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Research Article

Performance of Heuristic Optimization in Coordination of Plug-In Electric Vehicles Charging

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Abstract

A heuristic load management (H-LMA) algorithm is presented for coordination of Plug-in Electric Vehicles (PEVs) in distribution networks to minimize system losses and regulate bus voltages. The impacts of optimization period T (varied from 15 minutes to 24 hours) and optimization time interval (varied 15 minutes to one hour) on the performance, accuracy and speed of the H-LMA is investigated through detailed simulations considering enormous scenarios. PEV coordination is performed by considering substation transformer loading while taking PEV owner priorities into consideration. Starting with the highest priority consumers, H-LMA will use time intervals to distribute PEV charging within three designated high, medium and low priority time zones to minimize total system losses over period T while maintaining network operation criteria such as power generation and bus voltages within their permissible limits. Simulation results generated in MATLAB are presented for a 449 node distribution network populated with PEVs in residential feeders.

Index Terms- Heuristic optimization, electric vehicles and load management.

Introduction

Preliminary studies by Amin et al. (2005), Amin (2008) and Lightner et al. (2010) indicate that Plug-In Electric Vehicles (PEVs) will dominate the market in the near future as pollution-free alternatives to the conventional petroleum- based transportation. However, according to Moses et al. (2010), Masoum et al. (2011) and Moses et al. (2012), uncoordinated PEV charging specially at high penetration levels during the peak load hours may cause undesirable impacts on the power grid such as unpredictable system peaks, unaccepted voltage deviations, significant increases in losses and poor power quality, as well as overloading of the distribution and substation transformers. This has motivated researchers to propose and implement different PEV coordination algorithms.

In general, PEV chargers can be controlled to operate in charge or discharge modes with the energy being transferred from grid to vehicle (V2G) or from vehicle to grid (G2V), respectively. One of the first approaches for PEV coordination based deterministic and stochastic dynamic

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programing was presented by Clement-Nyns et al. (2010). Masoum et al. (2011) performed peak load saving with PEV coordination without considering the random nature of PEV arrivals and departures. A relatively fast PEV coordination algorithm suitable for online applications is proposed by Deilami et al (2011). Ashtari et al. (2012) predicted PEV charging profiles and electrical range reliability based on recorded vehicle usage data. Wu et al (2012) designed a minimum-cost load scheduling algorithm based on the forecasted electricity price and PEV power demands. In a research study by Khodayar et al. (2012) and Zhao et al. (2012), the PEV coordination problem is performed considering the impact of wind power generation. Wen et al. (2012) and Ma et al. (2013) have presented decentralized charging control algorithms considering large populations of PEVs. There are also many documents investigating the operation of PEVs in V2G mode to support the grid by performing frequency regulation and/or energy storage including the research performed by Bashash et al. (2012), Han (2010) and Sortomme et al. (2011).

This paper will first present a heuristic load management algorithm (H-LMA) to coordinate PEV charging activities while reducing system losses and regulating bus voltages over a 24 hour period. Then, simulation results will be presented for a 449 node distribution network populated with PEVs in residential feeders. Finally, the impacts of heuristic optimization parameters including optimization period T and optimization time interval Δt on the accuracy and speed of H-LMA will be investigated.

Problem Formulation

PEV charge coordination is a constrained optimization problem that could be solved by using online algorithms (i.e., PEV coordination is performed as soon as vehicles are randomly plugged-in) or offline schemes (i.e., all vehicles are assumed to be plugged-in according to their pre-known/forecasted charging patterns). This paper assumes the charging patterns of all PEVs are known or forecasted and utilizes a heuristic approach to solve the optimization problem.

The optimization problem objective function is formulated based on the minimization of total system power losses:

$$min\ W_{loss} = \sum_{t} P_t^{loss}, \quad t = \Delta t, 2\Delta t, 3\Delta t, \ldots T$$

(1)

$$P_t^{loss} = \sum_{k=1}^{n-1} R_{k,k+1}\left(\left|V_{k+1} - V_k\right|\left|y_{k,k+1}\right|\right)^2$$

(2)

Where Δt and T are the optimization time interval and period used for loss minimization. P_t^{loss} is the system power loss at time t (computed using the Newton-based power flow), V_k is voltage of node k at time t, and n is total number of nodes while $R_{k,k+1}$ and $y_{k,k+1}$ are resistance and admittance of line section between nodes k and $k+1$.

PEV coordination constraints are node voltage limits and system demand level at time t:

$$V^{min} \le V_k \le V^{max} \quad for\ \ k = 1,..,n. \tag{3}$$

$$P_{max\,demand,t} = \sum_{k=1}^{n-1} P_{k,t}^{load} \le D_{max,t} \tag{4}$$

$V^{min} = 0.9pu$, $V^{max} = 1.1pu$, and $P_{max\,demand,t}$ is the total power consumption at time t, $P_{k,t}^{load}$ is the power consumption of node k at time t and $D_{m,t}$ is the maximum demand level at time t that would normally occur without any PEVs.

The load flow and proposed algorithm are coded using MATLAB software package. All parameters and variables are written in complex rectangular form.

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Heuristic Load Management Algorithm (H-LMA)

A MATLAB based algorithm has been developed to perform PEV scheduling based on H-LMA (Fig. 1). The algorithm will perform loss minimization over the optimization period T using time interval Δt based on Eqs. 1-2 while considering the system constraints (Eqs. 3-4). Three charging time zones are defined:

- Red charging zone (18:00h-22:00h) coinciding with most of the on-peak period and is designated for high-priority PEV owners willing to pay higher tariff rates in order to charge their vehicles as soon as possible.

- Blue charging zone (18:00h-01:00h) intended for medium-priority consumers that prefer to charge their vehicles at partially off-peak periods and pay lower tariff rates.

- Green charging zone (18:00h-08:00h) when most PEV charging will probably take place due to the cheapest tariff rates as most low-priority consumers will require their vehicles fully charged for the following day.

The algorithm assumes all PEVs are plugged in at 18:00 (6pm). It begins by first reading the input parameters (e.g., bus and branch impedance data, nodes with PEVs, optimization period T, optimization time interval Δt , designated priority time zones, load profiles for PEV chargers and residential loads as well as system constraints) and performing initialization (e.g., selecting the highest priority group, time zone and PEV).

The main program loop is progressing from high to low PEV priority groups (e.g., red zone to green zone). Within the selected priority group, individual PEVs are temporarily activated to determine system performance at all possible PEV nodes and charging time combinations within that priority charging time zone. From these combinations, the algorithm selects the PEV within the group and the charging start time resulting in the minimum system losses, taking into consideration the charging duration and the current demand level. The physical node location at which PEV charging occurs is an important factor as it impacts the load flow, power losses in the cables and system voltage profile. Therefore, the H-LMA determines the PEV node and charging time that will result in the least system losses (Eq. 2).

If at any time the load flow indicates a constraint violation at any node (Eqs. 3-4), the algorithm will try the next possible charging start time such that the constraints are satisfied. Therefore, it may not be possible for all PEV owners to be accommodated in their preferred charging zones and must be deferred to the next possible hour. Once it has been determined which PEV node in that priority group can begin charging and at what time resulting in minimum system losses, the selected PEV scheduling is permanently assigned and the system load curve updated ready for the next iteration. This process is repeated for all nodes in that priority group before advancing to the next priority-charging zone (e.g., blue zone subscribers). At the end of this process, the H-LMA arrives at individual schedules assigned to all PEV chargers. The program then exits the main loop and computes the 24 hour load flow to print new system performances (e.g., all node voltage profiles and power losses).

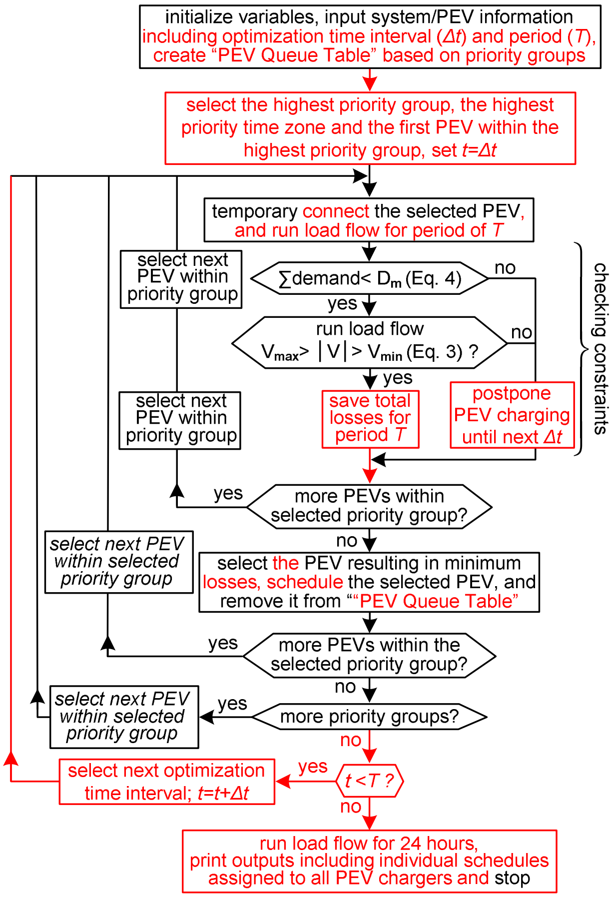


Fig. 1: Proposed H-LMA for Coordination of Pevs to Minimize Total System Losses over Period T Using Optimization Time Interval Δt Considering Node Voltage Profiles and Maximum Demand Level

Smart Grid Test System

The selected test system is a modification of the IEEE 31 bus 23 kV distribution systems (Deilami et al (2011)) combined with 22 residential 19 nodes LV 415 V networks populated with PEVs. The resulting 449 node system is supplied from the HV main bus via a 23kV/415V 100 kVA distribution transformer as shown in Fig. 2. System data are listed in the Appendix.

The peak power consumption of a house is assumed to be on average 2 kW with a power factor of 0.9. Four PEV penetration levels are selected including 16% (with nodes "o", "b" and "q" randomly designated with red, blue and green priorities, respectively), 32% (with nodes "o", "b, r" and "f, h, q" randomly designated with red, blue and green priorities, respectively), 47% (with nodes "o", "b, j, r" and "f, g, h, m, q" randomly designated with red, blue and green priorities, respectively) and 63% (with nodes "o, s", "b, d, j, r" and "f, g, h, k, m, q" randomly designated with red, blue and green priorities, respectively).

For this study, a 10 kWh battery capacity per PEV with a depth of discharge (DOD) of 70% and battery charger efficiency of 88% is assumed (Deilami et al (2011)) which will require a total of 8 kWh of energy from the grid to charge a single PEV. A standard single-phase 240V outlet (Australia) can typically supply a maximum of 2.4 kW. There are also 15A and 20A outlets (single-phase and three-phase) which can supply approximately 4 kW and 14.4 kW, respectively. In this paper, a fixed charging power of 4 kW is used.

Simulation Results and Discussion

Simulation results for uncoordinated and coordinated (using H-LMA of Fig. 1) PEV charging for the smart grid system of Fig. 2 are presented in Figs. 3-5 and Tables 1 and2.

Table 1: Comparison of Simulation Results for Uncoordinated and Coordinated (H-Lma, =15 Min, T=24 Hours) Pev Charging for the Smart Grid Test System of Fig. 3: Pevs are Assumed to be Randomly Arriving at Each Time Interval. For Comparison, Consumer Priorities are not considered and the Same Gaussian Random Distributions are Used in the Simulations.

Case Study	PEV Penetration level	CASE A: UNCOORDINATED PEV CHARGING (RANDOM CHARGING)			CASE B: COORDINATED PEV CHARGING (USING H-LMA OF FIG. 1)		
		Δloss* [%]	ΔV** [%]	I_{MAX}*** [%]	Δloss [%]	ΔV [%]	I_{MAX} [%]
NO PRIORITY, CHARGING PERIOD: 6PM-10PM	16%	2.3553	7.8499	0.5546	2.3332	7.646	0.47243
	32%	2.5312	9.2298	0.64324	2.4048	7.646	0.47243
	47%	2.9263	15.8182	0.77095	2.5849	10	0.51682
	63%	3.089	17.1467	0.88626	2.5963	9.9996	0.54002
NO PRIORITY, CHARGING PERIOD: 6PM-1AM	16%	2.3401	7.6984	0.52591	2.3149	7.646	0.44071
	32%	2.4712	8.5243	0.57259	2.4172	7.7832	0.45499
	47%	2.7659	13.9102	0.64256	2.5737	9.7039	0.45872
	63%	2.8706	14.7455	0.68842	2.6217	9.7946	0.49038
NO PRIORITY, CHARGING PERIOD: 6PM-8AM	16%	2.3141	7.7242	0.47831	2.2939	7.646	0.44071
	32%	2.3818	8.3553	0.52900	2.3411	7.646	0.44071
	47%	2.6188	13.6146	0.60348	2.4936	8.7893	0.44071
	63%	2.6184	14.3304	0.58385	2.4921	9.1211	0.44071

*) Ratio of system losses over 24 hours compared to total power consumption over 24 hours.
**) Voltage devataion at the worst bus.
***) Maximum of all distribution transformer load current.

A. Case A: Random PEV Charging

Simulation results of Fig. 3 and Table 1 highlight the detrimental impacts of uncoordinated PEV charging at four penetration levels. As expected and well documented, random charging, especially during the peak residential load hours (18:00-22:00), results in unpredictable power consumption peaks (Fig. 3(a), at 19:45 for 63% PEV penetration), unaccepted voltage deviations (Fig. 3(b), at node 15-i for 63% and 47% PEV penetrations at 19:45) and significant increase in losses (Fig. 3(c), 110kW, 85kW, 47kW and 30kW for PEV penetration levels of 63%, 47%, 32% and 16%, respectively, at 19:45). Detailed simulation results for this case study are presented in Table 1 (columns 3-5).

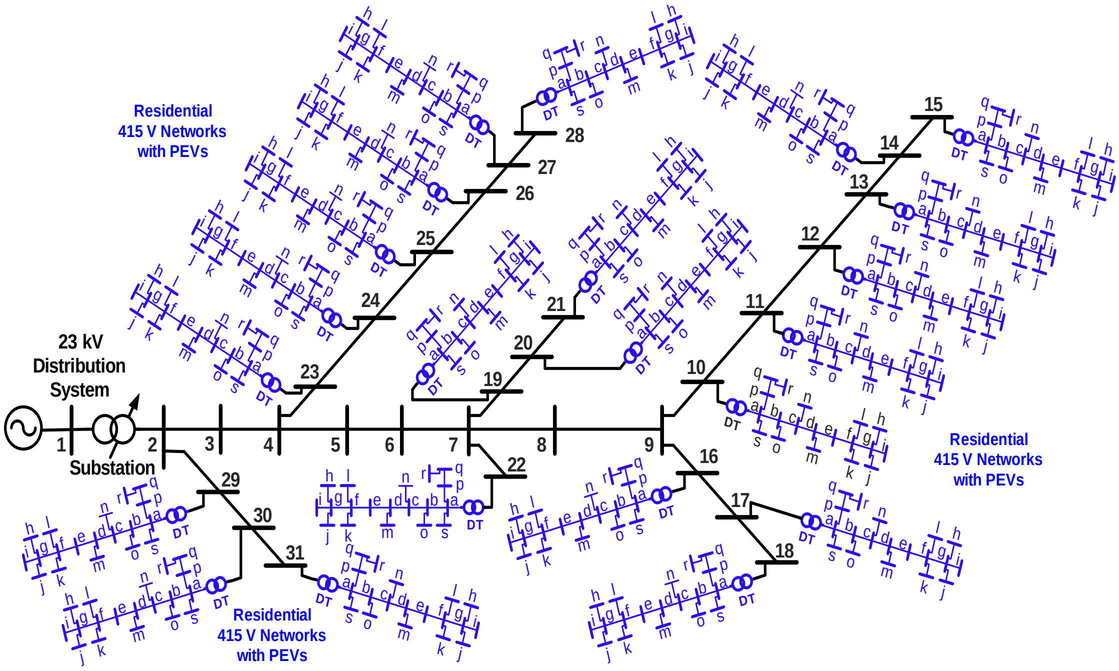
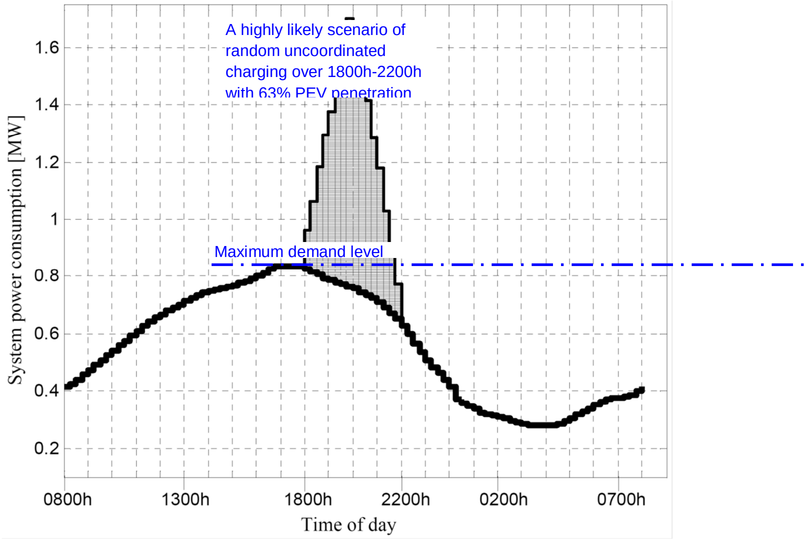


Fig. 2: The 449 Node Smart Grid Test System Consisting of the IEEE 31 Node 23 Kv System with Several 415 V Residential Feeders. Each Low Voltage Residential Network Has 19 Nodes Representing Customer Households Populated with Pevs Randomly Arriving within 24 Hours.



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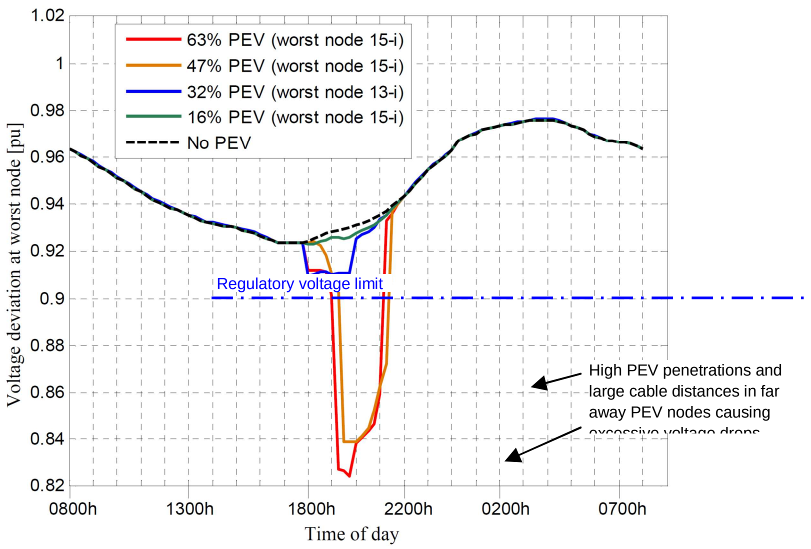

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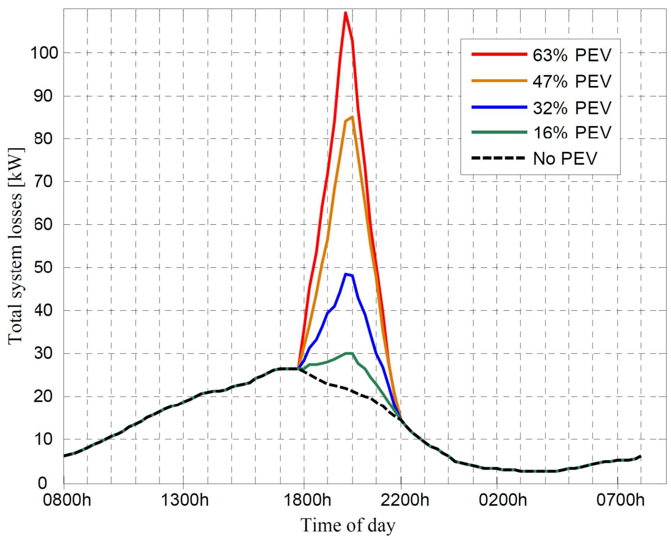

(c)

Fig. 3: Simulation Results (Δt =15 Min, T=24 Hours) for Random Uncoordinated PEV Charging Across the Red Zone (Case A1: 18:00h-22:00h); (A) System Power Consumption for 63% PEV Penetration, (B) Voltage Profile (For the Worst Affected Nodes), (C) Total System Power Losses.

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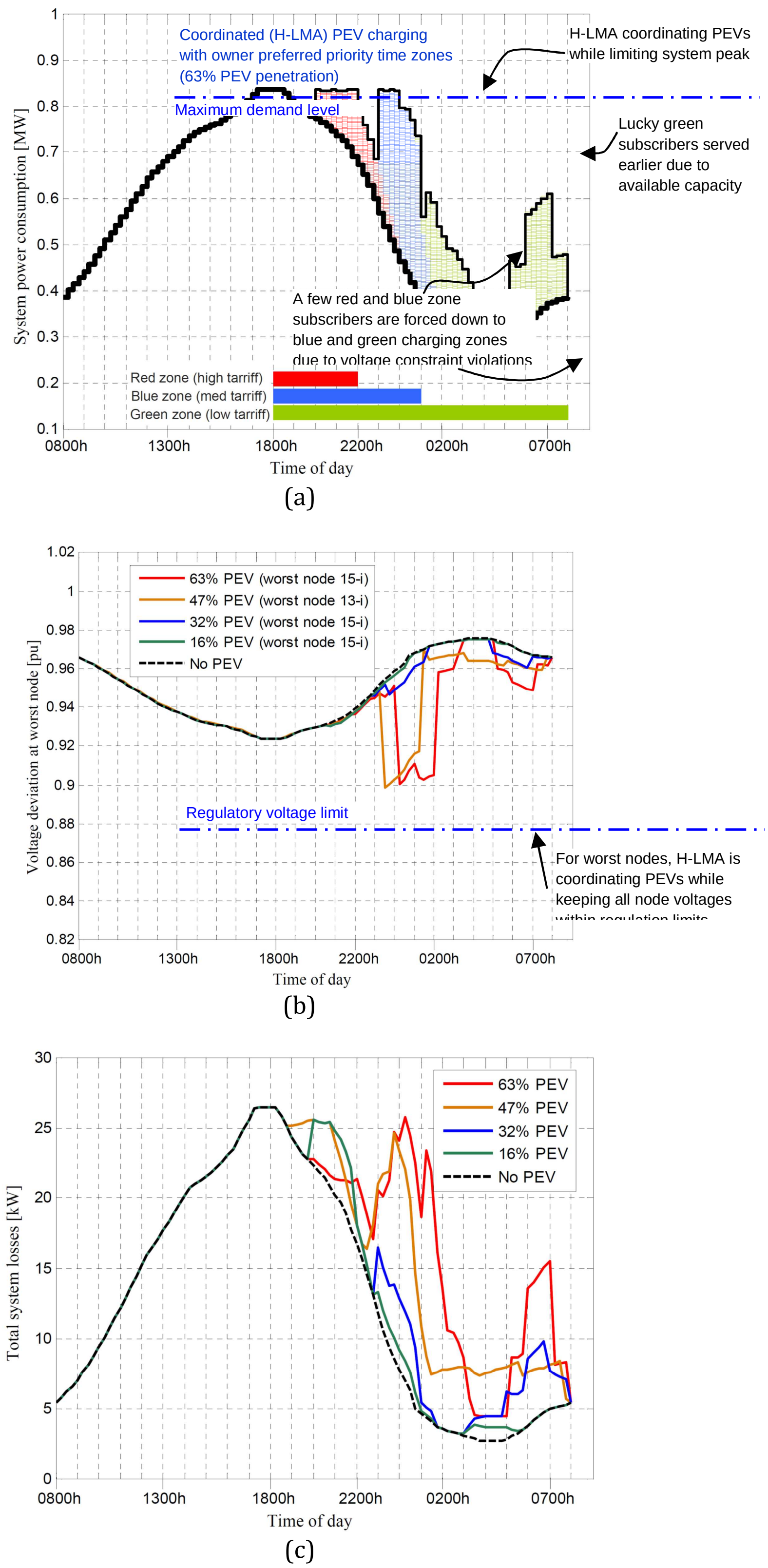

Fig. 4: Simulation Results (Δt =15 Min, T=24 Hours) for Coordinated PEV Charging Using the Proposed H-LMA of Fig. 1; (A) System Power Consumption for 63% PEV Penetration, (B) Voltage Profile (For the Worst Affected Nodes), (C) Total System Power Losses.

B. Case B: H-LMA Coordinated PEV Charging

Coordinated PEV charging is performed with (Fig. 4-5) and without (Table 1) PEV owner preferred time zone priorities. Compared to Case A, a significant improvement in smart grid performance is achieved. Most notably, the system demand peak has been reduced (Figs. 3(a) and 4(a)) which is more favorable from a standpoint of generation dispatch and preventing overloads.

Comparison of results also indicate the significant impacts of coordinated (H-LMA) PEV charging on voltage profile where the unacceptable voltage deviations of about 17% (Fig. 3(b)) at the worst bus for uncoordinated PEV charging is compensated to less than 10% (Fig. 4(b)) which is within the regulation limits. However, there is a trade off in that a few PEV subscribers who designated a preferred priority charging time zone were not accommodated in their requested charging zone (Fig. 4(a)) because the system reached a point where PEV loading caused voltage regulation to be violated. H-LMA handled these cases by attempting to schedule the PEV owners causing the violations to a charging time where the system is not under strain, thereby satisfying constraints.

The improvements in system efficiency with H-LMA coordination strategy are also evident in Table 1. Energy losses for the high penetration (63%) with H-LMA are limited to 2.59% of system consumption versus the worst uncoordinated charging scenario with losses of 3.09%.

Furthermore, peak power losses are limited to less than a third of the worst case random uncoordinated charging (Fig. 4(c)). The H-LMA charging also has positive impacts on peak transformer load currents. For many of the uncoordinated random charging scenarios (Table 1), distribution transformers are experiencing load currents of up to 0.88 pu, while with H-LMA coordination, transformer currents are reduced to levels of approximately 0.54 pu (Table 1).

C. Case C: Impacts of Δt and T on PEV Coordination

Detailed simulations are presented and compared in Table 2 to highlight impacts of Δt and T (Eq. 1) on the performance of H-LMA. In general, the speed and accuracy of the PEV coordination algorithms will depend on the selection of optimization time interval (Δt) and period (T).

The accuracy can be improved by using shorter time intervals (e.g., checking the status of PEVs and network as quickly as possible based on online information and measurements available through smart meters) and performing loss minimization over a long period (e.g., 24 hours). However, the drawback is the computing time will dramatically increase, especially in realistic large smart grids with many nodes and high penetration levels of PEVs. Therefore, a compromise should be made between the solution accuracy and computation time considering system size and the anticipated PEV penetration level.

Based on the results of Table 2, the practical options may be to use moderate time intervals with large optimization periods for offline PEV coordination (e.g., Δt =60 min and T=24 hours for applications where all vehicles are plugged-in or their charging patterns are known/forecasted before the start of optimization) and select small values for online PEV coordination (e.g., Δt =T=15 min to start charging batteries as soon as vehicles are randomly plugged-in).

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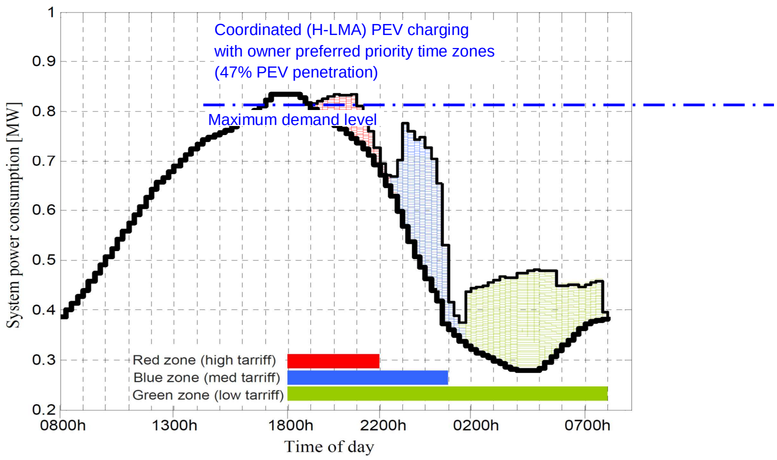
Table 2: Impact of Coordinated (H-Lma) Pev Charging with Diffident Optimization Time Interval ΔT And Period T (Eq. 1) Values on the Power Quality and Performance of Smart Grids Test System of Fig. 2.

Penetration of PEV [%]	COORDINATED PEV CHARGING (H-LMA) BASED ON LOSS MINIMIZATION (EQS. 1-4)				
	Δloss [%]	ΔV [%]	I_{MAX} [%]	E_{loss}* [kWh]	Computing time**
CASE B: Δt =15 MIN, LOSS MINIMIZATION OVER T= 24 HOURS					
16	2.336	7.646	0.443	326.4	15.7 mins
32	2.373	7.646	0.444	344.1	2.02 hrs
47	2.530	9.999	0.444	380.2	5.53 hrs
63	2.551	9.999	0.4801	396.9	6.29 hrs
CASE C: Δt = 60 MIN, LOSS MINIMIZATION OVER T= 24 HOURS					
16	2.319	7.646	0.440	321.2	5.2 mins
32	2.372	7.646	0.455	340.9	26.9 mins
47	2.520	9.996	0.441	375.6	1.14 hrs
63	2.530	9.562	0.450	390.4	1.55 hrs
CASE D: Δt = 15 MIN, LOSS MINIMIZATION OVER T= Δt = 15 MIN					
16	2.338	7.646	0.442	326.7	2.33 mins
32	2.375	7.646	0.462	344.4	17.67 mins
47	2.517	9.999	0.462	378.3	48.4 mins
63	2.529	9.999	0.458	399.4	56.9 mins

*) Total energy consumption over *T*.
**) Intel Core 2 Quad 3.0 GHz processor, 8 GB RAM, using MatLab ver. 7



(a)

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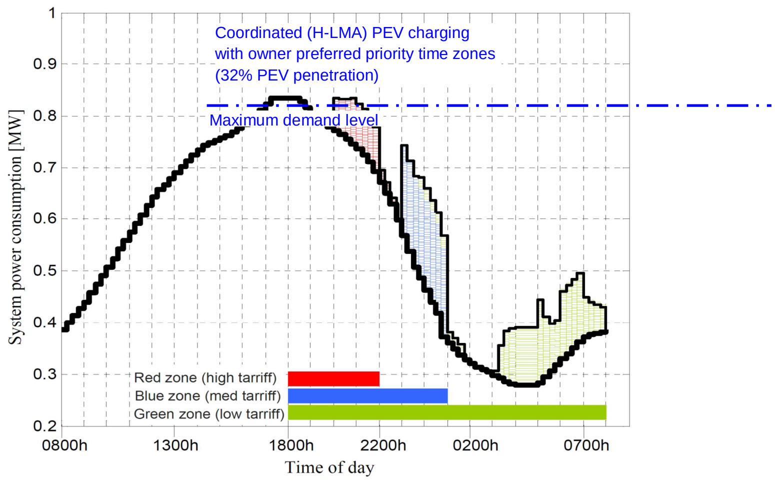

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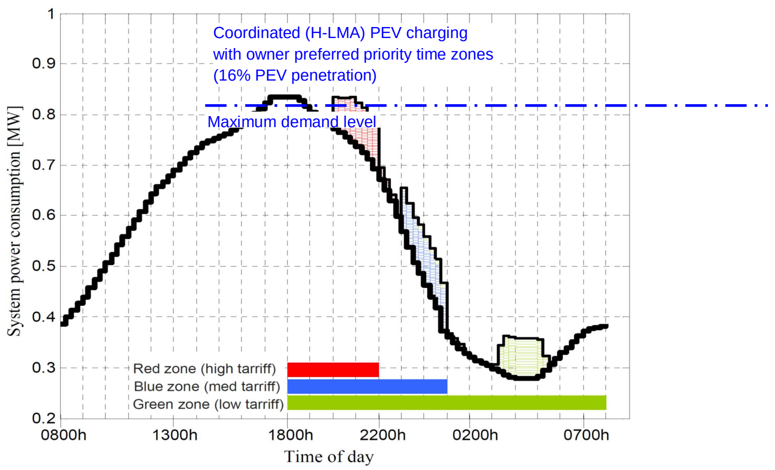

(c)

Fig. 5: System Power Consumption with Coordinated PEV Charging using the Proposed H-LMA (Δt =15 Min, T=24 Hours) for PEV Penetration Levels of; (A) 47%, (B) 32%, (C) 16%.

Conclusion

This paper investigates the impacts of optimization parameters including optimization period T and optimization time interval Δt on the accuracy and the speed of a heuristic load management algorithm (H-LMA) that coordinates PEV charging activities while reducing system losses and regulating bus voltages over a 24 hour period. Main conclusions are:

- H-LMA will limit overall system overloads and voltage fluctuations while reducing stress on distribution circuits such as cables and transformers.
- The speed and accuracy of H-LMA depend on the selected values for T and Δt .
- It is showed that optimization accuracy can be improved by using shorter time intervals and performing loss minimization over long periods (e.g,. 24 hours). This will however, require long computing times. Therefore, a compromise should be made between the solution accuracy and the associated computation time considering system size and the anticipated PEV penetration levels.

- For online PEV coordination, small time interval and optimization period should be selected to start charging vehicles as quickly as possible; otherwise moderate time intervals with a large optimization period should be selected for offline coordination where all vehicles are plugged-in or their charging patterns are known/forecasted ahead of time.

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Appendix

Parameters of the 19 bus low voltage and 31 bus distribution system are provided in Tables D1-D2 and Deilami et al (2011), respectively.

Table D1: Linear and Nonlinear (Pev) Loads of the Typical Low Voltage Residential System (Fig. 2)

Linear and PEV Load		Power	
Bus	Name	kW	kVAR
1 to 19	Linear loads	2.0	1.7
Selected buses	PEV charger	4.0	0

Table D2: Line Parameters of the Low Voltage Residential System (Fig. 2)

LINE		Line resistance R [Ω]	Line reactance X [Ω]	LINE		Line resistance R [Ω]	Line reactance X [Ω]
From bus	To bus			From bus	To bus		
a	b	0.0415	0.0145	f	l	1.3605	0.1357
b	c	0.0424	0.0189	d	m	0.140	0.0140
c	d	0.0444	0.0198	c	n	0.7763	0.0774
d	e	0.0369	0.0165	b	o	0.5977	0.0596
e	f	0.0520	0.0232	a	p	0.1423	0.0496
f	g	0.0524	0.0234	p	q	0.0837	0.0292
g	h	0.0005	0.0002	q	r	0.3123	0.0311
g	i	0.2002	0.0199	a	s	0.0163	0.0062
g	j	1.7340	0.1729	Distribution transformer reactance			0.0654
f	k	0.2607	0.0260				

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