicle will then start charging at the specified rate until the battery is fully charged. The charging rate is only reduced to prevent overheating issues. This method alleviates additional demand during peak hours, but can lead to many other problems. Since the charger is unaware of other vehicles and appliances, overlapping charging times can induce a secondary peak in the daily demand curve. With minimal communication between devices, this can be minimized.

2.2 Smart Meter Control

Smart meter charging links a PHEV and other controllable home appliances such as a laundry machine to an in home energy management system [25]. The aim of this architecture is to prevent aggregated loads within the home, reducing the peak usage and usage during peak hours. The smart meter schedules the vehicle to charge during the night when there is little usage. However, unlike delayed charging, the smart meter is aware of other usages, and can interrupt the vehicular charging while other appliances are running. This method only solves the aggregated demand within the home and during peak demand hours. Several houses connected to the same transformer can still create aggregated peaks. To solve this problem, a communication architecture between the smart meters would be required. Since these meters have low computational power, a centralized computer could perform scheduling quicker and more efficiently.

2.3 Group Scheduling

With wireless vehicle to vehicle communication, a group of vehicles in wireless proximity can create an ad-hoc network. In a parking garage equipped with charging stations, these vehicles can create a mutually beneficial schedule to prevent peaks in aggregated load for the group [26, 27]. This can also be accomplished by networking the chargers together. In these cases, a centralized controller is used to create a charging schedule according to electricity prices, and bill the charging vehicles. This is optimization is localized and does not completely solve the problem. In a distribution grid, groups of vehicular chargers can still create aggregated loads during lower priced time slots. To completely minimize the system impacts of vehicular charging and to prevent load aggregation, an optimized charging schedule must be created from a higher level perspective.

2.4 Heuristic Scheduling

Previous research in scheduling for vehicular charging has shown benefits in reduced peak demand, improved power quality, and economic incentives for both the end user, and the electrical utility. However, most of this research has been focused on the cost benefits for residential end users. A centralized entity for PHEV charge scheduling from the distribution grid perspective can also minimize the overall operating costs. This may slightly reduces the immediate economic incentives for the end users, but tariffs and reduced pricing provided by the utility can curtail this disadvantage and provide user motivation. Scheduling from this perspective can be computationally expensive and time consuming when a large number of PHEVs are connected to the grid. Therefore, it is beneficial to find methods that reduce the scheduling complexity and time.

The scheduling problem could be transformed into a linear equation [28]. These can be solved quickly and efficiently through methods such as sequential quadratic optimization or the Lyapunov Methods [29, 30]. However, these types of optimization assume vehicular charing will not affect the electricity prices. Even though this significantly reduces the complexity, it ignores the fact that high current chargers can have a significant impact the demand curve. The US DOE estimates electricity prices by 2030 will be affected by up to 5 percent with only a 25 percent penetration (an average of 1 vehicle for every 4 homes) of PHEVs utilizing scheduled charging. The level two AC vehicular charging standard allows a power draw of up to 19.2 kW, significantly larger than any existing household load [31]. This could have a major impact on real-time pricing. This constraint will reduce the effectiveness and accuracy of these scheduling algorithms.

The computational complexity can be greatly reduced by not enumerating possible scheduling cases that have a low probability of having low cost solutions. Sampling techniques such as the Monte Carlo method can be used to identify these cases [32]. The same techniques can also be used to find cases with a high probability of having low cost solutions. Using this information, methods such as Particle Swarm Optimization (PSO) can find a solution much faster [33]. This method uses feedback from evaluated cases to direct future computations towards neighboring candidates with a higher probability of the optimal solution. The method uses position and velocity to represent particles replicating the social behavior of a flock of birds or a school of fish. PSO is a generic method, and is limited by the assumptions it can make about the problem, reducing its effectiveness. Also, PSO is very sensitive to the initial conditions, and cannot guaranty an optimal solution. Another disadvantage of using PSO for this problem is when using a multi-objective function, PSO becomes more computationally complex and prone to converging on non-optimal solutions [34].

Chapter 3

Residential Distribution System Architecture

3.1 Introduction

A residential distribution grid typically spans a region the size of a neighborhood; distributing electricity to the houses. These grids typically operate at lower voltages than transmission lines, allowing for cheaper supporting structures to be used. This improved safety and allows for reduced line spacing requirements in overhead configurations. The network configuration is typically radial, however switches and interconnects can be implemented to reduce the severity of an outage scenario. Voltage regulators and capacitor banks are commonly installed to correct voltage drops and other power quality issues. To reduce power line losses, voltages are stepped down using distribution transformers to voltages usable in a standard household outlet. These transformers are located close to houses, and vary in size to support one or more connected houses.

3.2 The Distribution Grid

The IEEE 123 node test feeder is selected for the distribution grid because it is ideal for programs that can allocate load [35]. However, it was modified for the purposes of testing the optimization algorithms. The voltage regulators within the system are removed; viable solutions are constrained by adding requirements to keep the voltage within the set ratings. The shunt capacitors and in line switches are not removed, however the state of these devices remained static throughout the entire scheduling period, keep the feeder in a radial configuration. Originally, the nodes held a single complex demand for the testing and verification of analysis programs. This is replaced with generated load data for residential homes at 15 minute intervals for the 24 hour scheduling period. Fig. 3.1 shows one-line diagram of the distribution grid.

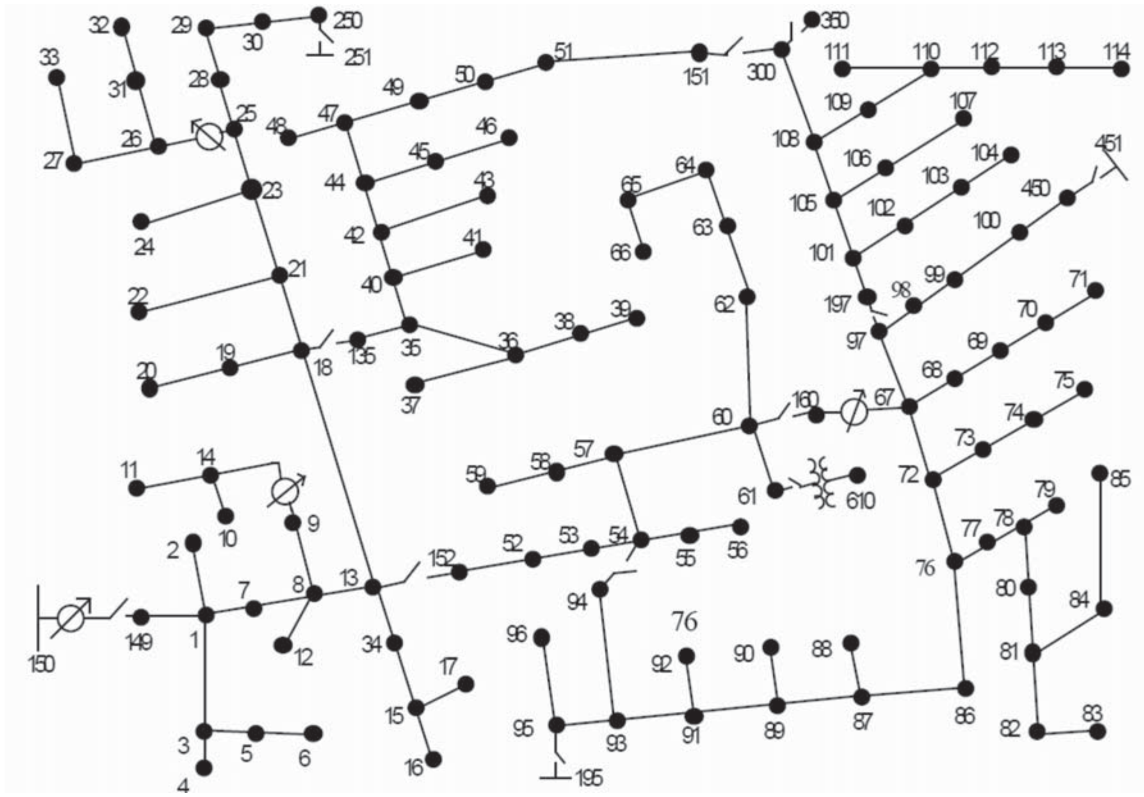

Figure 3.1: Layout of the IEEE-123 Node Test Feeder

3.2.1 Power Lines

Line data implemented in the test feeder was left unchanged in the setup of the system. There are 11 different overhead spacing and cable configurations, and one underground configuration. The majority of the power lines are overhead Aluminum Cable Steel Reinforced (ACSR) or All Aluminum (AA) conductors in three phase configurations with Wye loads. The average distance for each line is about 332 feet, typical of an urban environment. In all of the three and two phase overhead configurations, the neutral conductor has a smaller gauge because it was only required to handle the resulting current from the load imbalance. This reduces the initial investment cost, but causes higher line losses for imbalanced loads due to the higher resistance of the conductor. The rated amperage of each line introduces an additional constraint on the amount of power the system could handle. If the state estimation methods determines that a line is overloaded, all nodes located ’downstream’ of the line require load shedding. A downstream node requires the given power line to connect to the feeder head, or source of the power (if bidirectional chargers are used).

3.2.2 Distribution Transformers

The distribution system operates at 4.16 kV. Each node containes a single distribution transformer that steps this down to a usable 120 Volts per phase. Since the efficiency of the transformer depends on the loading factor, it is assumed that all transformers are ideal, and no losses are induced due to heat or coil impedance. This also allows the system to ignore transformer maintenance costs because running the transformers with higher loads improves efficiencies, but reduces the lifetime of the transformer. The phase configuration on each side of the transformer is not changed. This is because the Wye and Delta configurations supported the line rating constraints, alterations would only reduce the power capacity of the grid.

3.2.3 Spot Loads

The original spot loads connected to the distribution transformers can be classified into three categories: constant kW and kVAr, constant current, and constant impedance. The power usage of each node varies based on the input voltage. To reduce computational time and complexity, all loads are replaced with constant kW and kVAr. Many houses are randomly generated and connected to each distribution transformer. This is an iterative process which continues until the aggregated daily demand peak (kVA) matches the complex magnitude for the original load. This ensures the feeder will be running near capacity, not starting overloaded, but require scheduling for vehicular charging.

3.3 Residential Houses

Since scheduling is preformed using 15 minute intervals, the entire scheduling period requires 96 time slots. The average electricity used daily for each home is scaled to have a normal distribution of 30 kWh with a standard deviation of 5 kWh [24, 36]. All houses include a single connection to the transformer in the same wye/delta configuration as the original node. This load is considered to be a base load, which can not be altered in the case of load shedding.

3.3.1 User Preferences

For any given workday, the home is simulated to contain between one and three residents. The home has a morning departure between 6 am and 12 noon, and an evening arrival between 4 and 7pm . This was chosen based on Travel Trends Survey data collected by the US Department of Transportation [17]. The departure time is a user set preference, requiring the vehicle have a full battery by the time indicated. If the owner departs later than scheduled, the vehicle is simulated as disconnected since the stored energy can not be used and is required to keep the battery full. If the owner decides to leave earlier than scheduled, the system can not guarantee the battery will be fully charged. The arrival time represents a prediction based on user preferences, and historically archived data. Mobile networks such as VANET can be used to further improve the prediction accuracy, tracking the vehicle as it travels home while maintaining privacy [37]. It is assumed the arrival time predictions are accurate to prevent these errors from affecting the test comparison results.

Due to appliance usage, the energy usage peaks immediately before morning departure and after evening arrival. This is most notable with major appliances such as the water heater and an electric range or stove. These peaks determine the number of houses connected to the grid.

3.3.2 Appliance Usage

Each daily residential household load was randomly generated using appliance characteristics from GridLAB-D [38]. The appliances are separated into the following categories: plugs, lights, laundry, water heater, refrigerator, and HVAC. Any major appliances not included are assumed to be included in the plug load category. Each category includes a base load, usage load, and power factor. For example, the generated loads for lights include a randomly generated constant base load which encompassed automatic or safety lights, random load that is user controlled, and a constant power factor. The randomly generated loads for all houses is uniformly generated within a given usage parameter. For each load, the power factor is used to calculate the complex power demand. Since all of the appliances are connected in parallel, the aggregated usage is simply calculated using vector addition.

It is assumed laundry will be performed once per week, so each house has a one in seven chance of having this load for the given day, uniformly distributed. It should be noted that laundry also increases the usage of the water heater. It is also assumed that about 20 percent of the houses include natural gas water heaters, which do not require any electrical energy. This is also the case for home heating systems. However, air conditioning units which primarily run during the day, can not be run on alternative fuels, and all require electricity.

3.4 Plug-in Hybrid Electric Vehicles

PHEVs are randomly distributed throughout the grid. In order to schedule and control vehicular charging, it is assumed that a network infrastructure is already in place. This allows constraints to be collected and commands distributed to each vehicle. Each vehicle is modeled to have two distinct units, the battery, and the charger. It is assumed vehicles will be used for communing once per day, and arrive home with depleted batteries. If the vehicle requires additional energy for the commute, it will be required to be taken from external sources. For vehicles not participating in charge scheduling, they will be treated as a base load.

3.4.1 Battery

With the current technology, the targeted all electric range corresponds to a usable battery capacity of 10 to 20 KWh depending on driving conditions. Since Lithium-ion battery technology is being utilized, additional battery constraints must be included [16]. To prolong the battery life, the battery should never be discharged past a 30 percent State of Charge (SoC), nor charged beyond an 80 percent State of Charge. These batteries also require charging units which can charge the battery using current as well as voltage throttling. Heat generated through charging can reduce the battery lifetime as well. The charger must therefore monitor the cell temperatures and throttle accordingly. These additional constraints require an intelligent charging controller. The battery capacity of each vehicle are randomly generated using a normal distribution with a mean of 15 kWh, and a standard deviation of 3 kWh.

3.4.2 Charger

To minimize the required bandwidth and latency constraints required from the network for scheduling, the vehicular charging units are assumed to handle all battery related constraints and control. This includes automatically shifting the minimum and maximum SoC. For example battery with a 30 percent charge is viewed as empty to the scheduler since this energy cannot be used; the same for an 80 percent charge and the maximum perceived SoC. Therefore, a 16 KWh battery will be modeled as a 10 KWh device since it represents the usable energy for the vehicle.

It is also assumed that the charging units will also handle all charge throttling and heat dissipation issues. This includes throttling the current and voltage according to the SoC and cell temperature to maximize the battery lifetime. It is assumed the charging units rate the charging taking the battery's temperature into account, requiring no reduction in usage for this constraint. All charger ratings are selected using level two charging units, with the maximum charging rate chosen between three and six kW [31]. If the charger is capable of bidirectional power flow, it is assumed to follow all DG constraints according to the IEEE 1547 Standard [39].

3.5 Distribution Location Marginal Pricing

The pricing scheme named Distribution Locational Marginal Pricing (D-LMP) is implemented for the simulations [40, 41, 42]. This is an extension of the LMP market into the distribution grid. However, instead of bids per MWh, the market is transformed into a Time-of-Day Pricing method. This is accomplished similar to applying a low pass filter on the market's day ahead predictions. Prices are assigned to each node based on time slot usage. The electricity price for each time slot depends on a number of factors. Firstly, the minimum or base price received was dependent on the LMP market price prediction received at the feeder head. Then, losses incurred within the grid due to the usage are appended. Finally, the price is linearly increased to double the initial price based on the nodal and line usage, when compared to the rated capacity. For example, a node running up to half the capacity will receive the normal price, a node running at capacity will receive a doubled price. This scheme encourages schedulable loads to run during the base load hours. To prevent overloading for scheduling, if a node is running at capacity, vehicles will perceive the node at the given time slot as having an infinite price. This pricing scheme allows for unbalanced feeders to protect the distribution transformers and power lines from becoming overloaded. Without this, the maximum penetration that the feeder

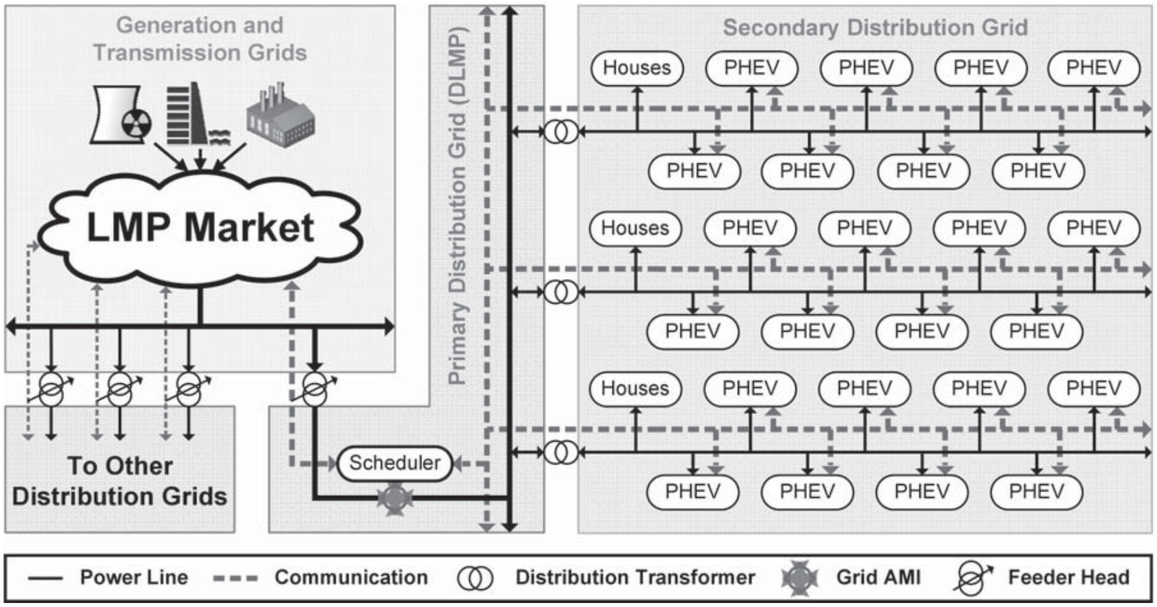

Figure 3.2: Distribution Location Marginal Pricing System Architecture

can hold is severely reduced. This encompasses all devices between the feeder head and the distribution transformers. Fig. 3.2 shows the D-LMP system architecture, including all entities from generation to the PHEV.

Chapter 4

Problem Formulation

4.1 Introduction

This chapter discusses the minimization function and how it was formulated. First, the constraints and problem formulation are outlined. Then, the minimization function is introduced. Finally, the losses in the distribution system which lead to higher operating costs will be discussed.

4.2 Nomenclature

x_v^h	Amount of power delivered to the battery of vehicle v during time slot h.
x_v^{max}	Maximum amount of power deliverable to the battery of vehicle v.
α_v	Departure time of vehicle v.
β_v	Arrival time of vehicle v.
SoC_v^h	State of Charge for the battery of vehicle v during time slot h.
Cap_v	Usable battery capacity of vehicle v.
$\vec{y_v}$	Complex charging demands from the grid for vehicle v.
ef_v	Efficiency and power factor conversion for vehicle v.
$\vec{M_k}$	Complex power demand from the grid for house k.
G_n^{max}	Phase rating of the distribution transformer at node n.
$\vec{V_n}$	Voltages at node n.
$\vec{I_n}$	Current at node n.
$\vec{P_n}$	Power demand at node n.
$P_f^{\vec{max}}$	Phase rating of the substation transformer at the feeder head.

4.3 Problem Formulation

Each time period vector h is represented within the daily time slot array denoted as H. For each vehicle v, the variable x_v^h represents the amount of power delivered to the battery by the charger. In order to limit this demand according to the charger's current ratings, the equations

$$x_v^h \leq x_v^{max}, \quad \forall h \in H \qquad and \tag{4.1a}$$

$$x_v^h \geq 0, \quad \forall h \in H \tag{4.1b}$$

are introduced. However, if bidirectional charging is used, (4.1b) would need to be reformulated to

$$x_v^h \geq -x_v^{max}, \quad \forall h \in H. \tag{4.1b}$$

Since it is assumed vehicles will be used for commuting once per day, that they will arrive home with depleted batteries, and that the vehicles will be plugged in the entire duration while home, the equation

$$x_v^h = \begin{cases} 0 & \text{if } \alpha_v \leq h \leq \beta_v \\ x_v^h & \text{otherwise} \end{cases} \tag{4.2}$$

constrains the vehicle to charging only while it is plugged in. In this equation, α_v and β_v represents the vehicle's departure and arrival times respectively. The SoC in watt hours for the vehicle's battery during each time frame iis formulated as

$$SoC_v^h = \sum_{x=\beta_v}^{h-1} \frac{x_v^x}{4}, \tag{4.3}$$

noting that the charging vector is divided by four since there are four time slots per hour. To model the physical limitations of the battery, the equations

$$SoC_v^h \geq 0, \quad \forall h \in H \tag{4.4a}$$

$$SoC_v^h \leq Cap_v, \quad \forall h \in H \tag{4.4b}$$

are introduced, limiting the SoC. To ensure the vehicle was fully charged at the desired departure time and empty at the arrival time, the equations

$$Cap_v = \sum_{h \in H} \frac{x_v^h}{4} \tag{4.5}$$

and

$$SoC_v^{\alpha_v} = Cap_v \tag{4.6a}$$

$$SoC_v^{\beta_v} = 0 \tag{4.6b}$$

are added to the list of constraints. Finally, each vehicle's complex charger demand from the grid is calculated using

$$y_v = \frac{x_v}{ef_v}, \tag{4.7a}$$

where ef_v represents the charger efficiency as well as the power factor alteration. This is expanded throughout the entire scheduling period using the vector notation to represent

$$\vec{y}_v = [\frac{x_v^1}{ef_v}, \frac{x_v^2}{ef_v}, \frac{x_v^3}{ef_v}, \ldots, \frac{x_v^{96}}{ef_v}]. \tag{4.7b}$$

Using the set $\vec{M}$ to represent the scheduling period's time slot complex power demands for a given household, the aggregated load for each phase of the distribution transformer is calculated using

$$\vec{G}_n = \sum_{k \in K_n} \vec{y}_v + \sum_{r \in K_n} \vec{M}_k. \tag{4.8}$$

In this equation, the set K_n contains a list of all vehicles and houses connected to the respective phase of transformer n. Since one of the constraints is to prevent the system from being overloaded, the constraint

$$|G_n^h| \leq G_n^{max}, \quad \forall h \in H \tag{4.9}$$

is added, where G_n^{max} represents the node's transformer phase rating.

Using the set $\vec{V}_n$ to represent the time slot voltage at each node,

$$\vec{I}_n = \left[\frac{\vec{G}_n}{\vec{V}_n}\right]^* \tag{4.10}$$

is used to compute the current, where $*$ stands for the complex conjugate calculation. Using a radial configuration for the grid, Kirchoff's Current Law (KCL) can easily be used to compute the total current passing through each power line. The current $\vec{I}_l$ is simply the summation of the currents for all downstream nodes from line l. Using these currents, the voltage for each node is calculated using

$$\vec{V}_n = \vec{V}_f - \sum_{l \in L} \vec{I}_l \cdot \vec{R}_l, \tag{4.11}$$

where $\vec{R}_l$ represents the resistance of line l, and the set $\vec{L}$ is a list of all power lines connecting node n to the head of the feeder f. Using Backward-Forward (Bw/Fw) Sweeping techniques, the state of the feeder is then computed for use in future calculations [43]. Since no voltage regulators are used, viable solutions are limited by power quality constraints through the equations

$$V_n^h \geq V^{min}, \quad \forall h \in H \tag{4.12a}$$

$$V_n^h \leq V^{max}, \quad \forall h \in H. \tag{4.12b}$$

From here, the power demand at the feeder head is calculated using

$$\vec{P}_f = \vec{V}_f \cdot \vec{I}_f^*. \tag{4.13}$$

Even though it is assumed the nodal transformers were bidirectional, an additional constraint is needed to prevent the feeder head from returning power to the LMP market. This is done using

$$|I_f^h| \geq 0, \quad \forall h \in H \qquad and \tag{4.14a}$$

$$|P_f^h| \leq P_f^{max}, \quad \forall h \in H \tag{4.14b}$$

to limit the grid's power usage.

4.4 Feeder Losses

Losses in the distribution grid attribute to higher operating costs for the system. These losses include reactive power, unbalanced phase loads, and demand curve peaks. Intelligent vehicular charging is used to reduce these losses. Using equation (4.13) to calculate the total power requirements for the grid, and equation (4.8) to calculate the residential power demand, the total losses for each phase of the system are formulated as

$$P^h_{loss} = P^h_f - \sum_n G^h_n. \tag{4.15}$$

This represents the apparent power losses in the system. Lower power factors induce reactive currents, which increase the apparent power. However, this additional power is not usable by the load, and is lost as heat in conductor wires. Since users are not billed for these losses, the losses associated with the reactive current for D-LMP are calculated using

$$P^h_{pf} = Imag\left[P^h_f\right]. \tag{4.16}$$

This loss is minimized through the use of shunt capacitors in the grid. When bidirectional charging is used, discharging at ideal power factors also helps to mitigate these losses.

Unbalanced phase loads in the system induce a current on the neutral power line which typically has a lower current rating and higher resistance [35]. Not only does this induce additional line losses, but increases current requirements as well. Since the line loss is equal to the line resistance times the square of the current, a balanced load reduces the losses exponentially. By integrating three-phase chargers, this loss was have minimized. Each day, the demand curve peaks in the morning and afternoon/evening. These peaks cause additional power to be lost in the same way as an unbalanced demand, due to the line current being squared. Not only does reducing the peaks usage lower power losses, but the base load is also increased. This allows the power to be generated at larger and more efficient power plants. When bidirectional charging is used to reduce peak impacts, limitations on charger efficiencies make it economically impossible to flatten the curve entirely, regardless of the net storage capabilities.

4.5 Distribution Location Marginal Pricing Algorithm

In order to calculate the estimated operating DLMP costs, a function is implemented to create time slot LMP market price predictions for a given load. This function produces a linearly increasing price versus demand, with a base cost of $40 per megawatt hour. Using the notation $\dddot{P}_f^h$ to represent the three phase combination and C_{LMP} to represent the feeders LMP cost, the equation

$$Cost\left[\dddot{P}_f^h\right] = \begin{cases} C_{LMP} & \text{if } P_f^h \leq \frac{1}{2}P_f^{max} \\ 2 * C_{LMP} * \frac{P_f^h}{P_f^{max}} & \text{if } \frac{1}{2}P_f^{max} \geq P_f^h > P_f^{max} \\ \infty & \text{otherwise} \end{cases} \tag{4.17}$$

shows the basic functionality of how D-LMP prices are derived from the cost function. Even though this is a simple calculation, it encompasses most of the major aspects of power losses with very little computation. All of the results of this predictor are assumed to be error free for the purposes of scheduling. Even though the use of a more intelligent cost predictor is not studied, one can be easily implemented without changing the optimization methods or this D-LMP cost calculator.

4.6 Minimization Function

The minimization function is formulated as:

$Minimize:$

$$\sum_{h \in H} Cost\left[\dddot{P}_f^h\right] \cdot \dddot{P}_f^h \tag{4.18}$$

$SubjectTo:$

$$\begin{aligned}
x_v^h &\leq \; x_v^{max} & x_v^h &\geq \; -x_v^{max} \\
|G_n^h| &\leq \; G_n^{max} & x_v^h &= \; 0, \quad \text{if } \alpha_v \leq h \leq \beta_v \\
V_n^h &\geq \; V^{min} & V_n^h &\leq \; V^{max} \\
|I_f^h| &\geq \; 0 & |P_f^h| &\leq \; P_f^{max}
\end{aligned}$$

Chapter 5

Methodology and Programming Approach

5.1 Introduction

The minimization function is solvable using a stochastic programming approach. This is split up into two methods, one for PHEV charge scheduling, and the other for scheduling vehicles with bidirectional charger support. The first method creates an optimal schedule for vehicular charging. Using this, the bidirectional supporting method expands the optimal schedule further to allow vehicles to return power to the grid. It is assumed that the AMI provides the predicted base household demand on each phase for all distribution transformers in the grid.

5.2 Charging Scheduling Method

In this method, vehicles take turns selecting times to charge according to the cheapest time slots with regard to availability constraints. To ensure fairness between vehicles, the order of the vehicles during each iteration is determined by their accumulated average charging cost per kWh. Since this method always chooses time slots with the lowest prices, the resulting operating cost is minimized. It is assumed that the vehicular availability does not prevent any vehicles from becoming fully charged. The program flowchart in Fig. 5.1 provides a more detailed view of this method.

During each turn, vehicles are restricted from choosing the following time slots: when they are not available, when they are already charging at the maximum rate, or when the grid is estimated to be operating at or above the transformer and line ratings. The rate at which vehicles can add to their charging vectors during each turn is limited to increase granularity and fairness. This rate is also constrained by the vehicle's SoC, current charging rate, and estimated grid usage. Once the battery becomes fully charged, the vehicle stops taking turns while the others finish.

It is assumed that price prediction requests and Bw/Fw sweeping methods are very time

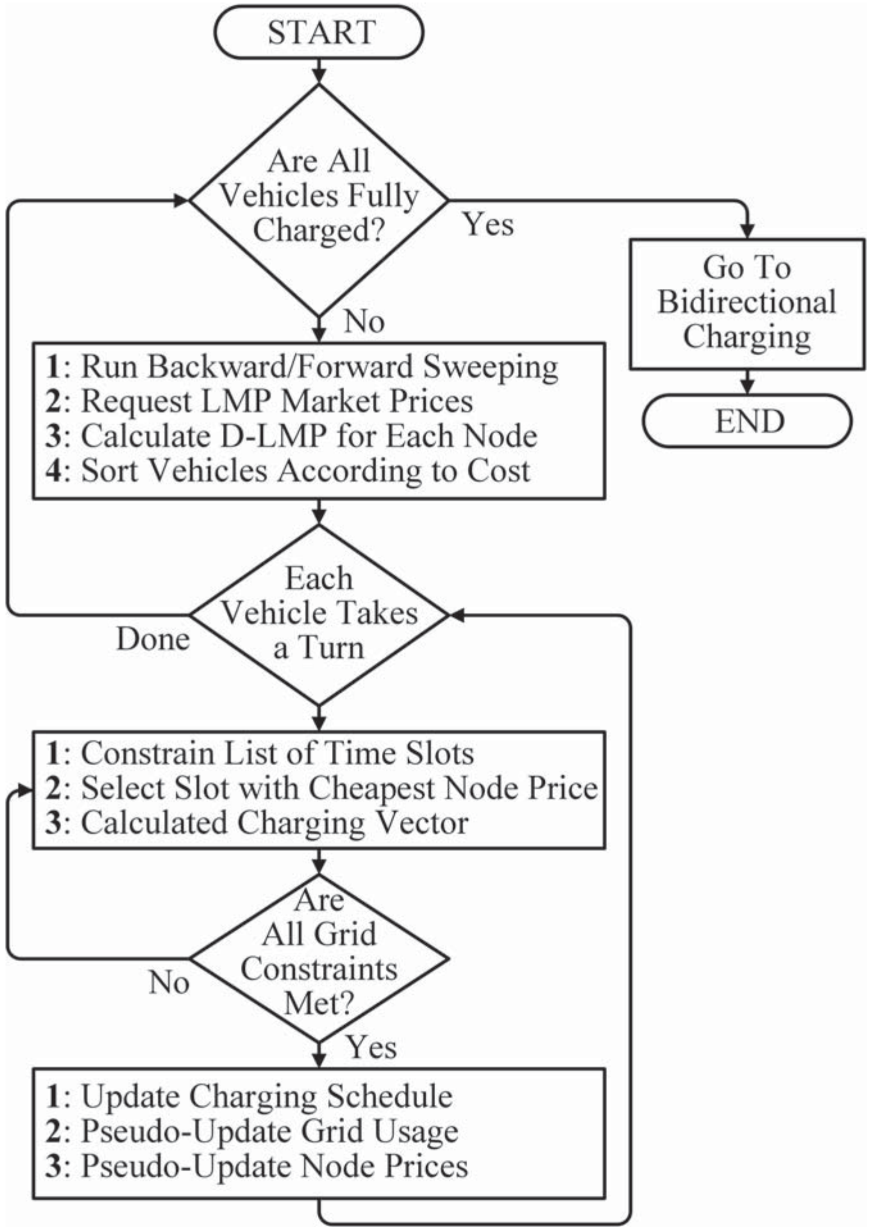

Figure 5.1: Program Flowchart of the Charging Method

consuming. Therefore, these calls are minimized using pseudo-updates on the node's usage and prices when each vehicle selected a charging time slot. If the prices are constrained by power line congestion, the prices for all nodes connected to that line are also updated. Not only does this save time, but this pseudo-update on the price removes the problems of linear optimization methods. Even though this scheme inherently causes errors, grid analysis and pricing requests are performed every top level iteration or so, which prevents the error from accumulating and affecting the results.

5.3 Bidirectional Charging Method

Using the charging schedule created by the previous optimization, the Bidirectional Charging method introduces bidirectional charger support. The goal of this method is to use the battery for temporary energy storage. Similar to the charging method, vehicles are also sorted to preserve fairness. During each turn, a vehicle selects a time slot with the highest price in order to determine if it is beneficial to sell energy at that time. Since vehicles start with the highest priced time slots and perform a greedy approach, the operating costs is again minimized, through the support of bidirectional charging. The method converges when no beneficial time slots can be found. Similar to before, the maximum amount of energy exchanged during each turn is limited to improve granularity and improve fairness. The program flow chart of this method is shown in Fig. 5.2. This method also has the unique capability to be interrupted before the process converges, providing a partial solution. Since this is a greedy algorithm, the majority of the improvement is gained during the initial iterations.

When selecting the time slots with the highest electricity price, the availability is

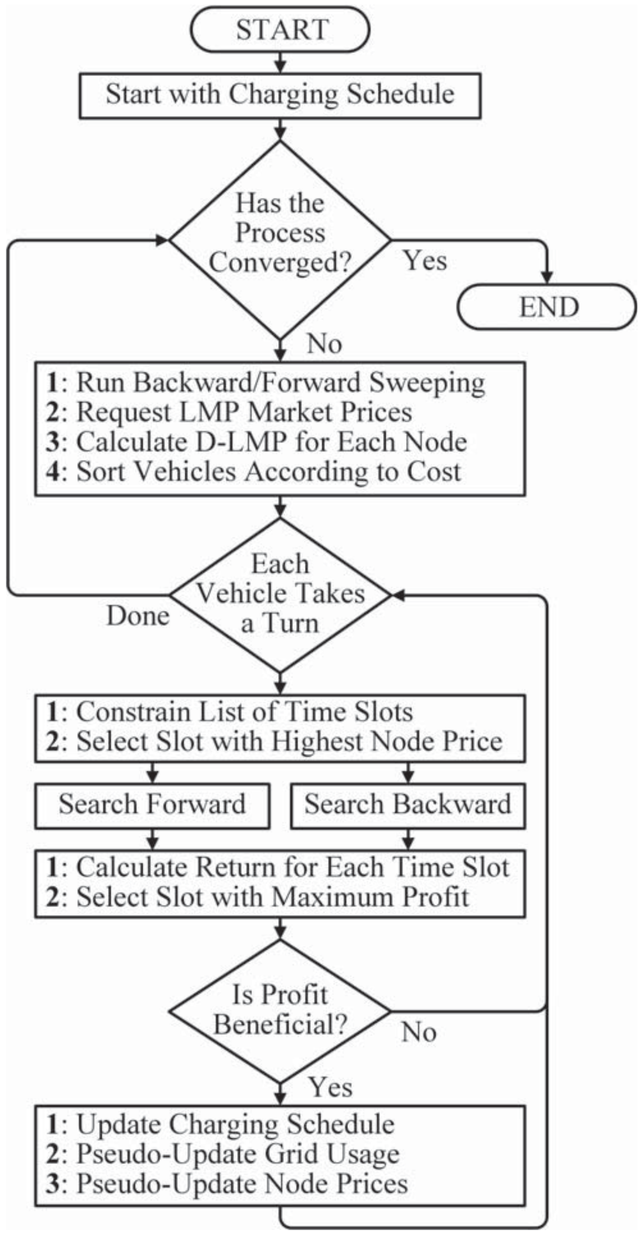

Figure 5.2: Program Flowchart of the Bidirectional Charging Method

constrained in the same way. However, time slots that were previously evaluated and did not yield a beneficial outcomes are also excluded. Even though the prices can increase from the previous evaluation, it is assumed it is still not beneficial due to the charger inefficiency. When a time slot is selected, the method performed a forward and backward search to calculate the maximum amount of energy that can be exchanged with other time slots.

When the method searches forward, it is looking to use the available SoC to sell energy and replenish the charge at a later time. As time increases from the selected time slot, the maximum amount of energy that can be exchanged is constrained by many factors, in addition to the vehicle availability. First, it is constrained by the available energy at the initial time slot as well as the discharging rate with respect to the charger rating. To prevent a negative SoC, energy availability for each slot is then constrained by the minimum SoC of the battery with regards to zero, for all slots until the initial one. Finally, each slot is further limited by its corresponding charging rate and grid usage availability. Also, the departure time slot can not be used to preserve the final full SoC. When the method searches backward, it is looking to buy energy and return it at the selected time. Similar to the forward search, as time decreased, the maximum amount of energy that can be exchanged is constrained by similar factors. However, instead of being limited by the SoC with regards to zero, it is limited with respect to the battery capacity. Once the calculations for the maximum available energy exchange is completed, estimated profits are then calculated for each slot. If the maximum profit reduces the system operating cost, the vehicle updates its charging schedule during the selected time slots, adding to the changing and discharging vectors with the calculated rate. Pseudo-updates are also used to reduce the optimization time.

Chapter 6

Results

6.1 Introduction

All simulations are run in Matlab® 7.12 (r2011a) using an Intel®Core$^{\text{TM}}$2 Quad 2.40 GHz Processor, with 3 GB of RAM, and Microsoft Windows XP with SP3. The Bioinformatics Toolbox is used to analyze the distribution grid's structure for the sweeping methods. For all of the simulations, the degradation of the battery lifetime due to bidirectional vehicular charging is not studied.

6.1.1 Generated Household Loads

When the aggregated household peak demand is set equal to the original feeder node data, the fully populated grid contains about 9000 houses. The histogram in Fig. 6.1 illustrates a sample distribution of the daily household load without vehicular charging. Similarly, Fig.6.2 shows a sample distribution of the departure and arrival times. To illustrate the daily demand curve, Fig. 6.3 displays a sample load curve from a randomly generated house, and the aggregated feeder demand. In this figure, it can be seen that while the household demand is unpredictable, the aggregated feeder demand is relatively smooth due to the randomness and number of houses used.

6.1.2 Generated Vehicle Loads

Vehicles are generated with varying parameters to test the scheduling algorithm. The vehicular battery capacity is the most important variable that affects the daily demand curve. The capacity is targeted to have a normal distribution with a mean of 15 kWh and a standard deviation of 3 kWh. The histogram in Fig. 6.4 displays this distribution of battery sizes. The charger efficiency also plays an important role in the scheduling outcome, especially when bidirectional charging is tested. The charger efficiency is generated to have part of a normal distribution between 90 and 95 percent efficiency, as shown in the

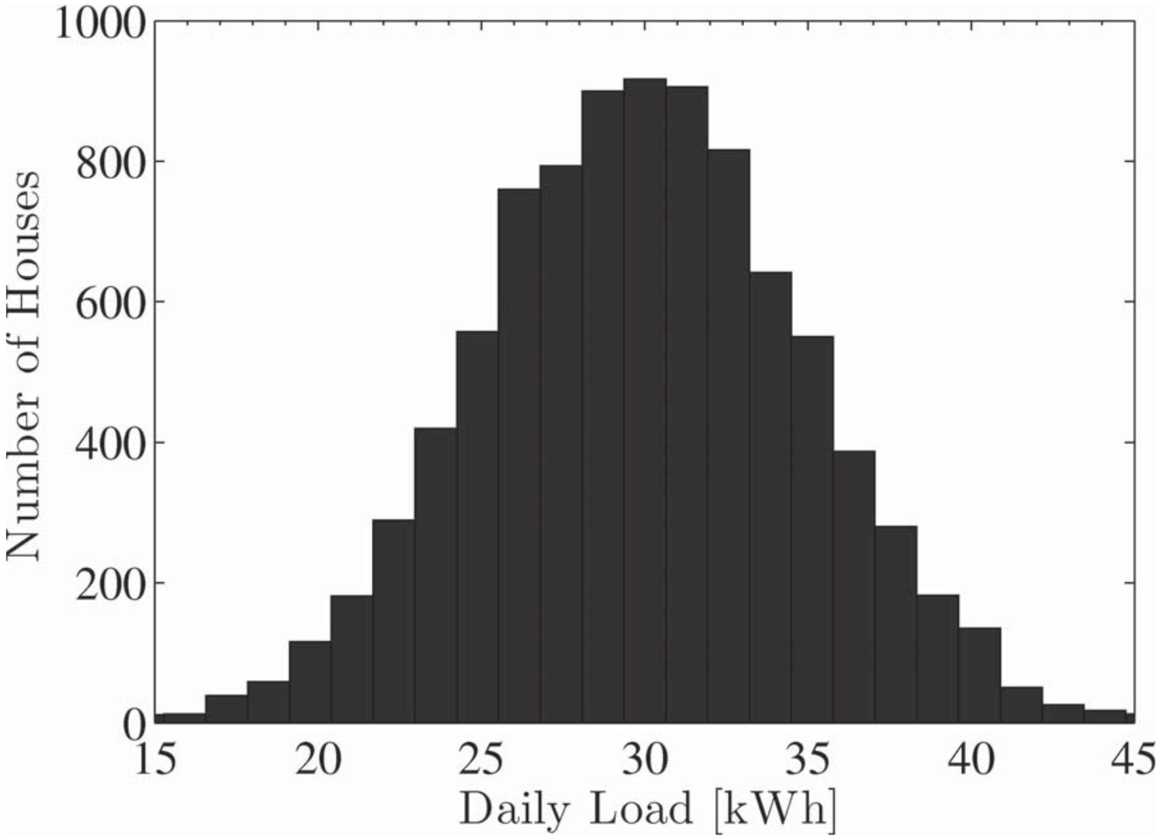

Figure 6.1: Example Distribution of the Daily Household Demands

histogram in Fig. 6.5. Even though it is assumed vehicles can discharge at an ideal power factor, this is not the case for charging. This value is also generated to have part of a normal distribution between 95 percent to ideal, as shown in the histogram in Fig. 6.6. All of these histograms are generated using a 35 percent PHEV penetration (3175 vehicles).

6.1.3 Grid Sweeping and Update Interval

Since pseudo-updates are used in the optimization methods, errors are introduced which slightly increases the overall operating cost of the solution. However, this increase

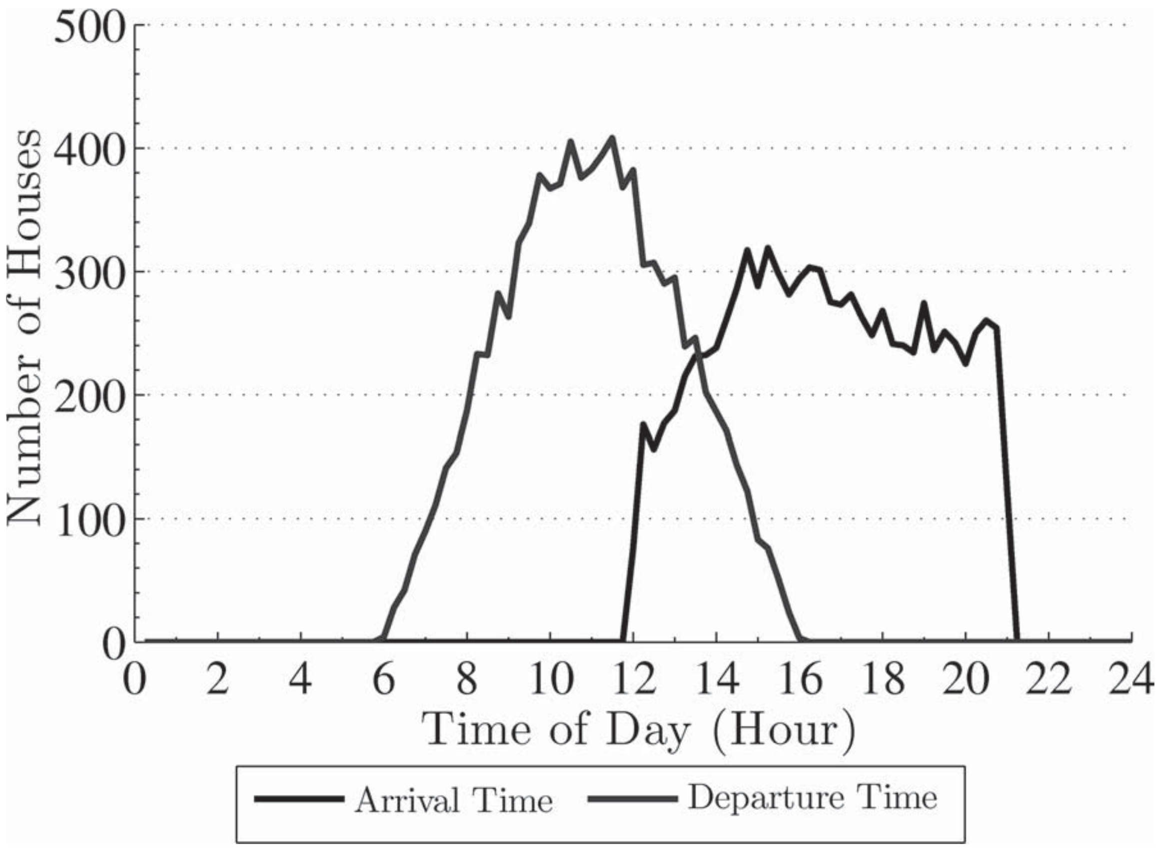

Figure 6.2: Example Distribution of the Household Departure and Arrival Times

is considered negligible. The pseudo-update for the energy usage performs a simple calculation which adds the additional charging load to the previous demand; however, it does not account for losses in the grid due to this additional load. The pseudo-update for the prices simply adds to the previous price, with respect to the ratio of the additional charging load to the current node usage. Also, instead of performing grid analysis repeatedly on every time slot, backward/forward sweeping is only performed on the time slots which the grid demand is changed due to vehicular charging. This reduces the computational time for the scheduling of over 5000 vehicles from 30 minutes to just under 10 minutes for both optimization methods combined. If the sweeping method diverges, it is required that the

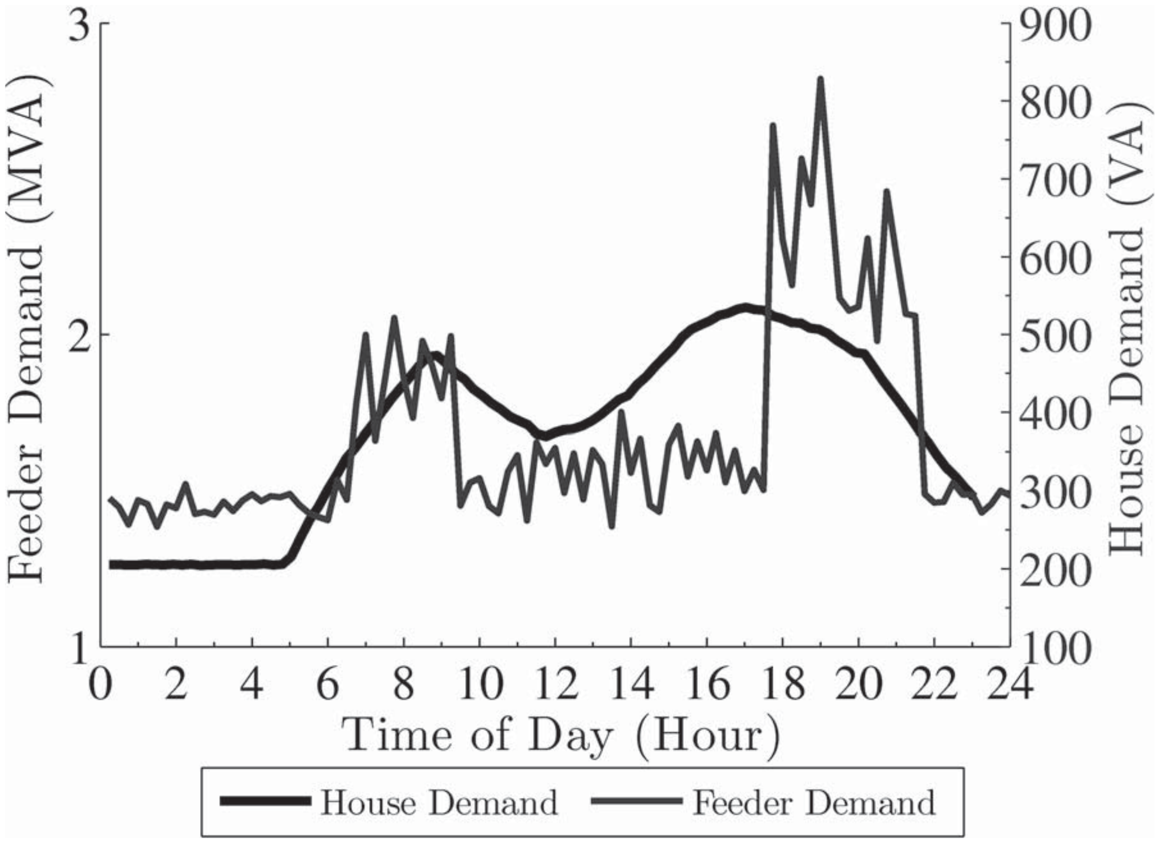

Figure 6.3: Example of a Generated Residential Demand

method start the iteration over with a smaller number of allowed pseudo-updates between calculations. However, this does not happen in the normal case, it only occurs when the feeder was severely overloaded. Table 6.1 shows the detailed results of the scheduling methods with various penetration of PHEVs.

6.1.4 The Cost Function

The parameters of the LMP market price prediction function are chosen so that the price will increase for higher ramping rates and peak demands. This in turn minimizes certain

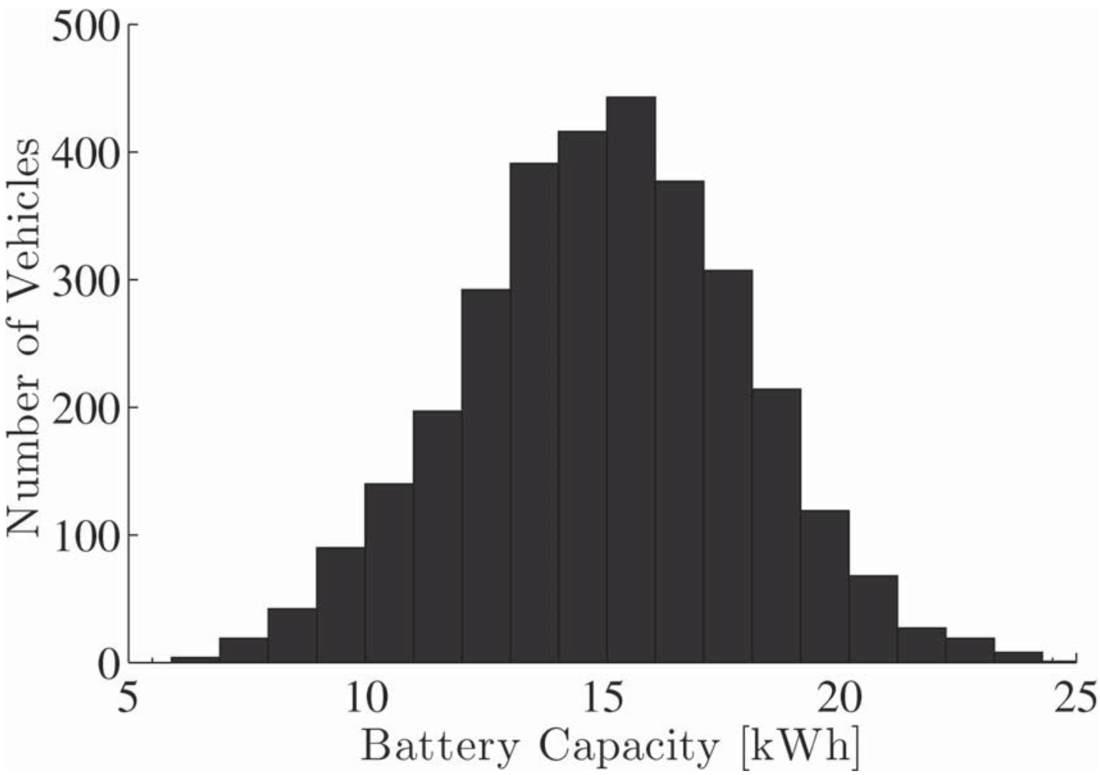

Figure 6.4: Example Distribution of the PHEV Battery Capacity

system losses. This also provides the cheapest operating cost for a flat daily demand curve. This allows for the highest penetration of PHEVs into the grid before the feeder becomes overloaded. Other price predictors and cost methods are not studied, but can be easily implemented. In most cases, the efficiency of the bidirectional supporting method is less than that of the charging method. This is due to the increased power flow through the battery chargers, which are not ideal.

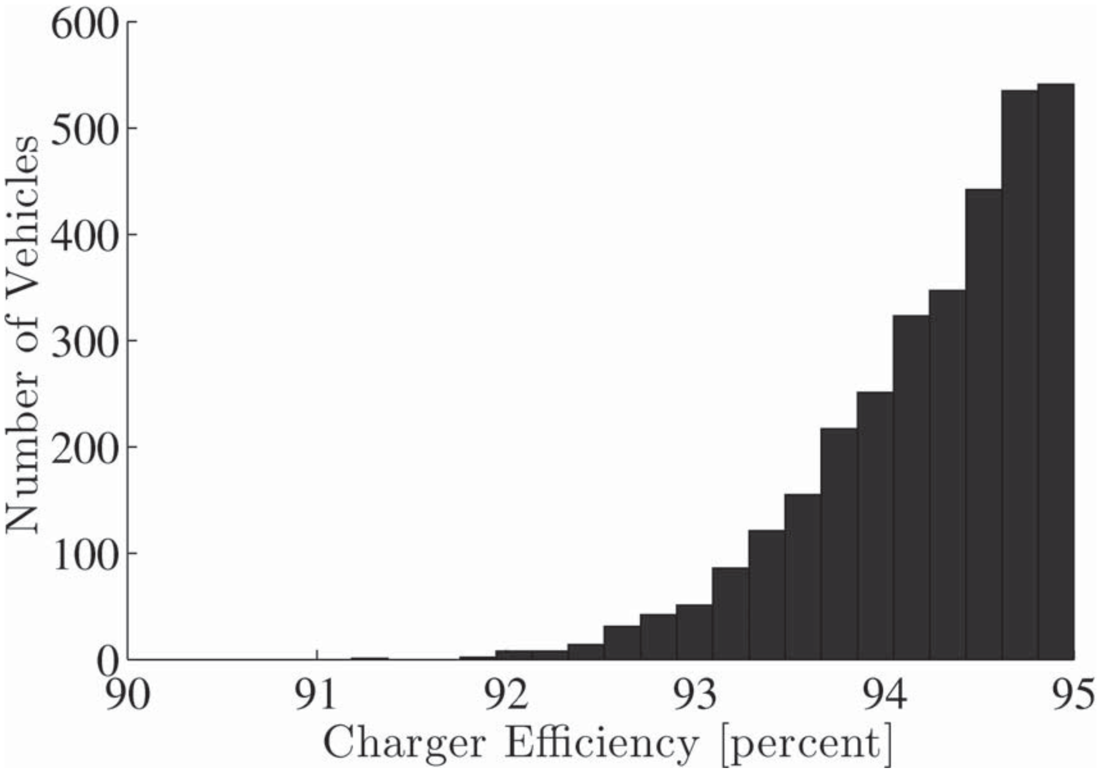

Figure 6.5: Example Distribution of the PHEV Charger Efficiency

6.1.5 Distribution Locational Marginal Pricing

Since the feeder is inherently imbalanced, it is crucial that D-LMP is included to prevent overloading with a high penetrations of PHEVs. Without it, certain distribution transformers would be severely overloaded while the rest of the grid remains well under the rating limits. It is found that as little as a 40 percent penetration of PHEVs starts to overload the feeder 6.10. Even though this pricing scheme is very useful in preventing overloading conditions, the prices assigned for the electricity at each node will not need to be the actual amount billed to the consumer. This scheme simply helps in the scheduling

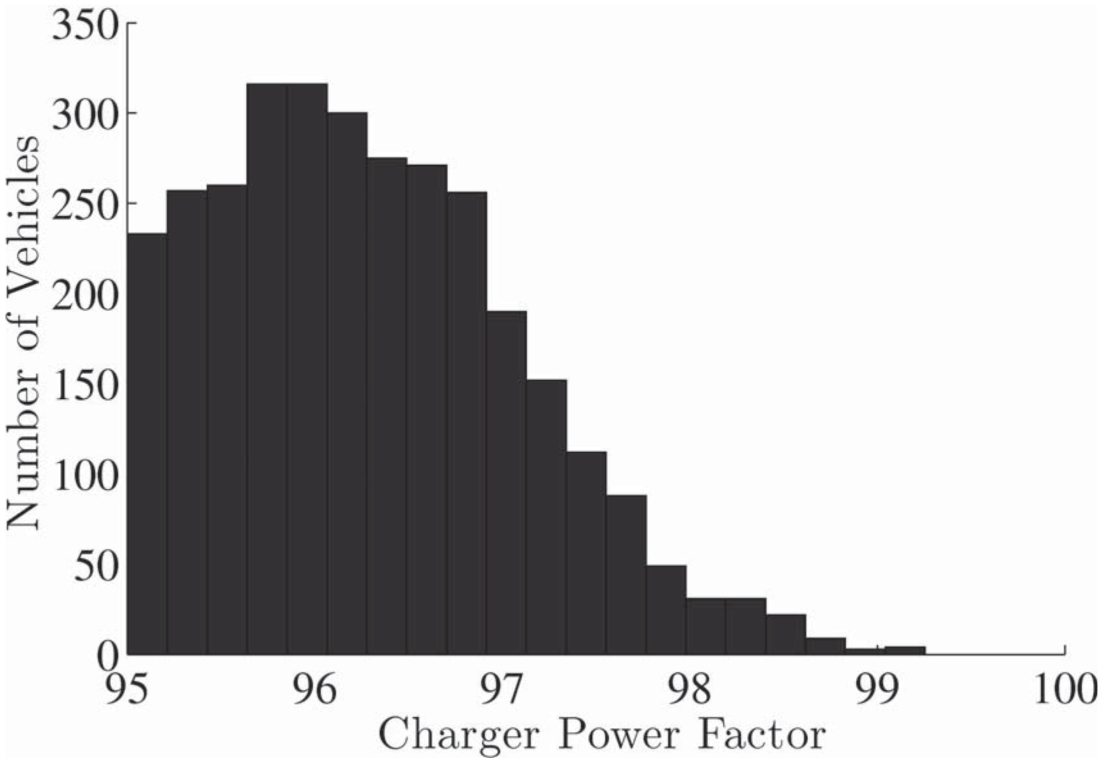

Figure 6.6: Example Distribution of the PHEV Charger Power Factor

of vehicles.

6.2 Scheduling Results

The results of the introduced scheduling methods are compared to locally scheduled and unscheduled charging techniques. In Fig. 6.7, it can be seen that the proposed scheduling methods prevent increases in the daily demand peaks, while only increasing and flattening the base load. If scheduling is not utilized, the grid can only handle a 10 percent penetration of PHEVs before it became overloaded. Fig. 6.8 shows the daily demand curves resulting

Table 6.1
Comparison of scheduling methods

Penetration	10	20	30	40	50	60	[%]
Vehicles	900	1800	2700	3600	4500	5400	
	Unscheduled Charging						
Operating Cost	31542	35539	40361	45793	52795	60737	[$]
Energy Usage	107.2	111.8	106.7	121.4	126.5	131.8	[MVAh]
Peak Demand	5802	6354	6925	7495	8436	8896	[kVA]
Efficiency	97.50	93.48	89.58	86.11	82.61	79.34	[%]
	Local Charging						
Operating Cost	30346	32703	35485	38623	42345	46597	[$]
Energy Usage	107.1	111.5	116.1	120.5	125.3	130.1	[MVAh]
Peak Demand	5275	5314	5530	5704	5897	6514	[kVA]
Efficiency	97.65	93.79	90.08	86.77	83.45	80.37	[%]
	D-LMP Charging Method						
Operating Cost	29519	31367	33639	36067	38857	41721	[$]
Energy Usage	105.9	109.8	113.8	117.8	121.9	125.9	[MVAh]
Peak Demand	5169	5196	5196	5212	5257	5355	[kVA]
Efficiency	98.67	95.25	91.84	88.79	85.76	83.03	[%]
	Bidirectional Charging Method						
Operating Cost	29458	31297	33604	36053	38852	41717	[$]
Energy Usage	106.0	109.9	113.9	117.8	121.9	125.9	[MVAh]
Peak Demand	5024	5013	5035	5141	5231	5342	[kVA]
Efficiency	98.58	95.15	91.79	88.77	85.75	83.03	[%]

from the various scheduling methods with a 20 percent penetration of PHEVs. The unscheduled charging method result sin an overloaded feeder for various time slots between the hours of 15 and 21. Due to the low number of available vehicles, the bidirectional scheduling method can not reduce the peak load by much in these scenarios.

When local scheduling is implemented, the grid is able to handle a 30 percent penetration of PHEVs, shown in Fig. 6.9. This is in stark contrast to the optimized scheduling methods which can handle much higher. With the additional vehicles posed by the higher penetration, the bidirectional charging method has enough availability and aggregated energy storage to have a significant impact on the peak demand.

Starting with a 40 percent penetration shown in Fig. 6.10, the charge scheduling method starts to increase the peak demand. At this point, if the D-LMP architecture is not used, distribution transformers will become overloaded. With a 50 percent penetration, the charging and bidirectional supporting methods have very similar results since the daily demand curve is becoming flat. This can be seen in Fig. 6.11. At this point, it is no longer be beneficial to run the bidirectional charging optimization.

Fig. 6.12 shows the result of the maxed out grid with a 60 percent penetration of PHEVs. In this setup, the proposed optimization methods paired with the cost function produce an almost ideal daily demand curve. This shows that in order to adopt to various renewable generation curves, only the cost function needs to be altered.

In summary, at lower penetrations, it can be seen in Figures 6.7, 6.8, 6.9, 6.10, 6.11, and 6.12 that the Bidirectional charging method have a larger impact on the peak load than at higher penetrations. This is because at higher penetrations the load induced by vehicular charging starts to outweigh and overtake the household base load. When the bidirectional method is no longer useful, the bidirectional vehicular chargers will be to improve power quality. They can also be used to improve reliability and act as a spinning reserve, similar to an uninterrupted power supply or battery backup.

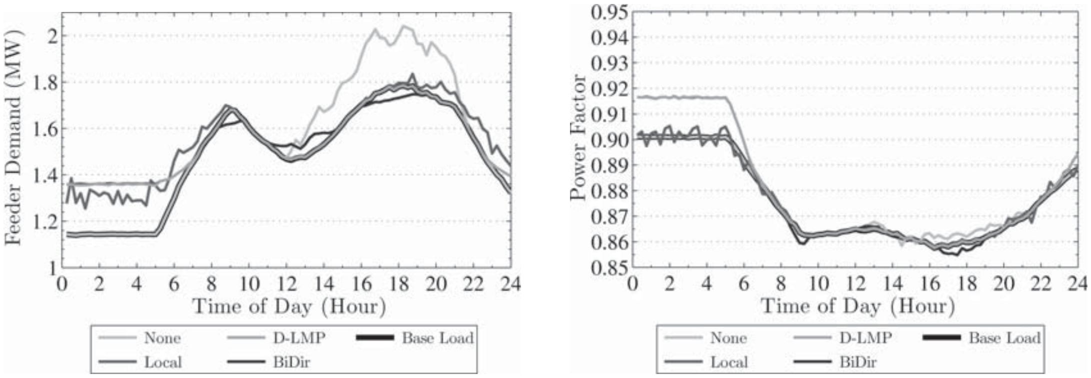

Figure 6.7: Phase A Feeder Demand with a 10 percent penetration of PHEVs

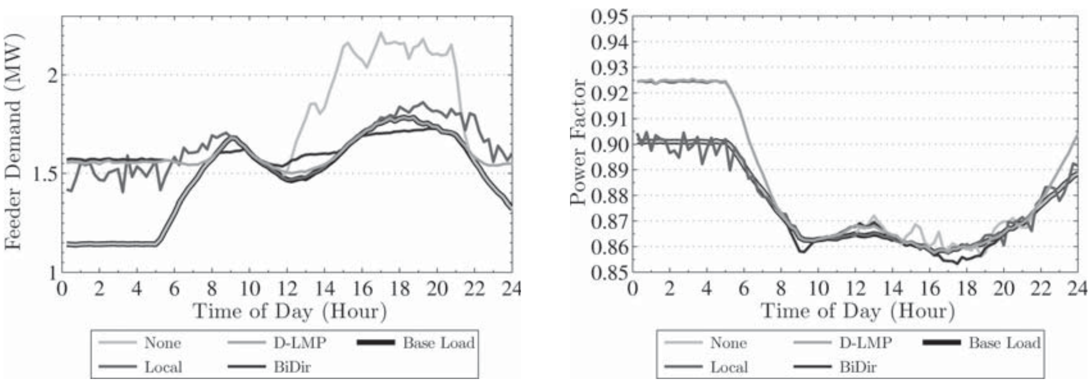

Figure 6.8: Phase A Feeder Demand with a 20 percent penetration of PHEVs

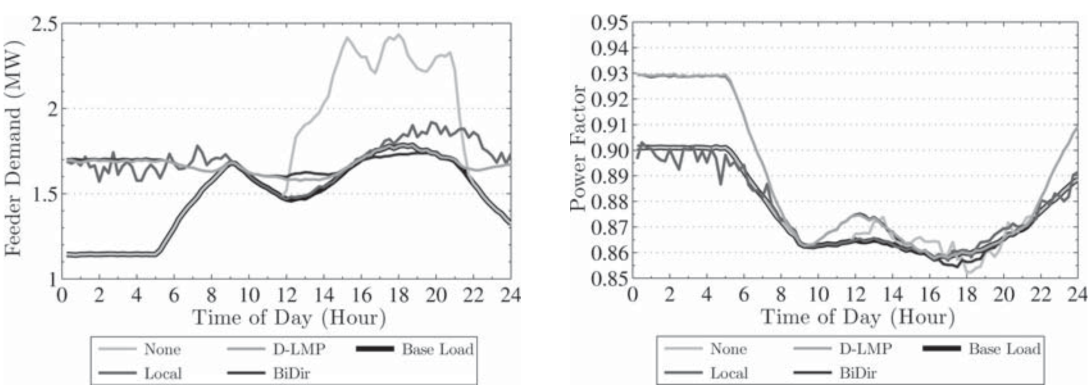

Figure 6.9: Phase A Feeder Demand with a 30 percent penetration of PHEVs

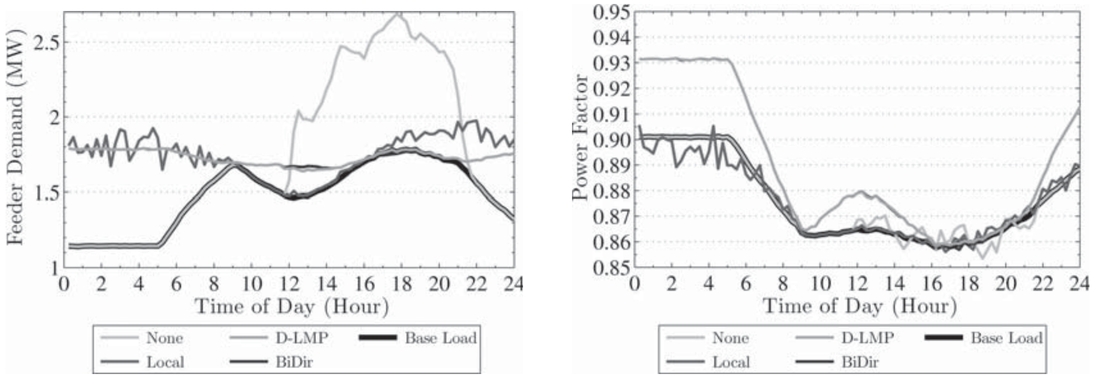

Figure 6.10: Phase A Feeder Demand with a 40 percent penetration of PHEVs

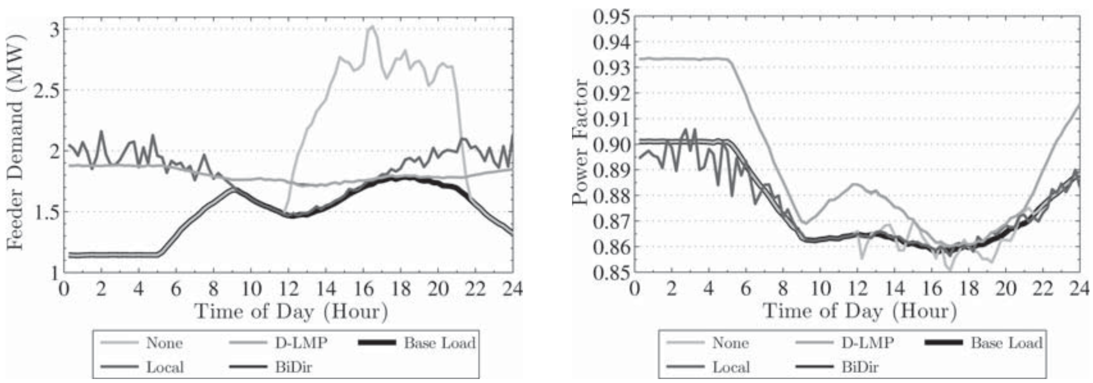

Figure 6.11: Phase A Feeder Demand with a 50 percent penetration of PHEVs

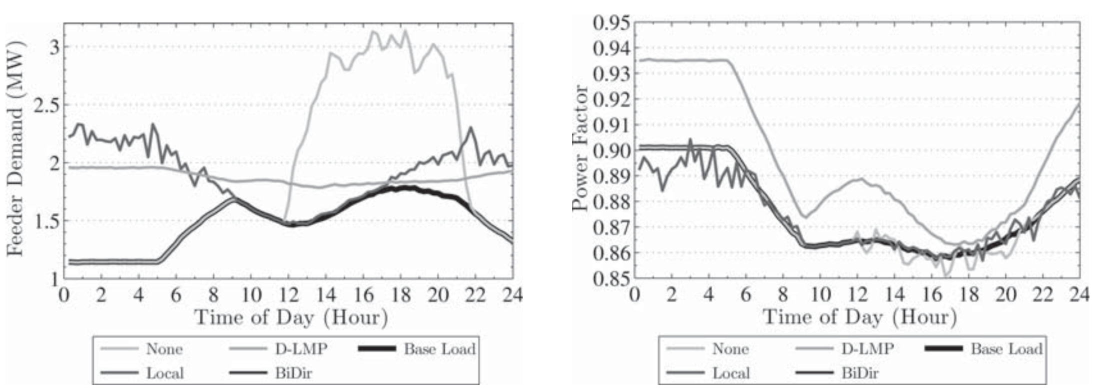

Figure 6.12: Phase A Feeder Demand with a 60 percent penetration of PHEVs

Chapter 7

Conclusion

7.1 Summary

In conclusion, the operating cost of the distribution system is minimized through intelligently scheduling PHEV charging. Previously the scheduling optimizations were run on the IEEE 13 node test feeder, producing similar results [35]. Using the current pricing function, the peak demands of the feeder are minimized. Also, the residential distribution grid can handle up to a 60 percent penetration of PHEVs with charge scheduling; in comparison to 10 percent with unscheduled charging and 30 percent with local charging. The methods produces a final demand curve with vary little variation, reducing the amount of energy needed from peaking power plants and spinning reserves. This further reduces the operating cost of the grid due to the cost function chosen. The daily operating cost of the residential distribution grid is minimized when the proposed methods intelligently scheduled the charging of participating PHEVs. This research is published and presented at the IEEE Transportation Electrification Conference and Expo (ITEC) in 2012 [44].

For vehicular scheduling to be adopted, there should be an incentive program in place for the consumer. This will provide them with a monetary gain for their participation and for reducing the lifetime of the vehicular battery if bidirectional charging is used. One example is to give participating vehicles cheaper pricing for the scheduled electricity than the rest of the uninterruptible household loads. This will provide the largest incentive to the consumer at the lowest cost to the electrical utility. If a vehicle does not participate in the charge scheduling method, it is assumed to be a part of the base load, and should not gain any incentives. This will be the case for all quick charge scenarios when the consumer needs a fully charged battery as soon as possible.

7.2 Future Work

7.2.1 Parallel Computation

To reduce the computational time of the stochastic implementation, the proposed scheduling methods can be partially run in parallel. This change will only require minor changes to the architecture of the optimization method, and no change to the minimization function. However, this will require a different simulation platform from Matlab® to run the simulations. With these scheduling techniques, the optimization methods can be run in real time, accounting for prediction errors while it iterates through the time slots each day. This will allow for comparison with a broader range of other optimization methods such as PSO.

7.2.2 Cybersecurity Concerns

If an incentive program is to be put into place, cybersecurity concerns for the communication and collected data will be introduced. Even though it is assumed the communication is inherent, it must also be assumed the communication methods will also support a level of encryption to protect user data from snooping attempts. It will require the devices scheduling the vehicles to have protection against outside attacks. However, the simplest problem for security is the charger unit. Tamper proof devices with protocol encryption will give the utility the means to ensure the charging schedule remains fair, utilized, and secure.

7.2.3 Vehicular Ad-Hoc Network Communication

Research in Vehicular Ad-hoc Networks (VANET) is proving to be useful for collecting vehicular data, specifically when the vehicle is traveling. The proposed VANET devices include a tamper proof communication interface which will adhere the cybersecurity issue solutions previously mentioned. This communication interface will not only be useful for collecting vehicular data and constraints when the vehicle is plugged in, but also while it is traveling. Using locational data and current traffic conditions, the system can more accurately estimate the arrival time of a vehicle. This does raise a privacy concern for the consumer which will require addressing. VANET communication will also be useful for distribution systems that include quick charging stations. Anonymous SoC information can be collected about vehicles on an express way, and used to predict when and where the vehicle will require charging. Using this, the grid can allocate resources for this quick charging load, improving the accuracy of the base load prediction.

7.2.4 Three Phase Chargers

Currently, all vehicles are connected to a single transformer phase. Expanding the charger to allow Level 3: three phase AC charging will allow for larger charger ratings. More importantly, this will allow scalable three phase charging to perform load balancing. This will reduce the power lost in the neutral cables which typically has a higher resistance. This will also allow for the integration of passive power factor correction when the charger is not in use. Another benefit of a three-phase charge scheduling algorithm is allowing DG sources to be placed throughout the grid to simulate renewable energy devices. With this implementation, the cost function will need to be altered to account for renewable generation in the available generation curves and pricing curves.

7.2.5 Distribution Locational Marginal Pricing

D-LMP shows many benefits in preventing an unbalanced grid from being overloaded. However, the impact of this architecture is not compared to simple Time-of-Day pricing methods. An in depth study of a method which reduces the resolution of the load predictions from the node level to the substation transformer will quantify the architecture's impact. This would illustrate the monetary benefits of integrating D-LMP into the system infrastructure. This will also allow for the testing of load prediction errors and their effects on the actual operating costs. It will also be beneficial to compare the results with different residential loading factors to show how the scheduling can ensure reliability and prevent load shedding when the feeder is initially overloaded due to the residential base load.

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