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Mobility-Aware Vehicle-to-Grid (V2G) Optimization for Uniform Utilization in Smart Grid Based Power Distribution Network

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Abstract

One of the critical bottlenecks of high penetration of Electric Vehicles (EV) is uncoordinated, simultaneous charging of many EVs that can potentially impact the electric distribution grid with unwanted peak load demand. V2G technology enables the bidirectional flow of electric energy where EVs can also discharge energy to the grid from their batteries aiming to lower the peak demand. Our V2G optimization approach employs mobility information to balance peak utilization among differently utilized distribution segments by assigning each EV to an optimal Electric Vehicle Supply Equipment (EVSE) enabled parking lot. By aggregating geographically dispersed EVs and micro-grids with renewable energy sources as a virtual power plant (VPP), we proposed a scalable VPP based V2G optimization architecture integrated with VANET. Compared with existing solutions, our convex optimization algorithm uses fewer variables, attains uniform utilization of grid nodes by optimal EV charging/discharging profiles. By simulation, we showed that this novel mobility-aware, scalable V2G optimization algorithm can reduce or significantly postpone the need of expensive upgrade of power distribution infrastructure.

Keywords V2G optimization · Smart grid · Electric vehicle · Grid utilization · Mobility · VANET

1 Introduction

According to the U.S. Department of Energy (DOE), transportation contributes roughly one third of all CO_2 emissions. In this context Electric Vehicles (EV) can play a major role of minimizing greenhouse gas emission. The EV market is growing rapidly and the penetration is forecasted as high as 26.9% by 2023 and 72.7% by 2045 [1]. But electric energy and power requirement of EVs are quite high. For example, a single EV with 30 kWh daily energy usage is equivalent to average electricity consumption of a US residence. Uncontrolled use of charging may increase risk of overburdening the existing distribution network grid such as undesirable peak demands [2]. The load demand varies with time of day, week etc. due to weather, human activity and some random factors such as time of using different household and commercial electrical appliances. The most significant challenge of the power distribution infrastructure is peak load demand. The designing of the capacity of electricity infrastructure is based upon peak load demand as it needs to deliver such amount when called upon. To cope with peak demand increase, electric utility companies, even after the intensive energy efficiency programs, often need to undergo expensive capacity upgrading by installing new transformers, reinforcing distribution feeders, transformers, etc., that are projected to operate beyond 100% of their ratings [3]. A critical bottleneck of deeper penetration of EVs into the automotive market is that if large number of EVs draw current from the grid during the high load situation, there can be significant amount of increase in the peak demand triggering capacity enhancement of existing electric infrastructure. This threat to power grid also draws attention to Independent System Operators of the electric power system and Regional Transmission Organizations (ISO/RTO) [4]. To overcome these challenges, smart grid technologies will be the primary means to manage electric vehicle charging by a proper communication architecture between EVs and the grid. Extensive research is underway to develop standards such as a framework released by National Institute of Standards and Technology (NIST) for Smart Grid covering interoperability standards to support

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electric vehicles [5]. Research on Smart Grid thrives to ensure full coordination between generated and consumed energy with advanced algorithms for forecasting generation and demand of the distribution grid [6].

With the advent of Vehicle to Grid (V2G) technology, EVs can also discharge power to the grid. Although discharging of a single EV individually cannot contribute much for load balancing and peak shaving, many EVs together can significantly improve these characteristics with V2G optimization. V2G application constitutes bidirectional power flow which includes electricity discharging from vehicle to grid and the charging EV with a rate control [7]. By utilizing the instant response characteristics of battery packs installed on EVs as distributed energy storage, V2G can offer ancillary services such as demand-response, frequency regulation [8]. The optimizations for maximizing the profit by utilizing EVs' battery resources for ancillary services are well studied. These optimization approaches, however, assumed the EVs were already connected to the Electric Vehicle Supply Equipment (EVSE) stations. The knowledge of an EV's mobility information such as current location, battery status well before its arrival at the EVSE station can be very advantageous in the V2G optimization problem. The utilization of this priori information of EV's mobility status by VANET communication has just begun [9]. There are also extensive researches on Intelligent Transportation System (ITS) and VANET that focus on accurate and timely traffic flow information. With such VANET system available, the optimization analysis can include priori information from the EV user at the beginning of its travel to a destination. We propose an optimization algorithm with a scalable architecture that takes this priori information into account. The motivation of our work is from the fact that in busy commercial areas with high energy consumption, there are a large number of commuters who drive to workplace and park their cars in business hours. With higher EV market penetration, current parking lots will be converted to EVSE enabled parking facilities. In that case, a certain part of the power distribution network connected with one of those EVSE lots can be over utilized while some other part is less utilized that would cause expensive infrastructure upgrade. In Fig. 1 it can be observed that there is difference of energy usage among blocks of the neighborhood of a busy commercial area [10]. As shown in Fig. 1, within 500 m at the most, there are many parking lots available (the locations of parking lots are collected from the google map). So, within preferred walking radius of a commuter, an EV can be guided to the optimal EVSE parking lot to balance the load utilization. Moreover, research on autonomous local transportation such as V-charge project [11] is accomplishing auto valet-parking of a vehicle after dropping the commuter in his/her destination, which will ensure a larger radius of parking preference. Furthermore, EV-batteries and other battery storage cells may serve as energy storage system for intermittent photovoltaic (PV) generation or wind turbines to timely match their peak output with the peak load demand of the electric grid. Thus, by aggregating geographically dispersed EVs and renewable energy based micro-grids, a virtual power plant (VPP) can be created to represent a new powerful tool to deal with power grid requirements. This paper provides a mobility-aware, scalable VPP based V2G optimization architecture for balanced utilization among electric nodes to maximize the lifetime of existing infrastructure.

The remainder of this paper is organized as follows. Section 2 describes the related works of V2G optimization; section 3 describes scalable V2G optimization architecture; section 4 explains optimization model; and section 5 presents the performance analysis. Section 6 concludes the paper.

2 Related works of V2G optimization

Many works in the literature addressed V2G optimization for ancillary services through coordinated charge/discharge scheduling among different EVs by bidirectional power flow model between EVs and grid [12–14]. Centralized scheduling by an aggregator is suggested with the concern of computational complexity of existing solutions such as linear programming. In [15], authors evaluate the large scale EV parking lots and analyze the impact of aggregated load by several thousand EVs into grid service under various charging scenarios. To tackle the computational challenge, some used metaheuristic approaches like Particle Swarm Optimization (PSO) [16]. Monte Carlo simulations are also used to evaluate the performance for practical systems [17]. Importantly, however, all of these works are limited to the scenario that optimization parameters such as departure time, arrival state of charge and desired final state of charge are only collected after EVs are already parked in EVSE facility.

Very few papers on V2G optimization addressed the issue of mobility aspect of EV utilizing VANET. In [18] authors include the VANET architecture in their V2G optimization work. They assumed that if an EV needs charging in the middle of its route, it can communicate with the aggregator to inform its route, charging preferences using the RSUs (road side units). With this provided information, the arrival time at a charging station can be estimated and aggregator can plan ahead about which charging station can be chosen in the EV's trajectory to minimize the average cost of charging. The range anxiety of mobile EVs are also considered in [9] where VANET enhanced smart grid is considered to provide an efficient coordinated charging strategy to route mobile EVs to fast-charging stations. These works, however, considered only the fast-charging requirement and range anxiety issues of the EV users. Also, their optimizations focused only on current grid situation rather than day-long load-profile optimization of distribution network. Regarding VANET, extensive

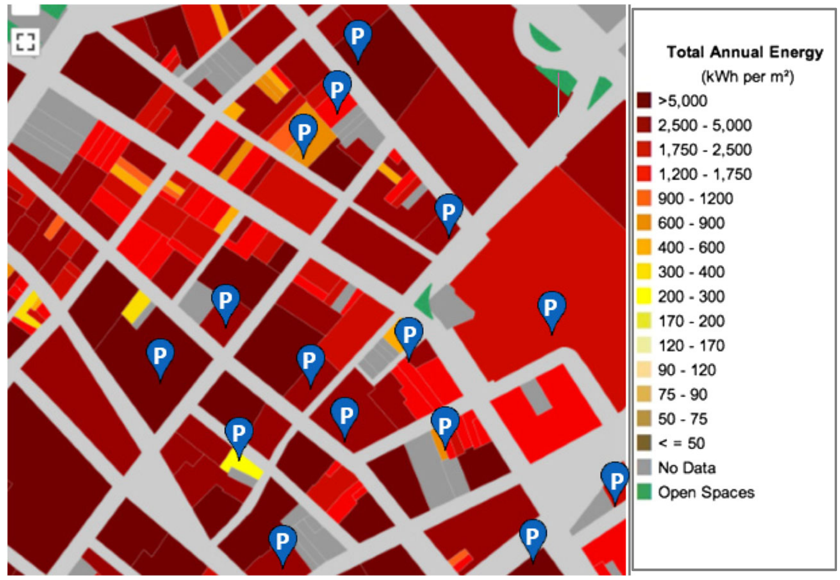


Fig. 1 Block-wise energy usage pattern and availability of parking lots in a busy commercial area of Manhattan, NYC

literatures reported on the research issues such as VANET routing, medium access, traffic management, and a variety of connected vehicle applications [19]. Road side units (RSU) of VANET system can collect messages from vehicles and forward this information to Traffic Management Center (TMC) by backbone internet [20]. Survey of a variety of traffic management approaches is reported in [21]. A central entity TMC plays the role of providing route guidance, travel duration and other EV information required for the optimization of V2G services. It should also be noted that in the near future, autonomous driving is projected to become a key component in the transportation industry [22]. Autonomous driving will filter out the randomness of human behavior and can reach closer to deterministic navigation system in the transportation network.

In contrast to existing VANET integrated V2G optimization works, our work focuses on a VPP based scalable architecture. It deals with the issue of long period (business hours) load-profile optimization in busy commercial areas by guiding each EV to an optimal EVSE lot and thus balances EV loads among different power network segments. This work also proposed a least-square convex optimization technique with fewer variables to minimize peak load at each particular EVSE lot. The scalability is achieved by distributed local controllers which solves the optimization independently.

3 Scalable V2G optimization architecture

Figure 2 presents the architecture of proposed mobility-aware V2G optimization where VANET solution (WAVE or LTE-D2D) provides the communication for EVs with the TMC and VPP Central Controller (VCC). For scalability, each geographic domain is considered to have independent authority for VANET and VPP and each authority again has its own hierarchical levels. The VPP Control Plane consists of VCC, Zone Controller (ZC) and Local Controller (LC). In the distribution network plane, each EVSE lot is controlled by an LC which is the lowest level node in the control plane hierarchy. EVs are interfaced with the distribution network through smart inverters that can receive an external command from LC to draw/inject power. An LC (located at the MV/LV transformer level) can cover one or more transformers that are connected to EVSE lot. A ZC connects the LCs within the same neighborhood; ZC (located at the HV/MV transformer level) can be assumed to cover several area substations. ZC coordinates and aggregates optimization messages between LCs and VCC. At the start of a travel, an EV contacts TMC via VANET informing its parking preference, current energy status and intended departure time and departure energy requirement. TMC's role is to perform real time traffic analysis and management by VANET system. Through VANET communications the up-to-date information such as required remaining travel time, any unexpected route changes of an EV can also be tracked to reach a given destination. TMC reports required mobility information to VCC which will be used as input parameters for optimization. VCC also collects information of power distribution network from utility control center for necessary optimization inputs such as forecasted load profile, capacity ratings at different segments. VCC maintains the mapping of ZCs to relevant geographic areas. By providing necessary inputs, VCC forwards the optimization problem to the corresponding ZCs. ZC assigns the optimization problem to the corresponding LCs by forwarding EV's information. LCs solve the optimization problem in parallel according to the load profiles, input parameters of EVs assigned at their individual nodes and send the optimization result to their ZCs. After getting results from LCs, a ZC can determine the optimal LC in its zone and forwards the selection information to

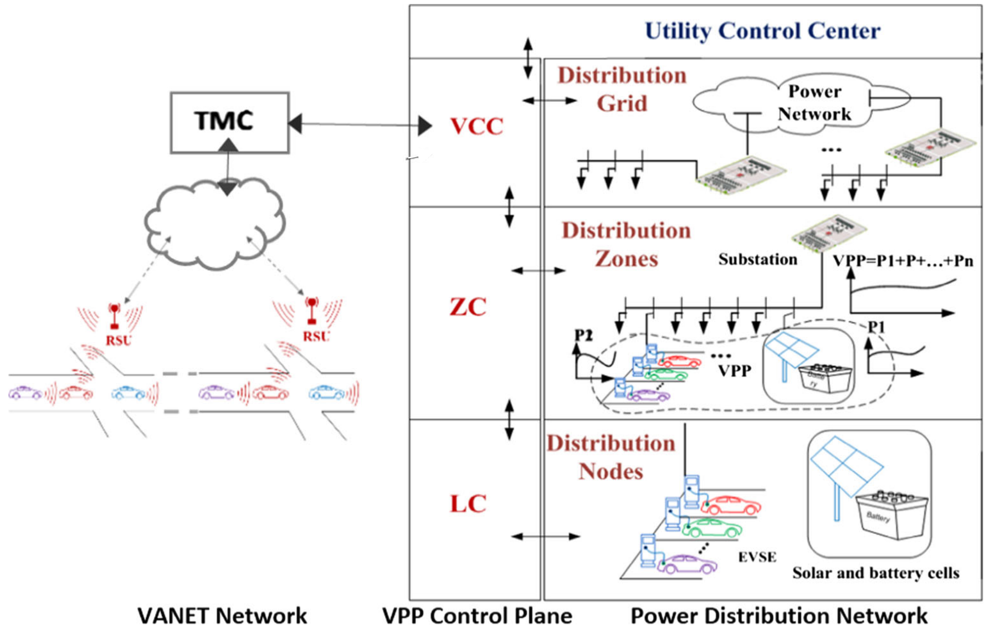


Fig. 2 Optimization architecture

VCC. As the optimization burden resides mainly in distributed LCs which runs optimization in parallel, this architecture is scalable and facilitates VCC to conduct necessary inter-system communications with VANET and Power distribution network.

4 Optimization model

Optimization in power distribution network mostly concerns about lowering the peak demand which is much higher than the average demand as shown in Fig. 3. For a given total energy demand in a certain period, the lowest possible value of peak demand can only be the average load demand when the peak demand is constant throughout the duration. To illustrate this as in Fig. 4, let us consider a base load, $f_0(t)$ at a node of the distribution network connected to an EVSE lot. Due to the additional energy requirement by the EVs, if these EVs draw their average load demand altogether, the total load demand also rises by the same amount from $f_0(t)$. To minimize the peak, our optimization strategy will be focused on valley filling (charging when $f_0(t)$ is lower than the total average load demand) and peak shaving (discharging when $f_0(t)$ is higher than the total average load demand) as depicted in Fig. 4.

In this optimization model, at an LC node, $f_0(t)$ represents the given forecasted load profile (excluding the electricity demand by EVs), $f_m(t)$ for forecasted power profile of micro-grid such as photovoltaic power of solar cells, and $(f_0(t)+f_m(t))$ for the base-load profile of optimization. Different methods of deriving

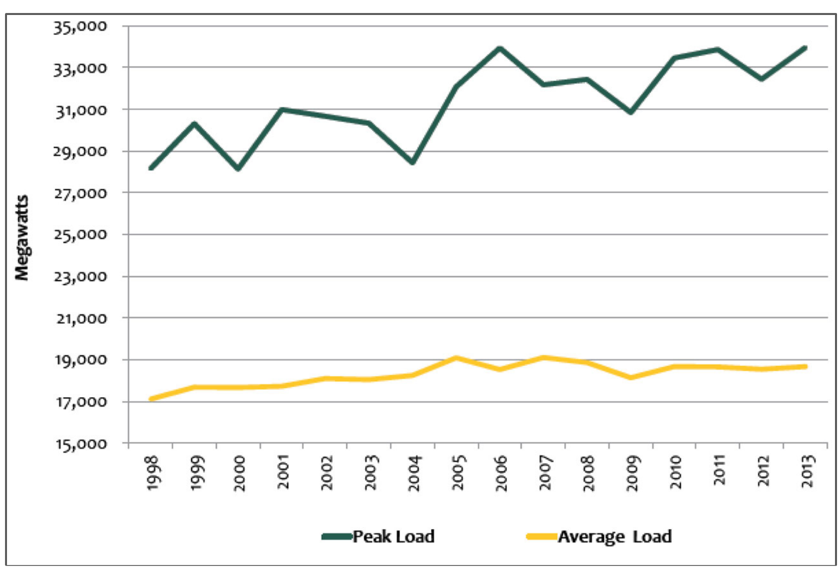


Fig. 3 Peak vs average load. *Source*: NYISO [23]

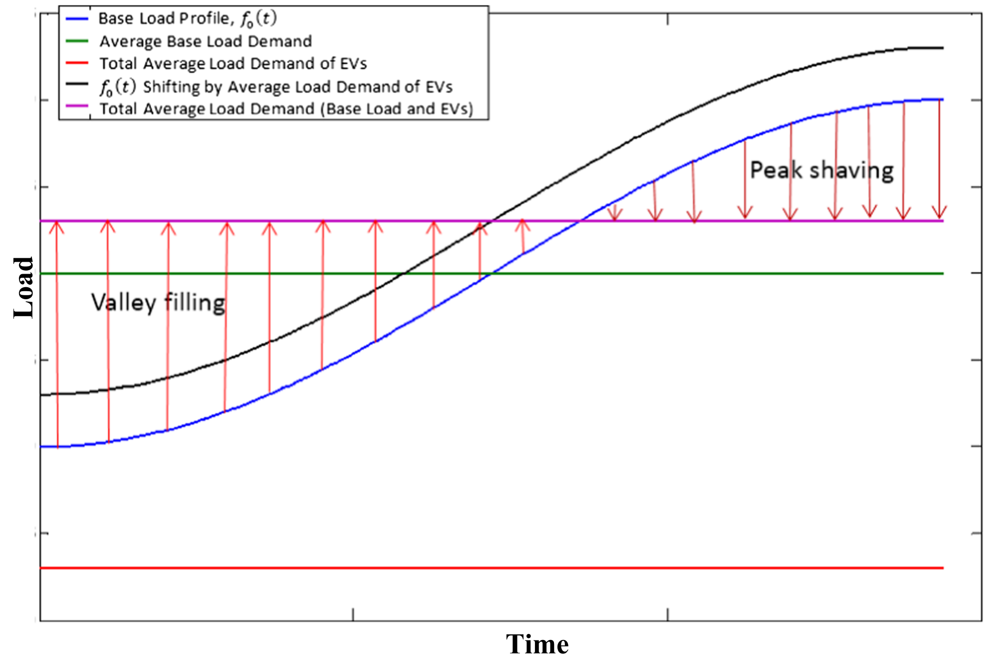


Fig. 4 Illustration of valley filling and peak shaving

forecasted load profiles have been proposed in the literature such as statistical analysis of historical data, Gray theory, artificial-neural-network methods, etc. [24–26]. We expect higher accuracy of the forecasts possible in the era of smart grid. In this paper, we assume that the forecasted load profile is given. Average load demand ($\overline{L}$) at an LC node is the average of base load ($f_0(t) + f_m(t)$) plus average demand of all assigned EVs. The nomenclature of the terms used in optimization model is defined in Table 1. In our optimization scenario, an EV (EV_i) at the time $T_{R,\ i}$ informs VCC of its parking zone preference including desired $E_{F,\ i}$, $T_{D,\ i}$. The VCC will also be informed about $T_{A,\ i}$ and $E_{A,\ i}$ by TMC. VCC forwards these information to corresponding ZC which in turn assigns the optimization problem to relevant LCs. According to the architecture described in the previous section we can divide our V2G optimization task in three subtasks: i) Load profile optimization at LC ii) Optimal EVSE lot selection at ZC iii) Final selection of EVSE lot at VCC.

Load profile optimization at LC In the context of optimal valley filling and peak shaving, we propose an efficient optimization approach at a particular LC. The optimization output from that particular LC will be charge/discharge profile function $g_j(t)$ for each EV already assigned to this LC such that combined EV load profile $g(t)\ (=\sum_{j=1}^{i} g_j(t))$ satisfies (1). The charge/discharge scheduling period is divided into timeslots, each with a fixed duration Δt. The optimization is performed at the arrival of one or more EVs' requests within the current timeslot and the scheduling horizon is from the next timeslot to the final timeslot (T_E) of the last departing EV among the assigned EVs at this LC.

$$\min_{g(t)} \left(\sum_t \left((f_0(t) + f_m(t) + g(t)) - \overline{L} \right)^2 \right) \quad (1)$$

$g_j(t)$ function, the updated profile of EV_j by optimization, is defined in either $T_{R,\ i} \le t \le T_{D,\ j}$ if $T_{A,\ j} \le T_{R,\ i}$ or $T_{A,\ j} \le t \le T_{D,\ j}$

Table 1 Nomenclature

$f_0(t)$	Given forecasted load profile (excluding the electricity demand by EVs)
$f_m(t)$	Given forecasted power profile of micro-grid
$\overline{L}$	Average Load Demand at LC
i, j	Index i for requesting EV and index j for any EV assigned at LC
$T_{R,\ x}$, $T_{A,\ x}$, $T_{D,\ x}$, T_E	Request, arrival, departure time of EV_x and final (end) timslot of optimization
	In calculation, $T_{R,\ x}$ is considered as the next timeslot of request time
$E_{A,\ x}$, $E_{P,\ x}$, $E_{F,\ x}$	Arrival, present and final state of battery energy of EV_x
$g_x(t)$	Charge/discharge profile of EV_x
min_curr_x, max_curr_x	Minimum current (maximum discharge rate) and maximum current limit of EV_x
min_E_x, max_E_x	Minimum and maximum battery energy of EV_x.

if $T_{A,j} > T_{R,i}$. To simplify latter expressions, let us define $T_{i,j}$ and $E_{i,j}$ as below:

$$T_{i,j} = \max\left(T_{R,i}, T_{A,j}\right)$$
$$E_{i,j} = \begin{cases} E_{A,j} & \text{if } T_{A,j} > T_{R,i} \\ E_{P,j}\left(T_{R,i}\right) & \text{if } T_{A,j} \le T_{R,i} \end{cases}$$

Present battery status, $E_{P,j}(t) = E_{A,j} + \sum_{T_{A,j}}^{t} g_j(t)$ is the amount of battery energy at t for an EV_i which already arrived at this LC. If all EVs would have arrived and departed at the same time, $\overline{L}$ will be simply $\left(\overline{f_0(t) + f_m(t)} + \overline{g(t)}\right)$. But since EVs will arrive and depart at different times we adapted a weighted average for $\overline{L}$ as (2):

$$\overline{L} = \frac{\sum_{j=1}^{i}\left(\left(\overline{g_j(t)} + \overline{f_j(t)}\right) \times \left(T_{D,j} - T_{i,j}\right)\right)}{\sum_{j=1}^{i}\left(T_{D,j} - T_{i,j}\right)} \tag{2}$$

Where, $\overline{g_j(t)} = \frac{\left(E_{F,j} - E_{i,j}\right)}{\left(T_{D,j} - T_{i,j}\right)}$ and $\overline{f_j(t)} = \frac{\sum_{T_{i,j}}^{T_{D,j}}\left(f_0(t) + f_m(t)\right)}{\left(T_{D,j} - T_{i,j}\right)}$.

The constraints for this optimization include maximum limit of charge and discharge rate of an EV, the required energy at the departure, allowed maximum and minimum threshold of battery energy at any instant, maximum rating (R) of the relevant electrical element (feeder cable/transformer) at this node. These constraints are listed in (3).

$$\left.\begin{array}{ll} min\_curr_j < g_j(t) < max\_curr_j & \forall EV_j \ \ \forall t \in \left(T_{i,j}, T_{D,j}\right) \\ \sum_{T_{i,j}}^{T_{D,j}} g_j(t) = E_{F,j} - E_{i,j} & \forall EV_j \\ min\_E_j < E_{P,j}(t) < max\_E_j & \forall EV_j, \forall t \in \left(T_{i,j}, T_{D,j}\right) \\ f_0(t) + f_m(t) + g(t) < R & \forall t \in \left(T_{R,i}, T_E\right) \end{array}\right\} \tag{3}$$

The common method of finding the solution is by dividing the total scheduling horizon in some number of timeslots and solving the optimal charging/discharging rate schedule using the rate at each timeslot as a variable. However this approach requires to solve many variables and hence not very scalable. For example with a granularity of 1 min and a scheduling period from 7:30 am to 5:30 pm, this common method will require to solve 600 variables for each EV. For a practical mobility aware V2G application where VCC needs to quickly respond back to the EV user, a V2G optimization approach with fewer number of variables is required. To address this scalability issue, we seek to obtain each individual EV's charging/discharging profile i.e. $g_j(t)$ function with only four variables as in eq. (4). The motivation of proposed $g_j(t)$ modelling is that the EV_j should charge or discharge proportional to the difference $D(t)$ between the base load $(f_0(t) + f_m(t))$ and average load demand $\overline{L}$ hence the variables x_{j2} and x_{j4}. By addition of offset variables x_{j1}, x_{j3} in $g_j(t)$, this model guarantees energy requirement by an EV. The two sets of variables (x_{j1}, x_{j2}) and (x_{j3}, x_{j4}) are to apply different rates in valley filling phase and peak shaving phase respectively for the same amount of deviation D(t) while satisfying constraints mentioned above.

$$g_j(t) = \begin{cases} x_{j1} + x_{j2}D(t) & \text{if } D(t) \ge 0 \\ x_{j3} + x_{j4}D(t) & Otherwise \end{cases} \tag{4}$$

Where $D(t) = \overline{L} - f_0(t) - f_m(t)$

Thus the optimization will solve only four variables x_{j1}, x_{j2}, x_{j3}, x_{j4} for each EV which models the EV's charge/discharge rate profile for its whole parking duration. With this modeling of $g_j(t)$ our optimization problem can be constructed as the least-square convex optimization problem as (5).

$$\min_{\boldsymbol{x}} \ \|\boldsymbol{Cx} - \boldsymbol{d}\|_2^2 \text{ Subject } \ \text{to} \boldsymbol{Ax} \le \boldsymbol{b} \tag{5}$$

Where $\boldsymbol{x}$ is the variable matrix to be solved at this LC. The objective (1) needs to be constructed as the objective of optimization problem (5) for exact interpretation of least square convex optimization problem. In (5), $\boldsymbol{C,d,A,b}$ are constant matrix and $\boldsymbol{x}$ is variable matrix to solve. To verify the construction, (6) is obtained by plugging charge/discharge function $g_j(t)$ in (4) into the objective (1).

$$\min_{g(t)} \ \sum_t \left(\sum_{j=1}^{i}\left(x_{j1} + \left(x_{j2}D(t)\right) + x_{j3} + \left(x_{j4}D(t)\right)\right) - D(t)\right)^2 \tag{6}$$
$$\text{if } D(t) \le 0, \ \ x_{j1} = 0, \ \ x_{j2} = 0,$$
$$\text{otherwise}, \ \ x_{j3} = 0, \ \ x_{j4} = 0$$

$\boldsymbol{C}$ matrix can be formed as:

$$\begin{pmatrix} c_{1,1} & c_{1,2} & c_{1,3} & c_{1,4} & \cdots & & \cdots & c_{1,4(i-1)+1} & c_{1,4(i-1)+2} & c_{1,4(i-1)+3} & c_{1,4(i-1)+4} \\ & & \vdots & & & \ddots & & & \vdots & & \\ c_{T,1} & c_{T,2} & c_{T,3} & c_{T,4} & \cdots & & \cdots & c_{T,4(i-1)+1} & c_{T,4(i-1)+2} & c_{T,4(i-1)+3} & c_{T,4(i-1)+4} \end{pmatrix}$$

C matrix has $4i$ entries in each row; four times number of EVs at this LC. Each column has T entries which is the number of timeslots starting from $T_{R,\ i}$ to the T_E. Elements of ***C*** matrix corresponding to timeslot $'t'$ (*defined in* $T_{R,\ i} \leq t \leq T_E$) and $'EV_j'$ are as follows:

If t'th timeslot falls in EV_j's parking duration

$$c_{t-T_{R,i}+1,4(j-1)+1} = \begin{cases} 1, & D(t) \geq 0 \\ 0, & otherwise \end{cases} \quad c_{t-T_{R,i}+1,4(j-1)+2} = \begin{cases} D(t), & D(t) \geq 0 \\ 0, & otherwise \end{cases}$$

$$c_{t-T_{R,i}+1,4(j-1)+3} = \begin{cases} 1, & D(t) < 0 \\ 0, & otherwise \end{cases} \quad t-T_{R,i}+1,4(j-1)+4 = \begin{cases} D(t), & D(t) < 0 \\ 0, & otherwise \end{cases}$$

If t'th timeslot does not fall in EV_j's parking duration, corresponding entries will be zero.

Constant matrix ***d*** can be formed as $\boldsymbol{d} = [d_1\ d_2\ d_3 \ldots d_T]'$ *where* $d_{t-T_{R,i}+1} = D(t)$ for $T_{R,\ i} \leq t \leq T_E$. Variable matrix, $\boldsymbol{x} = [x_{11}\ x_{12}\ x_{13}\ x_{14}, \ldots, x_{j1}\ x_{j2}\ x_{j3}\ x_{j4}, \ldots, x_{i1}\ x_{i2}\ x_{i3}\ x_{i4}]'$. Prior to optimization, $D(t)$ is calculated by the knowledge of forecast and inputs of EV information. Hence ***C,d*** are constant matrices and ***x*** is the variable matrix and thus the construction conforms to the form of (5). Similarly the constant matrices ***A,b*** which are coefficients of constraints can be constructed. After solving for ***x***, LC is ready to update/allocate each EV's charge/discharge profile if EV_i is finally selected for this LC. If this is "k"-th LC under the corresponding ZC, after calculating optimal $g(t)$, LC_k will report the maximum utilization (U_k) including EV_i. U_k can be found as follows:

$$U_k = \frac{\max\limits_t \left(f_0(t) + f_m(t) + g(t)\right)}{R_k}$$

Where R_k is the rated capacity at LC_k.

Optimal EVSE lot selection at ZC The novelty of our *mobility-aware* optimization lies in the fact that it can guide EVs to EVSE lots so that peak utilization among LCs can be minimum, i.e., a *min-max problem*. The ZC will compare each LC's new peak utilization by adding this EV_i and select the one for which maximum of peak utilization among all LCs becomes minimum. Suppose at this ZC, $\{LC_1, LC_2, LC_3, \ldots, LC_k, \ldots, LC_m\}$ is the set of LC nodes corresponding to this (EV_i) user's preferred parking spots. Let us define, when LC_k is chosen, PU_k^1 is the highest of $\{U_1, U_2, U_3, \ldots, U_k, \ldots, U_m\}$, PU_k^2 is the next highest and so on. It is to be noted that for selecting LC_k, only U_k value is updated; other values of U_1 to U_m remains unchanged. The selection matrix for choosing optimal LC is:

$$SM = \begin{pmatrix} PU_1^1 & PU_1^2 \cdots & PU_1^m \\ & \vdots & \vdots \\ PU_k^1 & PU_k^2 \cdots & PU_k^m \\ & \vdots & \vdots \\ PU_m^1 & PU_m^2 \cdots & PU_m^m \end{pmatrix}$$

The searching for optimal LC will be conducted column-wise starting from 1st column in SM matrix. Suppose MP_v is the minimum of column "v" of SM matrix. Selection of the optimal LC_k is based on two criteria: *i*) for some column "v" and any previous column "w" of column "v" in SM, there is exactly one row "k" for which $\left(PU_k^v = MP_v\right)$ *AND* $\left(PU_k^w = MP_w\right)$ *ii*) if one specific "k" is not found from 1st criteria, random selection of "k" from those "r" such that *for all* $w \in \{1, 2, \ldots, m\}$, $\left(PU_r^w = MP_w\right)$. After the selection, ZC reports the optimal LC for this EV_i in its zone to VCC.

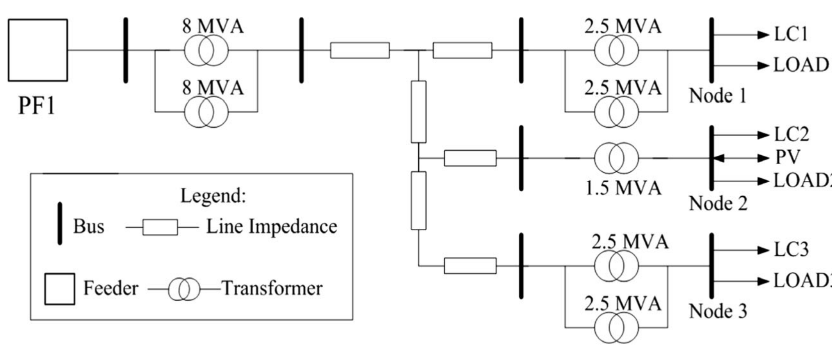


Fig. 5 Photovoltaic output power profile

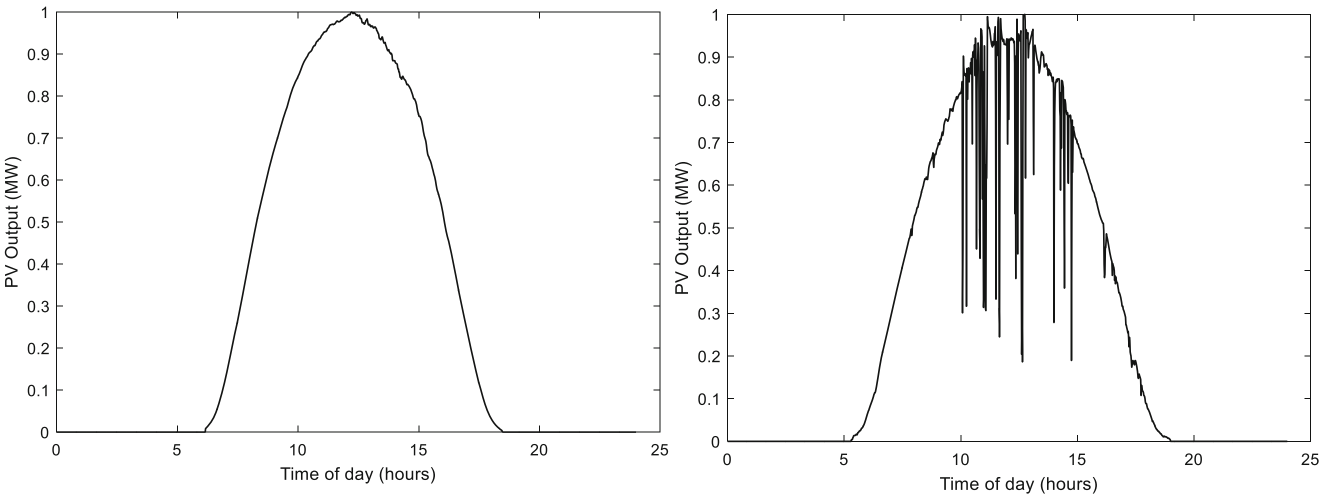


Fig. 6 Photovoltaic output power profile

Final selection of EVSE lot at VCC Since the division of ZCs will be done geographically, a user's preference spots will be most likely inside the same zone. In this case, VCC will determine the selection of the ZC as designated LC for this EV_i. For any such case of an EV_i's preferred spots fall in more than one ZC, VCC selects the optimal LC from the final selections of those ZCs by same method as described for ZC in previous part. After final selection at VCC, the user of EV_i knows its designated EVSE lot via TMC.

5 Performance analysis

The simulation of proposed optimization model was conducted using MATLAB/Simulink platform. Simscape Power Systems package for Simulink was used to simulate electric power flow of two primary feeders. One-Line diagram of the first primary feeder (PF1) is presented in Fig. 5 where LC1, LC2 and LC3 represent the LCs of three EVSE lots connected to the corresponding electrical nodes 1, 2, and 3. The second primary feeder (PF2) has the same configuration as PF1 where LC4, LC5, LC6 are connected to nodes 4, 5, and 6. For comparison these two feeders were assumed equally designed but differently loaded. To represent high and low utilization, the peak of the loads for the nodes 1, 2, and 3 of PF1 is set to 80% of the rated power of transformer and 40% for the nodes 4, 5, and 6 of PF2. Maximal load of 80% of the rated power of the transformers is above the n-1 criteria level which means if one transformer fails the other transformer cannot take the load. This typically happens in areas with very high load density and constant load growth over years. Photovoltaic (PV) generator is connected to node 2 and 4 with same PV output power profile; the maximum output is scaled to 1 MW. To investigate the V2G optimization performance with respect to PV power generation in different solar radiation situations, both sunny and intermittent cloudy day PV profiles as shown in Fig. 6 are used. These PV generation profiles were directly measured by one of the authors at a 500 KW PV power plant. The profiles are showing typical behavior of a multi kW PV power plant. All EVs of this simulation are assumed to prefer to park in any EVSE lot connected to these six nodes. CVX package for MATLAB was used to solve the convex optimization problem (5). We constructed our optimization problem according to the Disciplined Convex Programming method of

Table 2 Simulation parameters

EV battery	30 kWh capacity, 30A max charge / discharge rate
Number of EVs	4000
Arrival time	Normal Distribution, Mean 8:30 am, variance 1.2
Departure time	Normal Distribution, Mean 5:30 pm, variance 1.2
Arrival/Departure Energy (% of Battery Capacity)	Uniform Distribution.
	70% users: 10% to 50% arrival energy, 50% to 90% departure energy
	30% users: 70% to 90% arrival energy, 50% to 70% departure energy
Energy threshold	Max: 95%, Min: 5% of Battery Capacity
EVSE lots	6 lots, each with maximum accommodation of 700 EVs
Load capacity rating	As shown in Fig. 5

CVX tool [27]. The simulation parameters are listed in Table 2. We considered that 30% users will have extra energy at arrival than they need at departure time. This is because EV users can also charge at their homes after midnight at cheaper rates when the energy demand is very low. Users who do not live far away from their working place will not consume much energy for the travel and can get better incentive for this energy selling. To represent forecasted load profile, actual daily load data at each hour of New York City on a certain day is collected from NYISO [28].

Load profiles for the six nodes are made by interpolating hourly data for timeslot resolution Δt=1 min and by scaling the load profiles with peak load value of 80% and 40% of transformer rating as mentioned above.

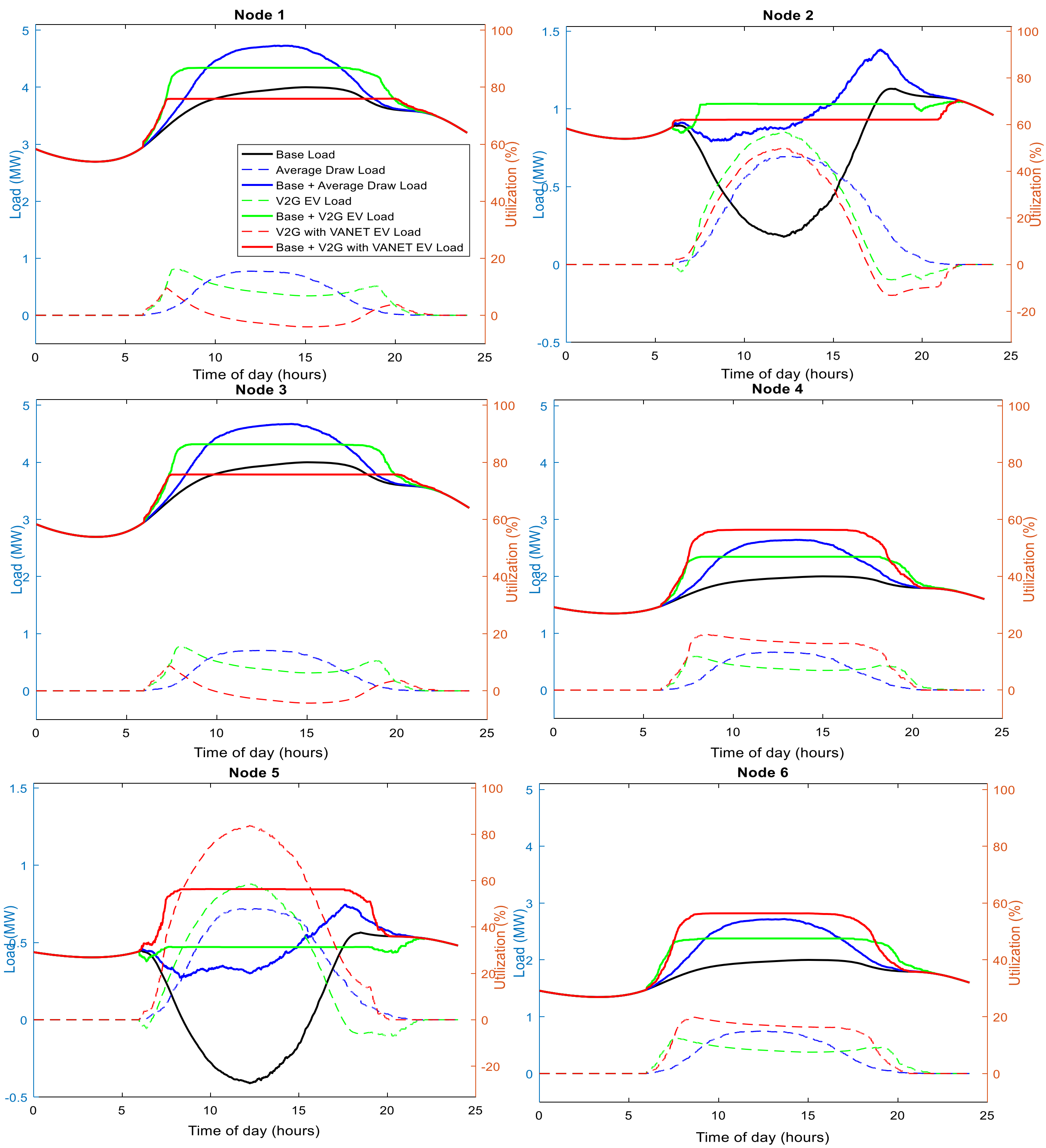


Fig. 7 Load profiles at six nodes with sunny day PV DATA

We investigated three scenarios in this simulation: (i) Average Draw: each EV goes randomly to any of 6 nodes and draws its required energy at average rate (ii) V2G Optimization without VANET: each EV goes randomly to any of 6 nodes and draws according to the provided optimal profile (iii) V2G Optimization with VANET: each EV goes to the node guided by VCC and draws according to the provided optimal profile. In these simulation scenarios the performance metric is the minimum of maximum peak utilization among 6 nodes after optimization. In Fig. 7 we plotted the base load profile, aggregated EV load profile and total load profile at six LC nodes for each of these scenarios with sunny day PV profile. Note that in this figure right side y-axis is used to show percent utilization. It can be observed that average draw case increases the peak load in all nodes which signifies the peak demand increase introduced by uncontrolled EVs; particularly

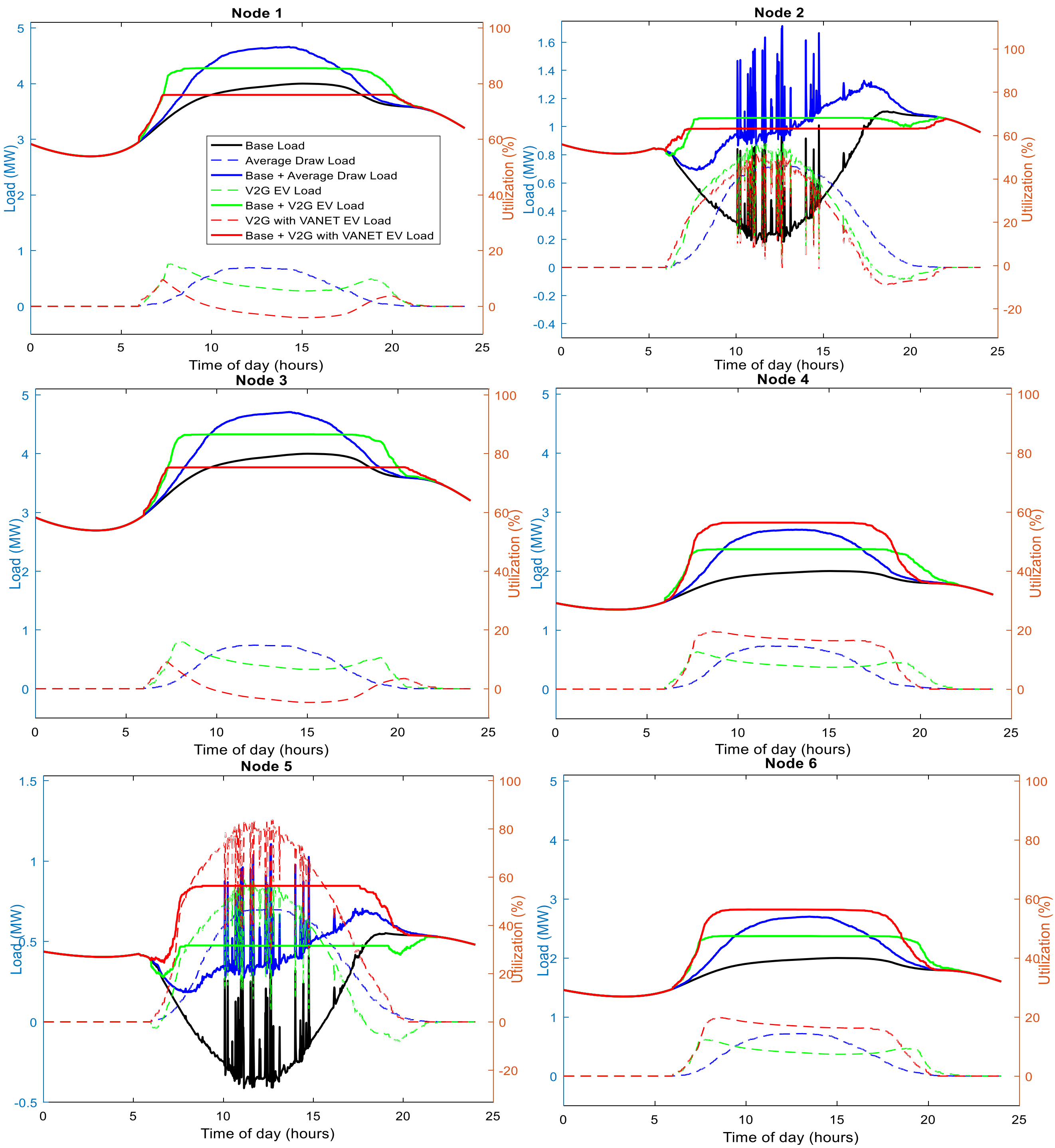
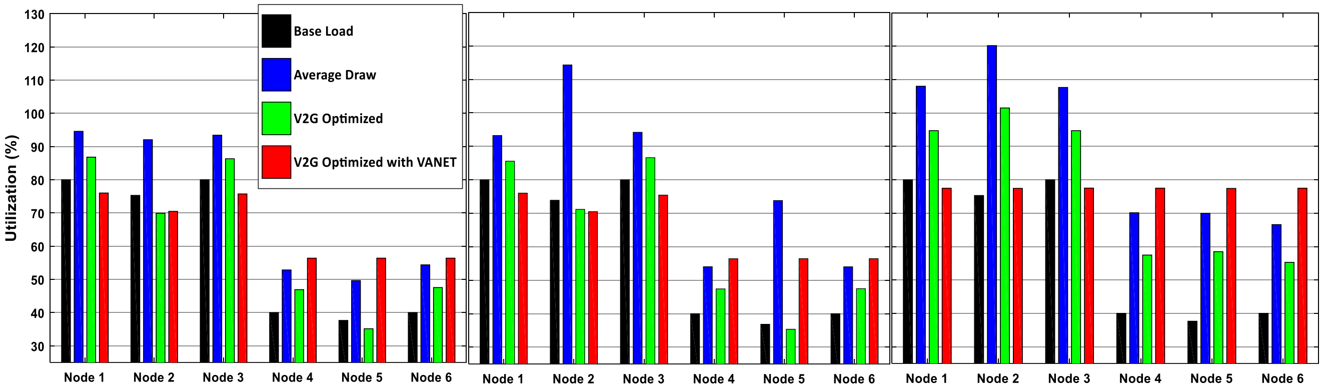


Fig. 8 Load profiles at six nodes cloudy day PV data



a) 4000 EVs, Sunny Day PV profile b) 4000 EVs, Cloudy Day PV profile c) 8000 EVs, No accommodation limit

Fig. 9 Peak utilization at six nodes

the worst situation is at nodes 1 and 3 which are experiencing about 95% utilization. Additional loads incurred by uncontrolled EVs is increasing the peak load to the limit of the infrastructure. This would cause expensive enhancement to guarantee reliable grid services and prevent outages caused by equipment overloading. Although V2G optimization without VANET has significantly lower peak load than average draw case, due to lack of mobility-awareness optimization outcome still suffers from very high utilization. Optimization with VANET achieves the minimum of maximum peak utilization among nodes. We can observe that for this case the maximum peak utilization is even lower than the utilization of the base load. This signifies the advantage of V2G optimization with the integration of mobility. The range of peak utilization is about 55% to 75% among six nodes for this mobility-aware optimization case while it is about 35% to 87% for optimization without VANET case. This shows the strength of the proposed model in minimizing maximum of peak utilization through balancing utilization among these nodes. Since the base load profile at node 1 and 3 are same, optimization with VANET case creates almost similar load profiles; same is for node 4 and node 6. Node 2 and Node 5's profiles are different due to the presence of PV generation at these nodes. By observing the aggregated EV load profile at different nodes, it can be noted that proposed model accomplishes highest discharging in high utilized nodes (node 1,3) and highest charging at the lowest utilized node (node 5) to achieve optimal balance of utilization. Resultant profiles from another simulation is plotted in Fig. 8 which is done only by changing PV profile to intermittent cloudy day. It can be observed that although there were frequent fluctuations in PV output power due to intermittent clouds, our proposed optimization scheme could overcome this effect and experiences nearly the same maximum peak utilization as the case of sunny day. In this cloudy profile situation, we can even observe more than 100% utilization at node 2 for average draw case. Figure 9a and b plot the bar chart of peak utilization for sunny day and cloudy day PV data respectively. It can also be noted that even with mobility awareness V2G optimization cannot make the peak utilization at each node equal. This limitation is due to real-world constraints of the number of EVs and the accommodation capacity at parking lots. Another simulation is done with 8000 EVs and no accommodation restriction to verify the performance of this optimization model without these constraints. The utilization bar-chart of this simulation is plotted in Fig. 9c. Here we can observe without accommodation limit and for higher number of EVs proposed optimization model completely balances peak utilization among all six nodes.

6 Conclusion and future works

This paper proposed a mobility-aware, scalable V2G optimization architecture in VPP context, and an optimization technique with fewer variables than conventional approaches, reducing computational complexity. By incorporating EV mobility, our algorithm can optimally mitigate peak demand and thus defer or prolong capacity upgrades for power distribution network. For scalability, the task of optimization is distributed locally at Local Controllers, Zone Controller makes optimal selection, and VCC performs the communication with VANET and Power distribution network. As our future work, we plan to focus on optimal incentive planning among different elements of the proposed architecture such as utility operator, EVSE lot and EV owners.

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