Chapter 2
Smart Coordination Approach for Power Management and Loss Minimization in Distribution Networks with PEV Penetration Based on Real Time Pricing

Bhuvana Ramachandran and Ashley Geng

Abstract The impact of Plug in Electric Vehicles (PEV) will be most significantly felt by the electric power distribution networks, and specifically by distribution transformers that exist on each neighborhood block and cul-de-sac as customers charge their PEVs. That impact is unlikely to be positive. Since PEV adoption is initially expected to cluster in neighborhoods where demand for PEVs is strongest, the new load may overload transformers, sap much-needed distribution capacity and also increase distribution network losses. Hence, the national goal of putting one million PEVs on the road by 2015 could easily impose a severe burden on the distribution network. Whether PEVs will help or hinder electricity provision will depend on how frequently and at what times the customers charge their vehicles. This behavior will be driven in part by the rate structures that are offered by utilities, as well as the price responsiveness of PEV owners to those rate structures. In this chapter, we propose a method to optimally charge the PEVs in order to minimize the system distribution network losses and to maximize energy transferred to PEVs. A novel short term prediction unit consisting of a receding time horizon method is proposed to forecast the PEV load and a multi objective bacterial foraging algorithm is used as an optimization tool. Also it is interesting to study the manner in which distribution network losses vary with PEV charging behavior. Hence the purpose of this chapter is to demonstrate a power management strategy using smart coordination approach to (a) design a charging and discharging infrastructure for the PEVs that maximizes energy delivered to PEV batteries and (b) reduce the distribution network losses to avoid overloading of the grid.

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2.1 Introduction

The growing use of electricity increases grid loading, power losses, and the risk of congestion. However, employing electricity for heating and transportation, also introduce a significant level of flexibility to the traditional consumption pattern [1]. Over the past 5 years, transportation sector has been revolutionized due to the advent of Plug-in Electric Vehicles (PEV). The growing societal awareness of environmental issues as well as ongoing concerns about reducing dependence on foreign oil or petroleum have made the concept of PEV very popular during the past few years [2]. Preliminary studies indicate that PEVs will dominate the electricity industry in the near future as pollution-free alternatives to the conventional petroleum based transportation and they will populate residential feeders, especially in USA and Australia. Due to the high penetration levels of PEVs, significant impacts will be felt especially at the distribution level [3–10]. In the absence of proper coordination, it is most likely that these PEVs will charge and discharge during the overall peak load period [3] causing severe branch congestions, unpredictable system peak demands, unaccepted voltage deviations, significant increase in losses and poor power quality. Some studies conducted by authors in [7, 9] have observed that the existing distribution system infrastructure would only support a very low PEV penetration level without grid operation procedure changes or additional grid infrastructure investments. To overcome these problems, several PEV coordination approaches have been suggested in literature [5, 11–17].

The charging and discharging process of PEVs can be controlled so that energy will be transferred from grid to vehicle (G2V) or from vehicle to grid (V2G) respectively. Several PEV coordination techniques based on deterministic and stochastic dynamic programing were discussed [5]. Several other authors have adopted prediction of PEV charging profiles and vehicle range reliability using recorded vehicle usage data and also designs a minimum cost load scheduling algorithm based on the forecasted electricity price and PEV power demands.

Many countries have ventured into smart metering and smart appliances to improve the system load profile and to reduce peak demand so that demand side management (DSM) can be implemented for load control and power management in the electrical grid [18–22]. PEVs can be utilized to provide ancillary services including energy storage and frequency regulation [16, 17, 23]. These added benefits of PEVs enable electric grids to rapidly heal and self-regulate under conditions of emergency thereby improving system security and reliability and efficiently manage energy delivery and consumption [24–30].

Majority of existing strategies on load control and power management treat loads as individual entities, even for loads sharing the same load characteristics. With such an approach, either computational complexity (for centralized schemes) or communicational effort (for decentralized schemes) would grow significantly as the number of loads in the network increases. In this chapter, we consider groups of loads rather than individual loads, by categorizing loads into a relatively small number of load types. With this scheme, the size of the proposed optimization problem does not change as the load population increases, which is a valuable feature for large-scale load management.

To accomplish these objectives, this chapter proposes a novel real time smart coordination approach using a receding time horizon method to coordinate multiple charging and discharging of PEVs while reducing system stresses that can severely impact grid reliability, security and performance [24]. Real time charging control issues were addressed by very few authors such as [12, 31] where it is very challenging to obtain performance guarantees. The proposed PEV charging algorithm developed for smart coordination consists of a forecasting module and an optimization module which will improve power system resource utilization. The forecasting module sends information about the number of PEVs in the parking garage and also their arrival and departure rates.

The module then calculates and forecasts the number of PEVs that will be present at the same time in the parking garage for the next time interval. The heuristic multi-objective optimization module takes in the present and future power demands for all loads including PEV's over a finite time interval. The aim of this optimization module is to maximize the energy delivered to PEV batteries and satisfy the SOC criteria for the PEV while including constraints related to the power grid and customer demands. The optimization module is also designed to minimize distribution network losses considering charging time zone priorities specified by PEV owners.

To validate the power management infrastructure and distribution network loss minimization, the smart coordination strategy is implemented on a IEEE 13 node test feeder and a 38 bus power system consisting of a mix of residential, commercial and industrial customers penetrated with PEVs. To estimate the economics of charging, simulation results will be presented for uncoordinated and coordinated charging scenarios for three different Time of Use (TOU) rates and different PEV penetrations.

2.2 Research on Smart PEV Charging Coordination

Literature review of research carried out in the area of coordination of charging and discharging of PEVs throws light on the two categories of work so far. One category of research was focused on charging and discharging decisions based only on the present information about the state of the grid. The second category is the one which is based on forecasted estimates of the state of the grid and future power demands in the grid are considered while making decisions about charging or discharging. In [12], a real time coordinated PEV charging approach was proposed in which the time varying energy process was accounted for and along with charging time and zone preferred by the PEV owner. A DSM based charge control was proposed in [32] where the objective was to provide dynamically configurable dispersed energy storage during peak demand and outage conditions. An optimal PEV charging model that responds to the time-of-use price in a regulated market is proposed in [33]. In these papers, the impact of present and future PEV charging and discharging decisions on the grid were not considered. This means that the charging of PEVs would not result in a target state of charge level for the PEVs and hence would affect the reliability of the power system.

Several other authors have proposed probabilistic models and charging coordination strategies considering day ahead or real time markets [16, 34, 35]. The optimization model used could be either single objective optimization (to optimize cost or losses) or multi-objective optimization (to optimize operating cost with losses). The ultimate objective of this research is to develop a smart coordinated charging and discharging framework for smart grids based on TOU rates which would improve the system reliability and security.

2.3 Electric Vehicles and Distribution System

If PEV owners were to simultaneously charge their vehicles in a small geographical area, the increased demand would cause severe problems for the utility that must serve the load reliably. If PEV owners were to simultaneously charge their vehicles in a small geographic area, the increased demand caused due to charging could cause major problems for the utility that must reliably serve that area. While simultaneous charging of PEVs at system peak could result in supply shortages or create a need for large new investments in expanding generating capacity and setting up new generation plants, the most serious concern due to simultaneous PEV charging will be the congestion problem at distribution level for most utilities (Fig. 2.1).

First, consider the effect of PEV adoption on system peak demand. Assume that one in every four homes owns a PEV, or roughly 250,000 residential customers with an electric vehicle in the example utility considered. Assume that half of these customers are simultaneously charging their vehicles at the time of the system peak (other owners may not yet be home from work or could already have a full charge). Assuming a charging demand of 3.3 kW per vehicle, the resulting increase in peak demand would be roughly 400 megawatts (MW) (calculation: 250,000 customers × 50 % peak-coincident charging × 3.3 kW). While not an insignificant number, a mid-sized utility with, for instance, 5,000–10,000 MW of existing load would have the capability to address this load growth over a long-term forecast horizon.

Now, consider what could happen at the distribution level. There is evidence to suggest that adoption of PEVs will be geographically "clustered." Assume that of the residents living on a street that is served by a single transformer and in a "green" neighborhood, half own a PEV. A charging demand of 3.3 kW could double the daily demand of these homes. As a result, if the PEV owners were all to plug in their vehicles when returning home from work in the evening, the load on that street's transformer could increase by 50 % (calculation: 50 % PEV ownership × 100 %

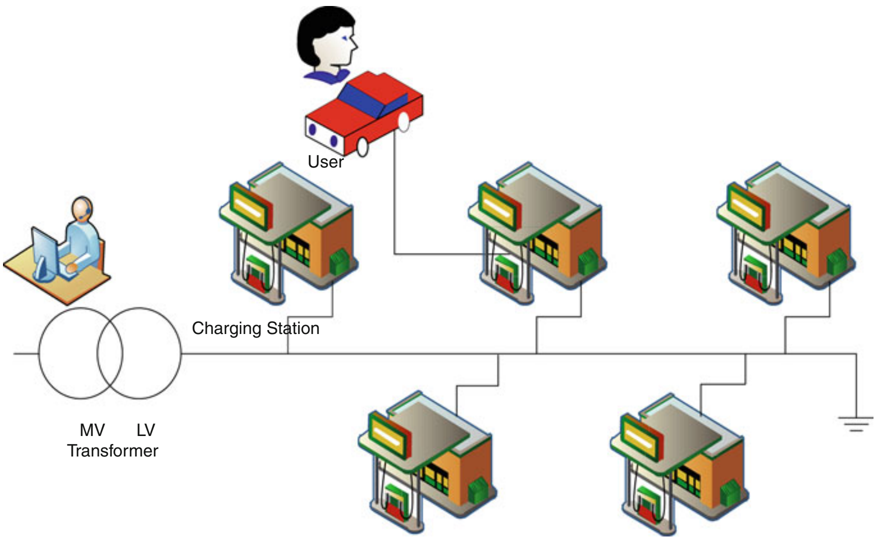


Fig. 2.1 Distribution network with PEV charging stations

increase in load per PEV owner). If the transformer was already being loaded at 70 % of capacity, then this increase would be enough to overload the transformer and create severe havoc in the distribution system. Dynamic pricing schemes, such as reduced rates for nighttime charging allow drivers to choose how to respond to change in prices. These pricing schemes allow users to choose their charging time and it does offer some relief to the grid in terms of motivating the user to charge during off peak periods by offering low tariff at those times. Such a smart grid can accommodate PEV charging according to schedule determined/chosen by the user.

Certainly, PEV adoption rates will vary from one service territory to the next, and the vehicles will be charged at varying rates and at different times of day. However, it is becoming clear that the existing generation resources will be in a much better position to accommodate future PEV market penetration than our distribution systems. Hence it is the distribution system infrastructure that needs to be restructured to accommodate high penetration of PEVs in communities.

2.4 Electric Vehicles and TOU Rates

The numerous potential benefits of widespread adoption of PEVs have been rated very high [36]. PEV are capable of reducing the greenhouse gas emissions due to reductions in the amount of gasoline burned by the vehicles internal combustion engines. Also since the price of gasoline is escalating, fueling with electricity is a least expensive option to the PEV owners. In a Smart Grid environment, if the owners decide to charge their vehicles late into the night, the vehicles represent an ideal off peak load that would complement new intermittent renewable energy resources such as wind and solar power.

The time and period of charging of PEVs could have a negative impact on the grid. Contrary to many expectations, PEVs will not result in unmanageable demands on generation resources. The real challenge would be at the distribution level. If all the residents of a small community purchased PEVs and they all charged at the same time, there would be a heavy spike in demand that could overload the transformers feeding those houses and would result in a severe damage to the distribution system. This could happen in reality if several of the PEV owners cluster in specific neighborhoods. Hence the utilities are trying hard to encourage off peak charging by allowing customers who own PEVs to take all or part of their electric service on some form of TOU pricing, often at higher voltages to facilitate faster charging. Many have approved TOU tariffs specially dedicated to PEVs. Several of the utilities offer different rates depending on whether the metering is done for the whole house or separately for the electric vehicle. It is somewhat common for utilities not to have created an EV-specific TOU rate, but to recommend that EV owners enroll in an existing residential TOU rate. TOU pricing is to encourage trend for charging PEVs efficiently since their owners can lower their electric bills by charging during off-peak hours.

PEV owners have the option to choose between charging based on convenience or only during those times when electricity costs are lowest. Saving money would motivate some owners to charge when the cost of charging is less. In the absence of incentives and benefits, PEV owners may not plug in their car for charging when they come back home at 6 pm and charge it to full capacity so that the vehicle is ready for them the very next morning. However, there are customers who might find it more convenient to charge their vehicle whenever they want to depending on their work schedule, availability for charging stations (Fig. 2.2) outside their home, extent of their tolerance to a less than fully charged battery and the regularity of their driving among other factors.

Fig. 2.2 Charging stations for PEVs

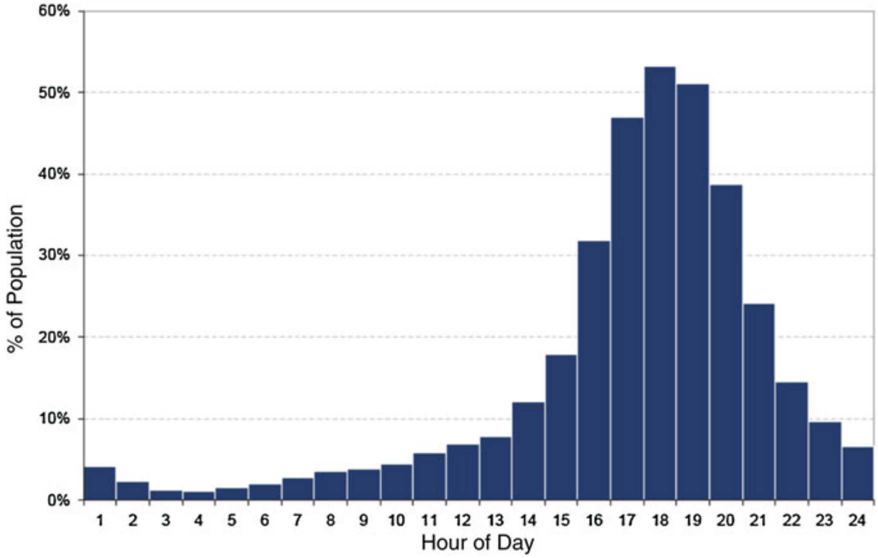


Fig. 2.3 Charging profile of PEV owners

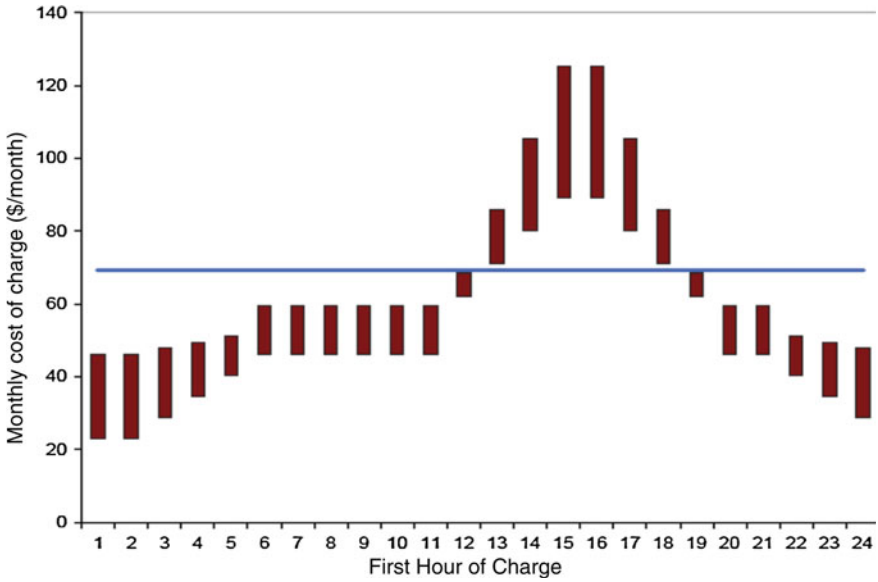


Fig. 2.4 Charging costs across TOU rates by time of day

An aggregated charging profile for the PEVs is given below in Fig. 2.3. Figure 2.4 shows the charging costs across TOU rates by time of day. A driver who is on the low TOU rate has the least incentive to charge during the cheapest periods, since their cost exposure is much less than that of an owner on either the medium or high TOU rates. A priori, one would expect drivers on the high TOU rate to display the largest price responsiveness and drivers on the low TOU rate to display the least.

Even in the high TOU rate case, the savings are modest. The difference between charging at 6 pm and 1 am is about $60 a month. Now the question arises as to whether a PEV owner will pay much attention to saving this sum of money. Research with other dynamic pricing and TOU pricing pilots suggests that despite the modest savings that accrue to customers on such pricing designs, people do move their load profiles in response to higher prices. Drawing upon empirical evidence from more than 100 tests with dynamic pricing, we would expect a peak-to-off-peak price ratio of 8:1 to produce a drop in peak load of around 15 %. The implied arc elasticity is fairly small (around −0.04) but is still capable of producing significant demand response with a potent rate design. Hence in this chapter we have implemented a real time pricing scheme for charge coordination of PEVs.

2.4.1 PEV Owners' Price Response and Distribution Transformer Overload

To conclude without any doubts that price responsiveness would alleviate any distribution transformer overload and loss issues, based on the TOU rates already established and the aggregate charging profile for the case study under consideration, price elasticity of demand of −0.04 is made use of. The percentage of customers charging during peak period would drop from 60 to 55 %. This is not beneficial to the grid operators trying to mitigate the adverse impact on the distribution system. Authors in [36] have tried various different price elasticities to effectively eliminate peak time charging.

2.4.2 Prediction of Charging Behavior

To predict charging behavior of PEV owners, a large number of volunteers were surveyed to study their charging behavior under various TOU rates. These volunteers were then randomly allotted to control groups and treatment groups where the control group members continue to drive their existing vehicles throughout the day whereas the treatment group members were supplied with a PEV. Both the control and treatment group's driving behavior was observed over a period of several months before and after the treatment group was supplied with PEVs. Results from the study carried out by [36] have shown that TOU rates may help reduce future grid reliability issues as PEVs penetrate the vehicle market. However, the extent to which properly designed rates would assist in maintaining grid reliability was not explored because of lack of information about the PEV owners' price responsiveness.

2.5 Coordinated and Uncoordinated Charging

To find applicable solutions to the problem of distribution transformer overloading, two general PEV coordination schemes have been considered in the literature.

- Centralized Coordinated PEV Charging—The system operator as a central controller sends commands through the smart grid communication network to each individual PEV to set the charging start time and rate. The decisions can be made based on several factors such as system capacity, system loss minimization, node voltage profiles, final state of charge, budget, etc. Therefore, a stable and more secure network can be achieved. However, centralized architectures with few central data stores require customer information and may lead to unscalable systems and costly initial infrastructure investments.
- Decentralized Coordinated PEV Charging—Each PEV is allowed to determine its own charging pattern. The decision can be made on the base of system capacity and conditions. The consequence of a decentralized approach may or may not be optimal, depending on the information and methods used to determine local charging patterns. Indeed, this approach does not require substantial knowledge of individual customers.

A comparison of both approaches is given in Table 2.1.

The phrase "decentralized" implies the ability of individual PEVs to make their own charging decisions. Most PEV charging algorithms have a centralized philosophy and structure, with all PEVs to be controlled from a central dispatch center. That is, PEV chargers cannot make any individual decisions on the starting time, rate and duration of their charging process. On the other hand, there are a few recently proposed

Table 2.1 Comparison of PEV coordination approaches

	Centralized PEV charging	Decentralized PEV charging
Idea	The system operator acts as central controller and sends commands through the smart grid communication network to each individual PEV to set its charging start time and rate. The decisions can be made based on several factors such as system capacity, system loss minimization, node voltage profiles, final state of charge, budget, etc.	Each PEV is allowed to determine its own charging pattern. The decision can be made on the bases of system capacity and conditions
Advantages and disadvantages	• More stable and secure network	• Easy to implement
	• Optimal coordination	• Preserves individual authority
	Centralized architectures with few central data stores may lead to unscalable systems and costly initial infrastructure investments	• Independent operations of PEV chargers • More dynamic and flexible system
	• Relies on customer information. Hard to implement	The results of a decentralized coordination approach may or may not be optimal

decentralized PEV coordinated charging algorithms, which rely on smart meter information and make their own individual decisions on charge time, rate and duration.

This chapter will first show the detrimental effects of uncoordinated charging of PEVs on distribution network and then introduces a new real time smart coordinated charging of PEVs in unbalanced residential network to control the distribution network losses and energy transferred to the PEVs. Detailed simulations are performed and presented to demonstrate the abilities of the proposed PEV charging algorithm. The main research goals are to formulate the optimal PEV coordination problem, define the objective function and select appropriate constraints such that the following requirements are fulfilled within a 24 h period:

1. Grid losses are minimized over the 24 h.
2. Each PEV charger operates independently and only relies on the information available at its own smart meter.
3. The distribution transformer loading is kept within its designated rated level to prevent possible damages to the equipment.
4. Finally, coordination is performed such that the system losses are minimized and energy transferred to the PEVs is maximized as a result of PEV charging activities.

The model developed in this chapter for smart coordination consists of a short term forecasting module and an optimization module. The short term forecasting module sends information about the number of PEVs in the parking garage and also their arrival and departure rates. The module then calculates and forecasts the number of PEVs that will be present at the same time in the parking garage for the next time interval. The heuristic multi-objective optimization module takes in the present and future power demands for all loads including PEV's over a finite time interval. The aims of this optimization module is to maximize the energy delivered to PEV batteries and satisfy the SOC criteria for the PEV while including constraints related to the power grid and customer demands.

The optimization module is also designed minimize distribution network losses considering charging time zone priorities specified by PEV owners. To validate the power management infrastructure and distribution network loss minimization, the smart coordination strategy is implemented on IEEE 13 node test feeder and a 38 bus power system consisting of a mix of residential, commercial and industrial customers penetrated with PEVs. To estimate the economics of charging, simulation results will be presented for uncoordinated and coordinated (centralized and decentralized) charging scenarios for different PEV penetrations.

2.6 Power Management

Electricity demand varies both by day and by year and since it is difficult to store electricity in large quantities it is produced at the same time as it is consumed. Hence, the variations in demand result in variations in the electricity generation and generation capacity must be designed to handle the peak demand. Similarly, the transmission capacity in the grid must be designed to handle the peak power in the system. The variation in electricity demand leads to increased cost of electricity since it requires a higher transmission capacity in the electric grid and since the electricity consumed during the peak is usually produced by generation plants with high production cost.

Power and Energy Management (PEM) can be performed on the supply side or demand side. On the supply side, PEM is undertaken when:

- There is a growing demand (demand requirement is higher than supply)
- There is a lack of resources (finance, energy) and PEM helps to postpone the construction of a new power plant.

On the demand side, energy management is used to reduce the cost of purchasing electrical energy and the associated penalties. The techniques used for PEM are aimed at achieving valley filling, peak clipping and strategic conservation of electrical systems. There are techniques that are used to decrease the need for additional capacity and the costs involved by increased fuel on the supply side. The implementation of the techniques leads to improving off-peak valley-hours and the load factor of the system. The common load management techniques to supply side or demand side are presented as load shedding and restoring. There are also more exotic means such as power wheeling, the installation of energy efficient processes and equipment, the use of energy storage devices, co-generation, use of renewable energy and reactive power control. Implementation of these techniques has found a steady increase in application and meets demand side management (DSM) objectives.

2.6.1 Power and Energy Management: Techniques

Energy management embodies engineering, design, applications, utilization, and to some extent, the operation and maintenance of electric power systems for the provision of the optimal use of electrical energy without violating other international standards. Load management in utility industries is the planning and implementation of the utility activities, which are designed to influence customers to use electricity in such a way, that it produces a desired change in the utility load shape. Different load management techniques have been proposed and used, e.g. time-of-use-tariffs, interruptible load tariffs, critical peak pricing, real-time pricing (RTP) and distribution system loss reduction [37, 38]. As stated in [38] different techniques can have differential impact on the electric grid.

Direct load control (DLC) This is the program designed to interrupt consumers' loads during the peak time by direct control of the utility power supply to individual appliances on a consumer premises. The control usually involves residential consumers. The cost benefit of DLC includes:

- Power system production cost savings.
- Power system generating capacity cost savings.
- Power system loss reduction.

The various control options for DLC are

- Direct load control, utility can switch off the load directly when required.
- Interruptible load control—the utility provides advance notice to the customer for switching off their loads.
- TOU tariffs, where utility rate structure is designed according to the time.

Mohamed and Khan [39] developed methods for classification of customers loads according to the size of load. Telephone, radio signal and power line were used to produce a signal that interrupted large industrial consumers. In this system, customers were required to reduce their electric demand to an emergency service load for only 10 min upon request. Under frequency, the relay was installed in the customer's loads, which responded very fast in the under frequency regime. Tools for evaluation of end-use monitoring DLC programs were described by [40] namely a duty cycle model (DCM) and demand side planning. The PC-based workstation had proven to be a viable and cost effective means of analyzing the voluminous data used in the program. The duty cycle model offered an integrated approach to DLC impact analysis. This is given by:

$$t = Average\,Load/Connected\,Load \tag{2.1}$$

In the case of PEM based on time dependent tariffs, load management is carried out by the influence of tariffs setting. The total cost of generating and delivering of electricity to consumers was being broken into four fundamental categories of services:

- Customer services,
- Distribution services,
- Transmission services,
- Generation services.

Integrated utilities in regulated states set the rates to cover the costs of all services. The electric consumers are billed as:

- Flat rate tariffs/two part tariff
- Time of use tariff
- Spot price

In a flat rate tariff, a customer pays the same amount for electricity at any time of day. In the TOU based method, the utility provides transparent information on the electricity price at different periods to the customers to encourage off peak and discourage peak period consumption by varying price of electricity. Time of use rates provide variation of the cost of energy by season or time of day. Rates are higher during peak demand periods and lower during off-peak periods. Some utilities have made TOU rates mandatory for large customers. Savings from time of use rates vary depending on the size of the peak/off-peak price differential and the length of the peak period. Another type of tariff setting for LM is spot price. The message is sent to customers to indicate the price of electricity for an instant of time. A spot price scheme is appreciable if electricity price fluctuation is high and if the consumer can anticipate the price behavior as well as being able to respond quickly when the electricity price is high or low.

2.7 Proposed Smart Coordination of PEV Charging Using Real Time Pricing

In the proposed approach, PEV owners are allowed to select one of the charging time periods and rates. Each PEV owner will provide to the system his charging tag number, required state of charge and parking duration. The command center receives and processes this vehicle data. The forecasting algorithm predicts the number of PEVs in the system during that time period. Forecasting algorithm will then be used to predict the number of PEVs that would be in the system during the next time interval. This forecasted data along with the actual data would then be sent to the centralized command center who will then operate the optimization module to schedule PEV charging until maximum energy is delivered to the batteries and distribution losses are minimized. This chapter explains in detail how PEVs can be scheduled using real time costs thereby reducing the burden on the local distribution networks. For online coordination of PEVs, a smaller optimization period should be chosen to start charging the PEVs as fast as possible.

2.7.1 Forecast Module for Predicting PHEV Owners Charging/Discharging Behavior/Schedule in a Smart Grid

A smart grid is a power grid with information transfer allowing agents on the grid to communicate and make decisions regarding load connections. One major advantage of a smart grid is the opportunity to more efficiently utilize the power that is generated. When considering a conventional power grid that uses load forecasting to predict power demands, it is possible to account for activities that have been exhibited for many years such as the cycle of the modern family to work or school and back home again. When an additional element outside of the historical forecasted data is added to the power demands it can be difficult to compensate. Such a scenario could present itself with the emergence of plug-in electric vehicles (PEVs). Not only is the additional load associated with PEVs uncertain due to their adoption rate, but it could also prove difficult to quantify because of the stochastic nature of vehicle use. This topic investigates the use of smart coordinated PEV charging on a smart grid allowing for a more manageable overall use of power. The information transfer is used by the PEV's control strategy to make efficient charging decisions.

Figure 2.5 presents a flowchart of the proposed approach. The first step is to gather the data needed for the study. From the data, four key parameters can be processed for further analysis: (i) the locations of the vehicles (i.e., where they can be charged); (ii) when they are parked (i.e. when they can be charged), (iii) the number of PEVs that are being charged and (iv) real time price during that interval. The second step is to formulate and implement the optimization models for different control strategies. The final step is to use the data in the models developed to

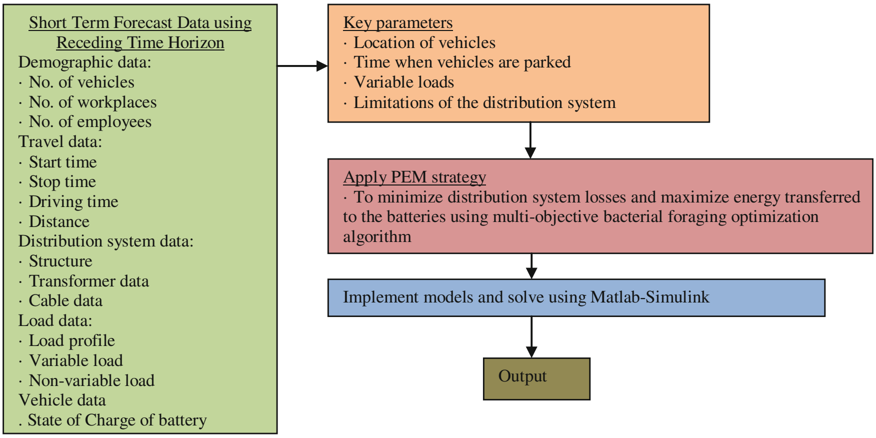


Fig. 2.5 Flowchart of smart coordination approach with forecasting module and optimization modules

evaluate the impacts of different control strategies on the distribution system. The optimization model is based on an AC optimal power flow framework which is described in [41], with the objective function being: maximization of energy transferred to the PEVs and minimization of distribution network losses. This model was developed using Matlab-Simulink.

2.7.1.1 Methodology

Uncontrolled PEV charging in a modern day grid with renewable energy resources may cause several local grid problem including additional extra power losses, voltage swings and power quality disturbances. Uncontrolled charging is the current practice for PEV charging and is expected to persist in the near future to enable a transition period for the PEV penetration to be significant, hence it paves the way for the coordinated charging, which is the second expected scenario. For this scenario, a coordinated charging system should be developed under the smart grid paradigm. This system must be able to deal with real-time measurements and parking lot dynamics through the utilization of the two-way smart grid communication infrastructure. The primary target of such a coordinated charging system is the best use of smart grid generation resources so that the PEV load can be shifted to optimal periods during PEV parking duration in order to maximize customer satisfaction without jeopardizing system equipment.

Smart coordination refers to coordinated charging and it has been shown that coordinated charging of PEVs can lower power losses and voltage deviation by flattening out peak power and improve the load profile. In the proposed approach, smart charging and discharging coordination architecture consists of two main modules: a prediction module, and an optimization module. The prediction module consists of a data collection and storage module which governs the collection of information related to current PEV power demands, the current state-of-charge (SOC) of PEV batteries, and the power demand of regular loads. In most cases, an aggregator is assumed to be in place to deal with PEV data collection and storage. The role of the aggregator is to collect information from the PEVs and send it to the grid operator, and to send charging/discharging decisions from the operator to the chargers. The short term prediction/forecasting module should provide accurate forecasts of future PEV power demands and regular loads in the power system. Based on this information, the optimization module should then make optimal coordinated charging and discharging decisions that guarantee maximum energy transferred to the customers PEVs and minimum distribution network losses (Fig. 2.5).

Accurately estimating the impact of PEV charging on electric power system components requires both component models and good estimates of the magnitude and timing of demand increases due to PEV charging. Early PEV research assumed very simple charging profiles, such as assuming that vehicles will charge daily starting at 17:00, 18:00 or 19:00 h, with batteries fully depleted at the start of each charge cycle. However actual PEV charging loads will depend highly on travel patterns, which vary tremendously from driver to driver and day to day. To better capture this variability in driving behavior, researchers have used either detailed GPS data for small groups of drivers, or survey data from larger populations. Authors have used data from 9 drivers to estimate variability in daily miles driven, but with fixed evening arrival times. Another study used GPS data from 76 vehicles to derive a stochastic model of miles driven and arrival/departure times. Other authors have used a larger set of GPS data to develop a Monte Carlo model that is similar to the one presented here, but the data are not used to model the miles driven, which is necessary to estimate the battery state-of charge on arrival.

In this chapter, the problem is formulated as an optimization problem with the objective function being a sum of convex and strictly increasing functions. This power scheduling problem is solved in a static fashion, that is, the optimization is performed only once before or at the beginning of the scheduling horizon. To take dynamic changes of loads into consideration, this chapter studies a real time implementation of the power scheduling. Our approach is to reformulate the optimization problem so that it is solved in the fashion of receding horizon. Generally, it works by solving optimization over the next T time steps, executes the first time step decision, and resolves the optimization problem for the next T time steps by incorporating new information available at the moment. Since the power management problem is not formulated in a traditional way, the receding horizon operation needs to be carefully designed. The main challenge comes from the fact that load groups may need to be reorganized during the execution.

The short term forecasting method implemented is the receding horizon formulation of power management problem discussed in [43]. Along this direction, two strategies are available: one is based on the conventional receding horizon idea, and the other is a reformed scheme with the merit of reducing online computational load. We assume individual EV charging loads (either residential or commercial) are connected to the power grid through a control unit. Each control unit monitors status of an EV battery, connect/disconnect load from the grid, and wirelessly communicates with a remote aggregator. The aggregator acts as a central scheduler and commander to communicate with the PEV owner/driver and to regulate the charging process of each load. Once a vehicle is plugged-in, the corresponding aggregator (e.g., parking deck operator) receives the battery state information (e.g., state-of-charge, state-of-health, voltage, and current) as well as customer information (e.g., customer identification, customer preference, and billing information) and sends in the real time pricing rate to the customer. Multiple aggregators serve as middleware between the central controller (e.g., distribution Company, and microgrid operator) and individual vehicles. Given the real-time information from multiple aggregators, the central controller performs the energy scheduling (optimization of losses and energy transferred) and sends back control signals periodically.

The load population is assumed to be large, by taking into consideration the anticipated high penetration level of PEVs. This requires our solution to the power management scalable and computational tractable. To this end, the PEV charging loads are classified into groups with the following definitions given in [43]:

Definition 1 *A load type* l^r is defined by $l^r = \{a^r, b^r, \tau^r, p^r\},\ r = 1, 2, \ldots, m$, where a^r is the (earliest) charging start time, b^r the (latest) charging completion time, τ^r is the required total charging period, and p^r indicates the desired power level required by the EV charging system which is assumed to be time-varying.

Definition 2 A *family of load requests* is defined as $\mathcal{F} = \{(l^1, N^1), (l^2, N^2), \ldots, (l^m, N^m)\}$., where l^r, $r = 1, \ldots, m$, is the r-th load type, and N^r is the total number of requests from customers for the type-r load.

Here, the scheduling horizon is discrete and consists of T time steps, which is denoted as $[1, T]$. For each time step, the power level p^r desired by type r loads may be different; therefore, we introduce the notation of *charging stages* below.

Definition 3 For each time step j of the charging process for type-r power loads, denote the demanded power level by $p^r(j), j = 1, 2, \ldots, \tau^r$. It is said that the type-r load requires τ^r *charging stages*, and the jth *stage power level* is $p^r(j)$. With the above definition, the power of type-r loads can be expressed as a power vector $p^r = [p^r(1), p^r(2), \ldots, p^r(\tau^r)]$. This is an ordered vector for which the stage $p^r(i)$ must be completed before the $p^r(j)$ stage starts, for any $i<j$. The completion of charging could be intermittent, i.e., charging stages could be discontinuous in time.

2.7.2 *Optimization Module to Minimize Distribution Network Power Losses for Power Management*

A common approach to deal with power management is to assign each individual load a vector of binary numbers (1 or 0); each number is used to indicate the on/off state of the power at one discrete time step. As the load population increases, the number of decision variables increase proportionally, and the searching space grows exponentially. Therefore, such approach is not scalable generally for centralized strategies.

This chapter focuses on groups of loads rather than individuals. With the definitions of load type and charging stage, the decision variables are chosen to be the total number of loads for each load type to be powered on for a certain charging stage at any discrete time instant. Symbolically, the decision variable is denoted by $\beta_k^r(j)$, representing the total number of type-r loads being charged at charging stage j at time step k, where $k \in [1, T]$ is the time index, $j \in \{1, \ldots, \tau^r\}$ the charging stage index, and $r \in [1, \ldots, m]$ the load type index. Then, the total power consumption of the entire power system at time k is:

$$L_k = \sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \beta_k^r(j) p^r(j) \tag{2.2}$$

The objective of power management is to minimize the total power losses and maximize energy transferred to the PEVs over time duration $[1, T]$. To this end, a multi-objective function

$$\text{Min} \sum_{k=1}^{T} C(L_k) + \text{Max} \sum E_D \tag{2.3}$$

is chosen where function $C(\cdot)$ is strictly increasing and convex. Convexity of the above cost function causes heavier penalty on larger instantaneous power losses, which is important in alleviating power loss values. More advantages of choosing such a cost function are discussed in [42]. E_D is the energy delivered to a PEV battery during the time interval [1, T]. Based on power flow constraints, bus voltages and generated real and reactive powers are specified. The decision variables are the voltage magnitudes and angles at all buses except slack bus and real and reactive power generated at slack bus. During each iteration of the optimization algorithm, voltage limits are checked to see if there are any violations.

The optimization problem of EV charging power management to minimize distribution network losses and maximize energy transferred is summarized below, and the detail can be found in [43] along with a two-layer strategy to reduce computation burden of the optimization. The total real and reactive power generated at each bus can be calculated based on current measurements and predicted data. The total real power consumed by load will be the sum of real power consumed by all other regular loads added to the real power consumed by 67 PEV load. Decision to charge or discharge is made based on the state of charge (SOC) of the PEV battery and is limited by the capacity of charger. Energy transferred to the battery is calculated as product of battery capacity and the difference between final SOC and initial SOC at a particular time interval. State of charge of the battery is limited by the desired SOC by the user. But also the incoming PEVs are expected to require a final SOC of 100 % when they leave and to arrive with a minimum SOC.

Problem P_p (***EV Power Management Problem***)
Find $\beta_k^r(j)$ to

$$\text{Min} \sum_{k=1}^{T} C\left(\sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \beta_k^r(j) p^r(j)\right) + \sum_{k=1}^{T} E_D \tag{2.4}$$

subject to the following constraints:

(a) $\beta_k^r(j) \in \mathcal{Z}^+$ for $k = 1, \ldots T, j = 1, \ldots \tau^r$, and $r = 1, \ldots, m$.
(b) $\beta_k^r(j) = 0$ for any $k < a^r$ or $k > b^r$.
(c) $\sum_{j=1}^{\tau^r} \beta_k^r(j) \le N^r$, for $k = 1, \ldots T, r = 1, \ldots, m$.
(d) $\sum_{k=1}^{T} \beta_k^r(j) = N^r$, for any $j = 1, \ldots, \tau^r, r = 1, \ldots, m$.
(e) $\sum_{k=1}^{n+1} \beta_k^r(j+1) \le \sum_{k=1}^{n} \beta_k^r(j)$, for all $n = 1, \ldots, T-1,\ j = 1, \ldots, \tau^r,\ r = 1, \ldots, m$.

Note that decision variables of problem P_p are number of EV charging loads which are integers and are not preferable by numerical optimization solvers. Assuming a large network with high population of EV loads, we can rewrite the problem with a set of new decision variables as defined below.

Definition 4 Given decision variables $\beta_k^r(j)$ of problem P_P, we define a *new set of decision variables* $\gamma_k^r(j)$ as the percentage of type-r load requests being switched on, i.e.,

$$\gamma_k^r(j) = \frac{\beta_k^r(j)}{N^r},\ r = 1, 2, \ldots, m \tag{2.5}$$

where N^r is the total number of the type-r loads. Note that the above new decision variables, $\gamma_k^r(j)$, are rational numbers, which can be easily used to replace $\beta_k^r(j)$ in problem P_P. Once the optimization problem P_P is solved, the aggregator can plan out a more specific schedule on power allocation, by indicating which exact load needs to be powered on/off for any charging stage at any time step. One approach to such power allocation is described in Algorithm 1 below. More specifically, the solution to Problem P_P produces number of requests $\beta_k^r(j)$, where k is time index, j is charging stage index, and r is load type index. In compact form, we write $\beta_k^r(j)$ as matrix B^r, for each load type r, as follows:

$$B^r = \underbrace{\begin{bmatrix} \beta_1^r(1) & \beta_2^r(1) & \cdots & \beta_T^r(1) \\ \beta_1^r(2) & \beta_2^r(2) & \cdots & \beta_T^r(2) \\ \vdots & \vdots & \vdots & \vdots \\ \beta_1^r(\tau^r) & \beta_2^r(\tau^r) & \cdots & \beta_T^r(\tau^r) \end{bmatrix}}_{\text{Time step } \rightarrow\rightarrow} \begin{array}{l} \text{Charging} \\ \text{Stage } j \\ \downarrow \\ \downarrow \end{array} \tag{2.6}$$

The problem P_P generates m of such matrix, $B^1, \ldots, B^m$, one for each load type. For each B^r, Algorithm 1 yields another matrix Λ^r with dimension $N^r \times T$:

$$\Lambda^r = \underbrace{\begin{bmatrix} \lambda^r_{1,1} & \lambda^r_{1,2} & \cdots & \lambda^r_{1,T} \\ \lambda^r_{2,1} & \lambda^r_{2,2} & \cdots & \lambda^r_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda^r_{N^r,1} & \lambda^r_{N^r,2} & \cdots & \lambda^r_{N^r,T} \end{bmatrix}}_{\text{Time step } \rightarrow\rightarrow} \begin{array}{l} \text{Individual} \\ \text{loads} \\ \downarrow \\ \downarrow \end{array} \tag{2.7}$$

Each row of Λ^r corresponds to each individual load of type r and each column corresponds to one time step. Each element, $\lambda^r_{i,k}$, is the charging stage number of load i at time k. Note that we set $\lambda^r_{i,k} = 0$ when the load is not served. Thus, we have $\lambda^r_{i,k} \in \{0, 1, \ldots, \tau^r\}$. Below is the algorithm which creates Λ^r from B^r.

Algorithm 1 ($Individual\ power\ allocation$)**:**

Given: $\beta^r_k(j)$, number of type-r loads being served with charging stage j at time step k, $j = 1, \ldots, \tau^r, k = 1, \ldots, T$.

Find: $\lambda^r_{i,k}$, charging stage index of type-r loads being served at stage $j = 1,2, \ldots, \tau^r$, at time step $k = 1,2, \ldots, T$.

Procedure:

For each row j of Λ^r, $j = 1, \ldots, \tau^r$

$temp = 1$;

For each column k of Λ^r, $k = 1, \ldots, T$

$\lambda^r_{i,k} = 0$;

For $i = temp\ to\ (temp + \lambda^r_{j,k})$

$\lambda^r_{i,k} = j$;

End

$temp = temp + \lambda^r_{j,k}$;

End

End

Here is an example to illustrate the algorithm. Suppose type-r loads have population $N^r = 10$, total number of charging stages $\tau^r = 3$, and scheduling horizon $T = 5$. The optimization problem P_p produces

$$B^r = \underbrace{\begin{bmatrix} 6 & 2 & 2 & 0 & 0 \\ 0 & 4 & 4 & 2 & 0 \\ 0 & 0 & 2 & 6 & 2 \end{bmatrix}}_{Time\ 1\ \rightarrow\ 5} \begin{array}{l} Stage \\ 1 \\ 2 \\ 3 \end{array} \tag{2.8}$$

Then, the outcome of Algorithm 1 generates

$$\Lambda^r = \underbrace{\begin{bmatrix} 1 & 2 & 3 & 0 & 0 \\ 1 & 2 & 3 & 0 & 0 \\ 1 & 2 & 0 & 3 & 0 \\ 1 & 2 & 0 & 3 & 0 \\ 1 & 0 & 2 & 3 & 0 \\ 1 & 0 & 2 & 3 & 0 \\ 0 & 1 & 2 & 3 & 0 \\ 0 & 1 & 2 & 3 & 0 \\ 0 & 0 & 1 & 2 & 3 \\ 0 & 0 & 1 & 2 & 3 \end{bmatrix}}_{Time\ \ 1\ \rightarrow\ 5} \begin{array}{l} Loads \\ 1 \\ \vdots \\ \downarrow \\ \vdots \\ 10 \end{array} \tag{2.9}$$

This matrix indicates at any time step, which charging stage each load needs to be served. A zero in the matrix tells that the corresponding load needs to be turned off at that time step. For instance, load 3 will be turned on at time step 1, 2 and 4, for charging stage 1, 2 and 3, respectively. In summary, the static approach to deal with the power management problem is solving the optimization problem P_p followed by executing Algorithm 1. Algorithm 1 is extremely light in computation effort, with complexity linearly proportional to the load population size and independent of how P_p is solved; therefore, next we only need to focus on the receding horizon implementation of the optimization problem P_p. Receding horizon (RH) control provides a method to extend the above static optimization work to real-time power scheduling so that the dynamic changes of the power network can be taken into account and real time pricing rates could be applied to the customers. In general, RH works by solving optimization over the next T time steps, executes the first time step decision, and resolve the optimization problem for the next T time steps by incorporating new measurement data available at the moment. In short, RH scheme repeats the process of optimization, execution, and adaptation.

In this section, we present two schemes of receding horizon optimization: a global scheme and a local scheme, for our power management problem. Both these receding horizon formulations deal with the power management problem for a fixed time duration $[1, T]$. The process of optimization is illustrated in Fig. 2.6. At each

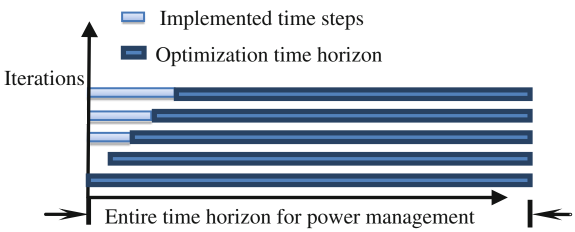


Fig. 2.6 Time horizons for receding horizon optimization

of iteration, the optimization problem will be updated by considering the changes of loads. For example, the entire time horizon is assumed to be $[1, 24]$ for 24-h period. The first iteration solve the optimization in time horizon $[1, 24]$, the second iteration considers optimization horizon $[2, 24]$, and so on. Our RH algorithm for power management problem follows the procedures listed in Algorithm 2. The formulation of receding horizon optimization problem mentioned in part c of Step 2 will be the focus of the rest of the section.

Algorithm 2 *(Receding Horizon Algorithm):*

Procedures:

Step 1. Set $k = 0$ *and solve optimization problem* P_p *followed by Algorithm 1.*

Step 2. At time step k:

a) Issue charging services scheduled at time step $k - 1$.
b) Collect updates in the network (dropouts and newcomers).
c) Solve the updated receding horizon optimization problem.

Step 3. Repeat *Step 2* procedure with $k = k + 1$ until $k = T$.

One major benefit of receding horizon approach is the ability to incorporate updated information; in EV charging power management, updates may include newly arrived charging requests as well as dropped outs. For example, a customer gets home late and plugs his EV to the grid hoping the charging to complete on time as usual. On the other hand, it is possible that existing requests are dropped from the system at time step k; for instance, some customers may unplug their devices in the middle of charging for an unplanned trip. The charging service requests come and go dynamically. The load controller equipped at the customer end monitors such condition and reports to the aggregator through a two-way communication link.

Complete Receding Horizon Optimization Consider the iteration at time step k. A few matters need our attention regarding the formulation of receding horizon optimization. First, decision variables here will be denoted by $\beta_i^r(j)$, instead of $\beta_k^r(j)$ as in problem P_p, to represent the total number of type-r loads being charged at charging stage j at time step i, where $i \in [1, T]$ is the time index, $j \in \{1, \ldots, \tau^r\}$ the charging stage index, and $r \in [1, \ldots, m]$ the load type index. The reason for this notation change is that only values of $\beta_i^r(j)$ at $i = k + 1$ will be implemented in this iteration, and the rest of values will be discarded. In addition, note that, at time step k, the loads being scheduled at past and present time steps, $1, 2, \ldots k$, have been implemented and cannot be rescheduled; hence we only need to solve for $\beta_i^r(j), i \in [k + 1, T]$. To keep the formulation consistent, we still consider the optimization horizon to be $[1, T]$ by constraining $\beta_i^r(j)$ to be zero for any $i \leq k$.

Secondly, due to the fact that problem P_p deals with groups of loads instead of individuals, the receding horizon optimization needs to be reformulated since individual loads in the same group may have undergone different charging services during previous execution stage. More specifically, for the same load type, at time steps $1, 2, \ldots, k$, some are powered on and others off, and for the ones being on, they may be at different charging stages. Therefore, at time step k, the optimization needs to keep track of and consider the existing state of the network due to all these executions.

Thirdly, before solving the optimization at time step k, the aggregator of the power system collects the messages sent from the loads about changes of the network. When a charging load withdraws its service request, a withdraw signal is triggered and sent by the load controller to the aggregator, similar to the case when a new charging request arrives. These changes are formulated below.

At time step k, let $D_k^r(j)$ denote the number of loads dropped out after they completed charging stage j and before their services are completed, where $j = 1, 2, \ldots, \tau^r - 1$. Note that a load is not counted as a dropout if its charging service is completed. Then, at time step k, the total number of type-r loads exiting abnormally from the network is

$$D_k^r = \sum_{j=1}^{\tau^r - 1} D_k^r(j) \tag{2.10}$$

Further, denote A_k^r the number of type-r loads newly arrived at the present time step k; thus, the total number of type-r loads currently in the network is

$$N_k^r = N_{k-1}^r - D_k^r + A_k^r \tag{2.11}$$

with $N_0^r = N^r$ and $k = 1, 2, \ldots, T - 1$.

Among the type-r loads in the network at time step k, we use $\theta_k^r(j)$ to denote the number of loads having completed stage j charging and waiting for stage $j + 1$, $j = 1, 2, \ldots, \tau^r - 1$. Then, it follows that,

$$\theta_k^r(j) = \theta_{k-1}^r(j) + \bar{\beta}_k^r(j) - \bar{\beta}_k^r(j+1) - D_k^r(j) \tag{2.12}$$

where $\bar{\beta}_k^r(j)$ and $\bar{\beta}_k^r(j+1)$ are calculated in the previous iteration and currently implemented, with $\bar{\beta}_k^r(j)$ being the number of loads served with stage j charging at the current time step, and $\bar{\beta}_k^r(j+1)$ being the number of loads served with stage $j + 1$ charging.

With the above notation, we present below the receding horizon optimization problem solved at each time step k in Algorithm 2.

Problem P_p^{CRH} (***Complete Receding Horizon Optimization***) Find $\beta_i^r(j)$ to

$$\text{Min} \sum \sum_{i=1}^{T} C\left(\sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \beta_i^r(j) p^r(j)\right) + \text{Max} \sum_{i=1}^{T} E_D \tag{2.13}$$

subject to the following constraints:

(a) $\beta_i^r(j) \in \mathcal{Z}^+$ for $i = 1, \ldots T$, $j = 1, \ldots \tau^r$, and $r = 1, \ldots, m$.
(b) $\beta_i^r(j) = 0$ for any $i < \max(a^r, k + 1)$ or $k > b^r$.

(c) $\sum_{j=1}^{\tau^r} \beta_i^r(j) \leq N_k^r$, for $i = 1, \ldots T$, $r = 1, \ldots, m$.
(d) $\sum_{i=1}^{T} \beta_i^r(j) = N_k^r - \left[\theta_k^r(j) + \theta_k^r(j+1) \cdots + \theta_k^r(\tau^r)\right]$, for any $j = 1, \ldots, \tau^r$, $r = 1, \ldots, m$.
(e) $\sum_{i=1}^{n+1} \beta_i^r(j+1) \leq \sum_{i=1}^{n} \beta_i^r(j) + \theta_k^r(j)$, for all $n = 1, \ldots, T-1$, $j = 1, \ldots, \tau^r$, $r = 1, \ldots, m$.

The constraints of problem P_p^{RH} are explained in the following. Constraint (a) requires number of loads to be integers, and constraint (b) states that no type-r loads will be scheduled beyond its required horizon $[a^r, b^r]$, and no loads will be scheduled for present or past time steps. Note that due to constraint (b), the cost function satisfies

$$\begin{aligned} &\sum_{i=1}^{T} C\left(\sum_{r=1}^{m}\sum_{j=1}^{\tau^r} \beta_i^r(j) p^r(j)\right) + \sum_{i=1}^{T} E_D \\ &= \sum_{i=k+1}^{T} C\left(\sum_{r=1}^{m}\sum_{j=1}^{\tau^r} \beta_i^r(j) p^r(j)\right) + \sum_{i=k+1}^{T} E_D \end{aligned} \tag{2.14}$$

That is, as iteration advances, the lower bound of the optimization time horizon increases while the upper bound keeps the same, which is consistent with the optimization time horizon illustration in Fig. 2.7.

The last constraint (e) sets the sequencing requirement of charging stages, i.e., for any loads, charging stage $j+1$ cannot start before completion of stage j. The left side of the inequality is the total number of loads having been serving with stage $j+1$ charging up to time step $n+1$, and the first term on the right,

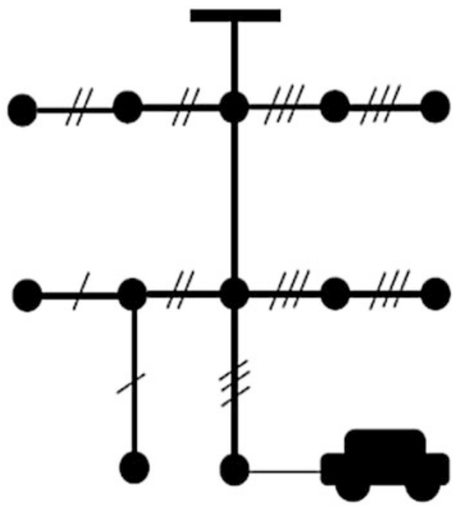


Fig. 2.7 IEEE 13 node system

$$\sum_{i=1}^{n} \beta_i^r(j) = \sum_{i=k+1}^{n} \beta_i^r(j), \tag{2.15}$$

represents the number of loads having gone through stage j during duration $[k+1, n]$, and the second term $\theta_k^r(j)$ includes the number of loads having gone through stage j before or at time step k. Two terms on the right together comprises the number of loads completed stage j prior to time step $n+1$.

The constraint (c) and (d) will be explained with the matrix

$$B^r = \underbrace{\begin{bmatrix} \beta_1^r(1) & \beta_2^r(1) & \cdots & \beta_T^r(1) \\ \beta_1^r(2) & \beta_2^r(2) & \cdots & \beta_T^r(2) \\ \vdots & \vdots & \vdots & \vdots \\ \beta_1^r(\tau^r) & \beta_2^r(\tau^r) & \cdots & \beta_T^r(\tau^r) \end{bmatrix}}_{\text{Time step } \to\to} \begin{array}{l} \text{Charging} \\ \text{Stage}\, j \\ \downarrow \\ \downarrow \end{array} \tag{2.16}$$

Column sum of the matrix B^r is the total number of loads being powered on at one time step, and this number should be less than the total number of loads currently being present in the network; this explains constraint (c). Row sum of the matrix is handled in constraint (d), which is the total number of loads being allocated at each charging stage over time. This number should be no more than the number of loads currently in the network waiting for the service. This number is obtained by the total number of loads N_k^r in the network subtracting the sum, $\left[\theta_k^r(j) + \theta_k^r(j+1) \cdots + \theta_k^r(\tau^r)\right]$, which contains the loads which doesn't need stage j charging.

Overall, this complete receding horizon algorithm for power management is summarized in Algorithm 3.

Algorithm 3 ($Complete\ Receding\ Horizon\ Algorithm$)

Procedures:

Step 1. Set $k = 0$, $\theta_0^r(j) = 0$ and $N_0^r = N^r$. Solve optimization problem P_p^{CRH} to obtain $\beta_i^r(j)$ for $i = 1, \ldots, T, j = 1, \ldots, \tau^r$, and $r = 1, \ldots, m$.

Step 2. At time step k:

a) Issue charging services $\beta_k^r(j)$ for all j and r.
b) Let $\bar{\beta}_k^r(j) = \beta_k^r(j)$ for time step k, and obtain $D_k^r(j)$ and A_k^r from the aggregator. Update:

$$N_k^r = N_{k-1}^r - \sum_{j=1}^{\tau^r-1} D_k^r(j) + A_k^r \tag{2.17}$$

$$\theta_k^r(j) = \theta_{k-1}^r(j) + \bar{\beta}_k^r(j) - \bar{\beta}_k^r(j+1) - D_k^r(j) \tag{2.18}$$

c) Solve the updated receding horizon optimization problem P_p^{CRH}.

Step 3. Repeat *Step 2* procedure with $k = k + 1$ until $k = T$.

Partial Receding Horizon Optimization In the previous scheme of complete receding horizon optimization, the power management optimization is redone at each iteration for the entire network of EV charging. Here, we present a scheme by optimizing only a small part of the network.

Let us consider the formulation of the optimization problem for time step k. New EV charging requests may arrive at time step k, and we denote them as a new-arrival family $\tilde{F}_k = \{(l^1, \tilde{N}_k^1), \ldots, (l^m, \tilde{N}_k^m)\}$ with $l^r = \{a^r, b^r, \tau^r, p^r\}$ representing the type-r load characteristics, $r = 1, 2, \ldots, m$. Note that the only difference between $\tilde{F}_k$ and F (existing loads) is the population size of each load type. At this time step, previous approach is to execute the scheduled action for time step k, update the status of the existing requests, and combine the existing and new-arrived requests as a new family of power tasks. Here we look at a somewhat different action.

Now we consider the existing condition of the network at time step k. From the scheduling of the last iteration, $\beta_i^r(j)$ indicates the number of type-r loads being served with charging stage j at time step $i = k, k+1, \ldots, T$. With the same notation as in the complete receding horizon scheme, let $D_k^r(j)$ denote number of loads dropped out after they finish charging stage j at time step k. For convenience of formulation, define

$$D_i^r(j) = \begin{cases} D_k^r(j) & i = k \\ 0 & i \neq k \end{cases}. \tag{2.19}$$

Without considering newcomers, based on the previous iterative optimization, the power load at time step i, for $i = k+1, \ldots, T$, is

$$\bar{L}_i = \sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \left[\beta_i^r(j) - D_i^r(j)\right] p^r(j) \tag{2.20}$$

Again, we allow $i = 1, 2, \ldots, T$ by constraining $\beta_i^r(j)$ to be zero for $i = 1, 2, \ldots, k$, since the charging services have been conducted at these time steps and rescheduling is no longer necessary.

At time step k, the optimization problem here will keep the schedule from the previous decision, and allocates only the new arrivals. For this reason, the first part of $\bar{L}_i$ in 0 never changes from iteration to iteration, so $\bar{L}_i$ can be obtained recursively by

$$\bar{L}_i = \bar{L}_i - \sum_{r=1}^{m} \sum_{j=1}^{\tau^r} D_i^r(j) p^r(j) \tag{2.21}$$

The optimization is formulated below as problem P_p^{PRH}.

Problem P_p^{PRH} (*Partial Receding Horizon Optimization*)

Find $\tilde{\beta}_i^r(j)$ to

$$\text{Min } \sum_{i=1}^{T} C\left(\sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \tilde{\beta}_i^r(j) p^r(j) + \bar{L}_i\right) + \text{Max} \sum_{i=1}^{T} E_D \tag{2.22}$$

subject to the following constraints:

(a) $\tilde{\beta}_i^r(j) \in \mathbf{Z}^+$ for $i = 1, \ldots T, j = 1, \ldots \tau^r,$ and $r = 1, \ldots, m.$
(b) $\tilde{\beta}_i^r(j) = 0$ for any $i < \max(a^r, k+1)$ or $k > b^r.$
(c) $\sum_{j=1}^{\tau^r} \tilde{\beta}_i^r(j) \leq \tilde{N}_k^r,$ for $i = 1, \ldots T,\ r = 1, \ldots, m.$
(d) $\sum_{i=1}^{T} \tilde{\beta}_i^r(j) = \tilde{N}_k^r,$ for any $j = 1, \ldots, \tau^r, r = 1, \ldots, m.$
(e) $\sum_{i=1}^{n+1} \tilde{\beta}_i^r(j+1) \leq \sum_{i=1}^{n} \tilde{\beta}_i^r(j),$ for all $n = 1, \ldots, T-1, j = 1, \ldots, \tau^r,$ $r = 1, \ldots, m.$

In the above formulation, $\bar{L}_i$ are known constants for $k = 1, 2, \ldots, T$, as calculated in 0, which indicates the power amount at each time step if the charging schedules for the existing EV loads keep the same. The decision variables are $\tilde{\beta}_i^r(j)$, the number of newly-arrived type-r requests. Note that the optimization is conducted only on the new arrivals. In the situation where traffic of new arrivals is light, this small-size scheduling problem can be conveniently solved with heuristic algorithms such as Largest Energy Consumption First and Longest Process Time First.

In summary, the procedure of partial RH algorithm is listed as Algorithm 4 below.

Algorithm 4 (*Partial Receding Horizon Algorithm*):

Procedures:

Step 1. Set $k = 0$. Solve the original optimization problem P_p to obtain $\beta_i^r(j)$ for $i = 1, \ldots, T, j = 1, \ldots, \tau^r$, and $r = 1, \ldots, m$.

Let $\tilde{\beta}_0^r(j) = \beta_0^r(j)$ and

Calculate

$$\bar{L}_i = \sum_{r=1}^{m} \sum_{j=1}^{\tau^r} \beta_i^r(j) p^r(j) \tag{2.23}$$

Step 2. At time step k:

a) Issue charging services $\beta_k^r(j)$ for all j and r.
b) Obtain $D_k^r(j)$ and F_k from the aggregator. Update:

$$\bar{L}_i = \bar{L}_i - \sum_{r=1}^{m} \sum_{j=1}^{\tau^r} D_i^r(j) p^r(j) \tag{2.24}$$

c) Solve the updated receding horizon optimization problem P_p^{PRH}.

Step 3. Repeat *Step 2* procedure with $k = k + 1$ until $k = T$.

The goal of optimization module is to minimize the distribution network losses and to maximize the energy transferred from the grid to PEVs. Hence the optimization problem is a multi objective optimization problem for which we have used a bacterial foraging optimization algorithm. Bacterial Foraging Optimization (BFO) algorithm has been applied to model the E. coli bacteria foraging behavior for solving optimization problems. It is known that bacteria swim by rotating whip-like flagella driven by a reversible motor embedded in the cell wall. For E. coli have 8–10 flagella placed randomly on a cell body. When all flagella rotate counterclockwise, they form a compact, helically propelling the cell along a helical trajectory, which is called run. When the flagella rotate clockwise, they all pull on the bacterium in different directions, which causes the bacteria to tumble. The cycle of optimization can be divided into three parts: Chemotaxis, Reproduction, Elimination and Dispersal. Interested readers can refer to [44] for more detailed explanation about BFO. The following section explains Multi Objective bacterial Foraging Optimization method.

Since the BFO algorithms could solve single-objective optimization problems, the idea of solving multi-objective optimization problems with BFO algorithms was tested. However, the purpose of multi-objective optimization problems is to find all values which are possibly satisfied to all functions. Since different decision makers have different ideas about objective functions, it is not easy to choose a single solution for a multi-objective optimization problem without interaction with the decision makers. Thus, all we could do is to show the set of Pareto optimal solutions to decision makers. The main goal of multi-objective optimization problems is to obtain a non-dominated front which is close to the true Pareto front. The details of the new optimization algorithm based on BFO are given in the following sections.

In what follows we briefly outline the Multi-objective Bacterial Foraging Optimization (MBFO) step by step:

Algorithm 5 $(Multi - Objective\ Bacterial\ Foraging\ Optimization$

Algorithm MBFO

```
Begin
    Initialize all the parameters and positions
    While (a terminate-condition is met)
        For (Elimination-dispersal loop)
            For (Reproduction loop)
                For (Chemotaxis loop)
                    Compute two fitness functions J1 and J2 .
                    Let J last1 = J1, and J last2 = J2
                    Update of the positions
                End For (Chemotaxis)
                Compute two health values Jhealth1 and J health2
                Sort bacteria based on health values
                Copy the best bacteria
            End For (Reproduction)
            Eliminate and disperse each bacterium with probability Ped
        End For (Elimination-dispersal)
    End While
End
```

2.8 Case Study Simulation and Results

For verification and validation of the proposed smart coordination infrastructure, two test systems were considered for simulation purposes. The first system is a IEEE 13 node distribution system with PEV charging system (Figs. 2.7 and 2.8).

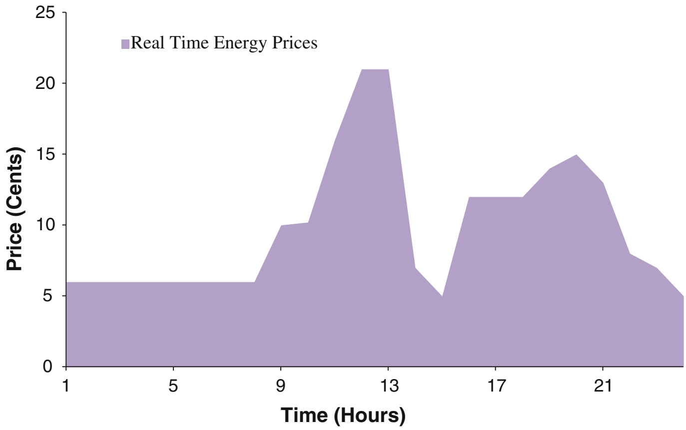


Fig. 2.8 Real time energy prices

Different penetration levels of PEVs have been considered. Reference [45] obtained that the capacity of this network for PEV charging station is equal to 1.2 MW, in case of unity power factor consideration. In this study, we have considered 20, 40 and 60 % penetration level based on the maximum capacity of the charging station, to see the impact of PEVs charging demand's increment on losses in the lines and energy transferred. In addition, the supervision system is considered in parallel to compare the improvement level of voltage profile and losses reduction. The results of supervised charging are labeled as coordinated, whereas unsupervised charging results are marked as uncoordinated.

In order to assess the state of a smart grid subject to PEV charging as well as generation status, voltage profile, and power losses necessary for the objective function and checking of constraints, a modified Newton-based load flow routine is used. All loads are modeled as constant power loads with their real and reactive powers updated through a daily load curve for each time interval the load flow is performed.

IEEE 13 node system The results of simulation are presented in Figs. 2.9 and 2.10. In Fig. 2.9, charging power of arriving vehicles in uncoordinated charging makes a peak demand at 19:00, which is increasing with more penetration level. While in the smart coordinated charging, the same charging power is distributed after the peak-hours until departure time of the vehicles. So the vehicles will be charged at the off-peak hours from 22:00 to 9:00 approximately. In addition, with the help of V2G application, from 13:00 to 20:00, capable vehicles with respect to their arrival SOC, participate in injecting power to the grid, i.e., V2G is enabled.

These results could be considered as global optimum, as a multi-objective bacterial foraging optimization algorithm has been considered to minimize cost of power losses and maximize energy transferred, where at each instant the a priori optimal result is taken into account. Finally, from network losses point of view, it is

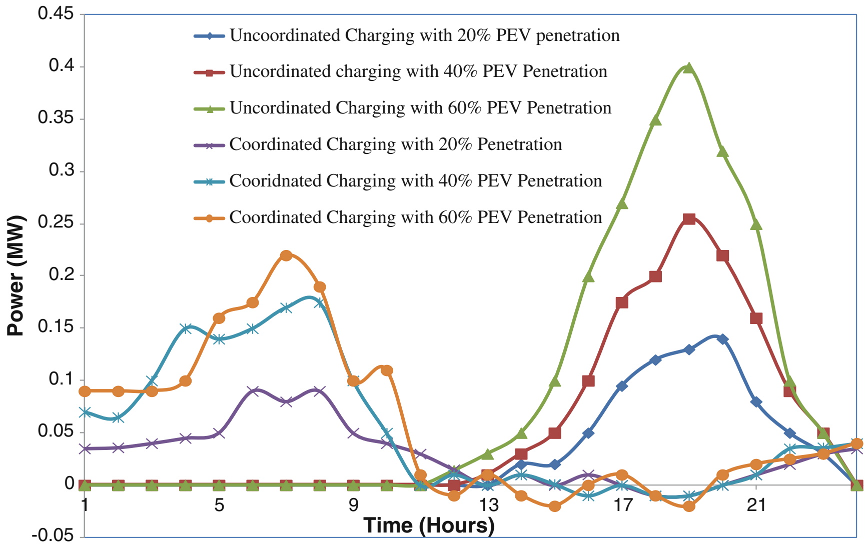


Fig. 2.9 Power drawn by PEVs for charging

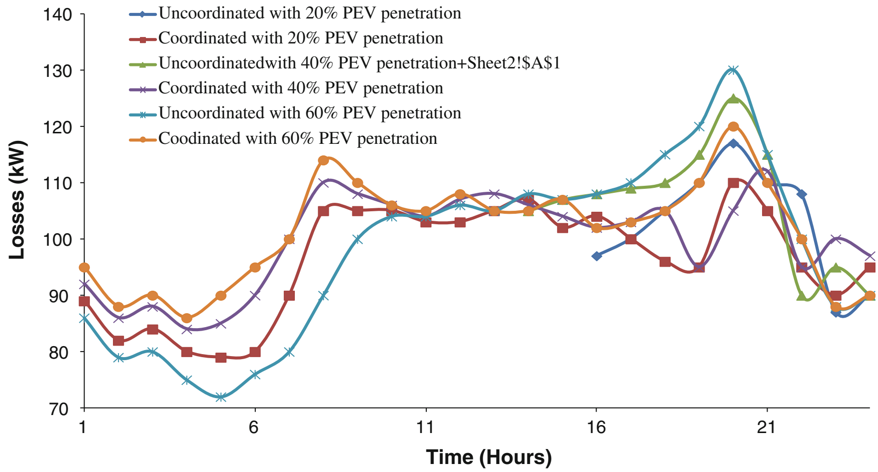


Fig. 2.10 Variation of total power losses in the system

shown in Fig. 2.10 that maximum losses at 20:00 with 50 % penetration is reduced with using coordinated charging strategy. Peak-hours charging avoidance is an important criteria from loss reduction point of view, which in this algorithm is implemented successfully. The multi objective bacterial foraging algorithm has resulted in a minimum loss and also maximum energy transferred to the PEVs. Under uncoordinated operation of the system and, low penetration of PEVs, the

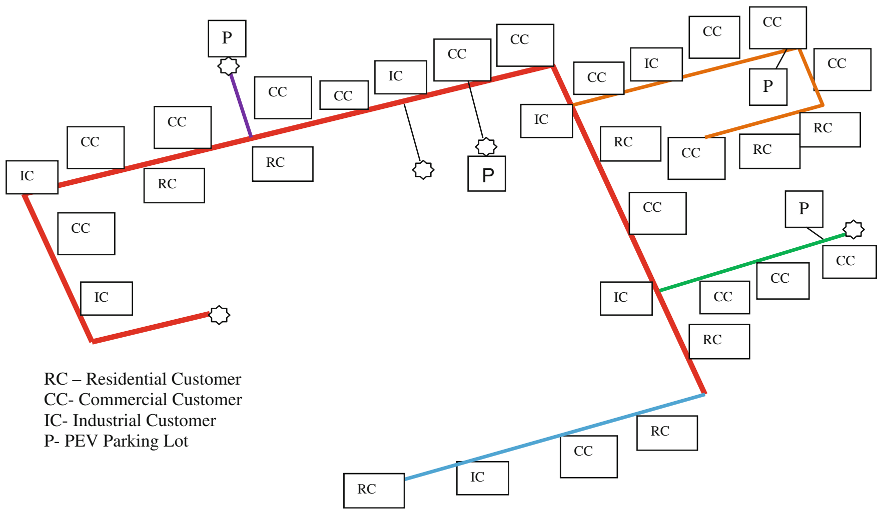
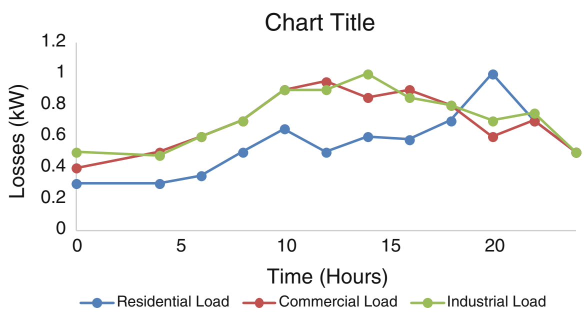


Fig. 2.11 Distribution feeder—38 bus system

system allows all the PEVs to be charged without violating the technical limitations and constraints imposed on the system. On the other hand, the smart coordination method even during the regular load peak, PEV charging is limited due the prediction module and optimization module functioning hand in hand to reduce the power losses and to maximize power transferred so that system reliability is preserved.

Bus Distribution Test Feeder The total system peak load is 4:37 MVA. The system line data, customer type, and load point demand are as given in [46]. The system contains four parking lots as shown in Fig. 2.11. Two cases of PEV penetration levels (20 and 40 %) were considered because above 40 % penetration level, PEV loads resulted in violation of several system constraints under uncoordinated charging. Load profile is given in Fig. 2.12.

Fig. 2.12 Load profile of the 38 bus system with residential, commercial and industrial loads



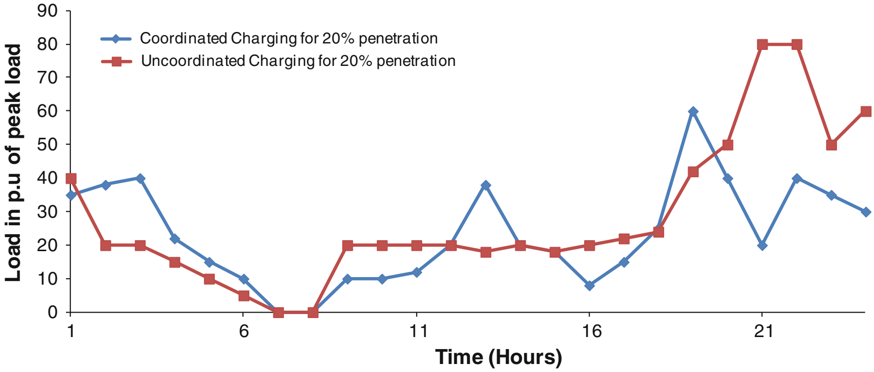


Fig. 2.13 Variation of total power losses in the system for 20 % penetration

The resulting coordinated and uncoordinated charging results for 20 and 40 % penetration of PEV's is shown in Figs. 2.13, 2.14 and 2.15.

Comparing the uncoordinated charging and smart coordination results, it is evident that a significant improvement in performance is achieved with the help of the proposed approach. Most importantly, the system peak demand is reduced which is very advantageous from the standpoint of generation dispatch and preventing overloads. Comparison of results in Figs. 2.9, 2.10, 2.12, 2.13, 2.14 and 2.15 also indicates that energy transferred to the PEV is increased compared to the uncoordinated case. Furthermore, peak power losses have been reduced to a fraction of the uncoordinated case. The computing time required by BFO to arrive at these solutions was in the range of 3 ms for each time period considered.

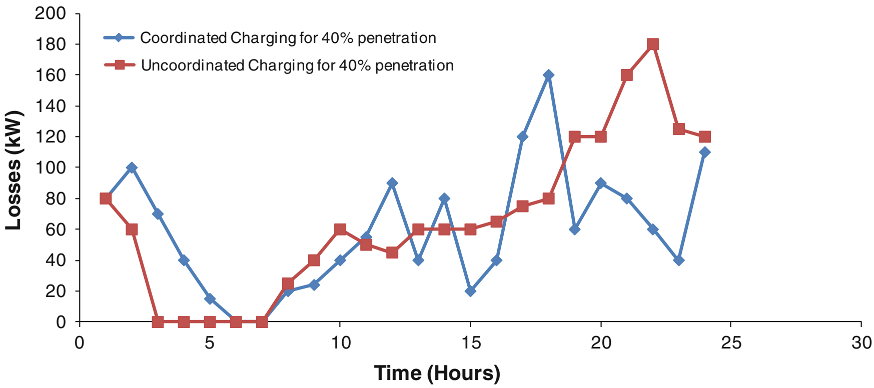


Fig. 2.14 Variation of total power losses in the system for 40 % penetration

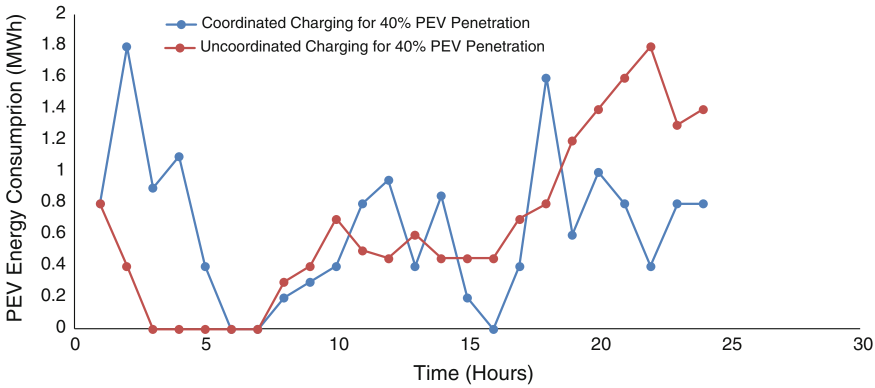


Fig. 2.15 Variation of maximum energy transferred to PEV over a 24 h period in the system for 40 % penetration

2.9 Conclusion

In this chapter, a real time system for managing the dynamics associated with charging/discharging of PEVs in a grid has been proposed. The smart coordination approach for power management incorporates a forecasting module and an optimization module. For a superior coordination of PEV charging/discharging, the forecasting module comprising of a receding time horizon approach provides information about the PEV loads for the next interval. Then the optimization module comprising of BFO based technique guarantees that the power management strategy results in minimum distribution network losses and maximum energy transferred to the PEV. This smart coordination approach has been implemented on two different test systems with varying levels of penetration. The results from simulation demonstrate the versatile performance of the smart coordination approach. This implementation is very appropriate for practical implementation as the computation time required by receding time horizon method and BFO based approach are of the order of milliseconds.

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