This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

Energy Management in Smart Distribution Systems with Vehicle-to-Grid Integrated Microgrids

H. S. V. S. Kumar Nunna, *Member, IEEE,* Swathi Battula, Suryanarayana Doolla, *Senior Member, IEEE,* and Dipti Srinivasan, *Senior Member, IEEE*

***Abstract*—In modern electric power systems, Plug-in Electric Vehicle (PEV) with Vehicle-to-Grid (V2G) potential are becoming reliable and flexible resources for energy balancing under varying energy supply and demand scenarios. In this evolving paradigm, designing energy management strategies for feasible and cost-effective utilisation of V2G is one of the several challenges faced by the utility operators and regulators. This paper proposes two energy management strategies to effectively utilize V2G potential of PEVs in managing energy imbalances in grid-connected microgrids. The contributions of the paper are in twofold. First, it proposes a novel bidding strategy for PEVs offering V2G by including the projected battery degradation cost to integrate them into microgrid operation. Second, two energy management strategies are proposed for inclusion of V2G into the microgrid operation based on the forecast accuracy on energy supply and demand, and market prices. The proposed V2G integration strategies are implemented using a multi-agent system developed in Java Agent DEvelopment framework and applied to a microgrid case study system. The simulation results and their analysis show that V2G can be used to maximum depth of discharge levels if the electricity price variation is high and battery cost of PEVs is low.**

***Index Terms*—Demand response, Energy markets, Microgrid, Multi-agent systems, Plug-in electric vehicle, Smart distribution system and Vehicle-to-Grid.**

Acronyms

ABC	Artificial Bee Colony.
ABC-ROC	Artificial Bee Colony-Rate of Change.
ASA	Auction Supervising Agent.
BDC	Battery Degradation Cost.
CB	Cost of Battery.
CDA	Continuous Double Auction.
CSE	Cost of Stored Energy.
DG	Distributed Generator.
DGA	Distributed Generation Agent.
DI	Demand Interval.
DOD	Depth of Discharge.
EVA	Eelctric Vehicle Agent.
EVLA	Electric Vehicle Load Aggregator.
G2V	Grid-to-Vehicle.
GA	Genetic Algorithm.
GBP	Grid Buying Price.
GGA	Global Grid Agent.
GSP	Grid Selling Price.
JADE	Java Agent DEvelopment.
LI	Leaving Interval.
MAS	Multi-Agent System.
MCP	Market Clearing Price.
PEV	Plug-in Electric Vehicle.
PLA	Point Load Agent.
SI	Starting Interval.
SOC	State of Charge in kWh.
SPA	Second Price Auction.
V2G	Vehicle-to-Grid.

This work was supported in part by the Energy Market Authority of Singapore under EIRP programme with grant number R-263-A66-279 and IIT Bombay seed grant project 09IRCC040.

H. S. V. S. Kumar Nunna, Swathi Battula and Dipti Srinivasan are with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore 117580. (email: elekumar@nus.edu.sg, eleswat@nus.edu.sg and dipti@nus.edu.sg).

Suryanarayana Doolla is with the Department of Energy Science and Engineering, Indian Institute of Technology Bombay, Mumbai, India 400076 (email: suryad@iitb.ac.in)

Nomenclature

Δt	Duration of demand interval in hours
M	Total number of PEVs
P^i_{PEV}	Power rating of i^{th} PEV in kW
SOC^{edd+}_j	SOC available after travelling EDD while SOC_{LI} equals to SOC_j with no V2G in interval j
$SOC^{V2G,edd+}_j$	SOC available after travelling EDD while SOC_{LI} equals to SOC_j with V2G in interval j
SOC_j	SOC at the end of interval j
SOC_{edd}	SOC required for the expected driving distance
SOC_{max}	Maximum limit on SOC
SOC_{min}	Minimum limit on SOC
x^i_j	Decision variable to indicate charging or discharging of i^{th} PEV in interval j
$y(t_s, t_e)$	Set of demand intervals considered for the study between the starting time (t_s) and ending time (t_e)
ECR	Energy Consumption Rate in kWh per mile
EDD	Expected driving distance in miles

I. Introduction

Energy management in conventional power systems is a challenging task due to dynamic nature of the demand. It is more challenging when the supply is dynamic due to high penetration of intermittent sources of energy such as solar or wind power. This scenario demands an appropriate mix of flexible resources, such as Demand Response (DR) and spinning reserve, to maintain and operate the utility grids reliably [1], [2]. In the context of smart grid, PEVs can be used as one of the resources to maintain the energy balance in the system and as an ancillary service provider [3], [4]. The aggregated effect of PEVs can be used to safeguard the quality of power being served to the end-users [5]. It can also be used to aid the utilities in managing peak demand [6].

PEVs with bidirectional power transfer capability provide both Grid-to-Vehicle (G2V) and V2G services. When compared to the PEVs offering G2V, the vehicles offering V2G service have additional energy levelling potential due to their discharging ability when needed. However, frequent filling and draining of batteries causes degradation of rated life cycles and eventually demands replacement of batteries periodically. Therefore, while designing energy management strategies for V2G the implications of battery degradation must be taken into account. Hence, each charge-discharge cycle of the battery must be given a certain cost component of degradation and this has to be offset by either monetary incentives or profit gained through charge-discharge operations.

In recent years, many attempts have been reported in the literature on effective and feasible utilisation of V2G. For example, an optimization model to reduce dependency on the utility grid by scheduling the charging and discharging of PEVs offering V2G in a two microgrid system is proposed in [7]. The economic feasibility of exporting power back to the grid (V2G service) under varying electricity price scenario by incorporating Battery Degradation Cost (BDC) of Lithium ion battery is studied in [8] and [9]. This study also quantified the minimum required variation in electricity tariffs for making the V2G profitable. Reference [10] presents a feasibility study on V2G for different types of PEV batteries by considering the battery cost and degradation characteristics. In [11], an energy management model is developed for a residential microgrid with renewable sources and V2G considering the PEV owners behavior and battery wear cost. Similarly an integrated energy management system for managing PEVs and battery swapping stations in a smart microgrid with interruptible loads is presented in [12]. In this work, authors have proposed pricing scheme for fixing the PEV charging cost under both grid connected and islanded mode of operation of the microgrid.

Some of the attempts focused on pricing policy for PEVs with V2G connected in multi-microgrid scenario. For example, a distributed dynamic pricing policy for optimal charging of PEVs to minimize the supply-demand mismatch is proposed in [13]. In this study, two types of prices, home and roaming prices, are introduced for charging and discharging of PEVs in a multi-microgrid scenario. Similarly, a distributed real time electricity allocation scheme is proposed for grid connected residential microgrids with V2G to improve the efficiency and reduce the average cost of electricity purchase in [14].

In [15], a decentralised energy management system for charging and discharging of PEVs is proposed without compromising on the quality of service offered to the PEV owners. In this, sub-aggregators are introduced where the PEVs' charging is scheduled by sub-aggregator while the central aggregator ensures that circuit loading limits are not violated. Similarly, reference [16] proposed a centralized real-time charging management framework for PEV aggregator participating in whole-sale electricity markets. In this work, authors have formulated a linear programming problem that can be solved very fast in real-time considering PEVs' charging priorities. In the work reported in [17], a new energy scheduling method is proposed to schedule V2G by optimizing the overall cost of energy in distribution systems with renewable electric sources. In this work, the scheduling of PEVs is prepared for a double tariff structure that has only two prices, high day time tariff and low night time tariff.

Despite the attempts reported in the literature, some of the important aspects are not studied so far such as the economic viability of V2G with BDC for different Depth of Discharge (DOD) levels under uncertain energy supply and demand scenario. This is a significant problem to be addressed when intermittent sources of energy have a dominant share in the total generation mix. The higher levels of intermittency leads to predominant variations in the prices of electricity in spot markets. This variation needs to be considered while designing efficient and economically viable utilisation policies for V2G. This paper proposes energy management strategies for economically feasible utilisation of V2G in competitive electricity markets where the electricity price variations are high. The proposed strategy is implemented using a Multi-Agent System (MAS) developed in Java Agent DEvelopment (JADE) framework. This is suitable for distribution systems with intermittent Distributed Generators (DGs) and PEVs offering V2G. In this study, a smart microgrid connected to a distribution system is used as a case study to embody the effectiveness of the proposed energy management strategies for V2G.

The rest of the paper is organised as follows: the proposed energy management strategies for feasible utilisation of energy from PEVs with V2G is presented in Section II. It also details the MAS framework designed to execute the proposed strategies. The mathematical modelling of the proposed strategies is described in Section III. Section IV presents a case study and simulation results with detailed discussion and analysis. Section V concludes the paper.

II. Proposed Energy Management Strategies for Microgrids with V2G

Economic viability of PEVs with V2G is mainly affected by variations in cost of electricity and degradation cost of the batteries which in turn depends on Cost of Battery (CB), battery type and DOD [8]–[10]. In this study, Lithium–nickel–cobalt–aluminium (NCA), which is the battery used in Tesla Model-S PEVs, is used for the analysis [18]. Fig. 1 shows the relation between the cycle-life and DOD for a Li-ion NCA battery. From the graph, it can be observed that BDC varies in proportion to the DOD. Therefore, the BDC of a Li-ion NCA battery for a discharge cycle can be approximated as [10]:

$$BDC = (\frac{1}{f(DOD_2)} - \frac{1}{f(DOD_1)})CB \tag{1}$$

and

$$f(DOD) = 10^{N_{DOD}} \tag{2}$$

where DOD_1 and DOD_2 represent DODs such that $DOD_2 > DOD_1$, N_{DOD_1} and N_{DOD_2} are the number of cycle-life (in $\log$ scale) corresponding to DOD_1 and DOD_2 respectively. The revenue gained by i^{th} PEV from one charge-discharge cycle can be expressed as,

$$R^i = (D_k^i - C_j^i)P_{\text{PEV}}^i \Delta t \tag{3}$$

and the corresponding profit (H^i) is,0

$$H^i = (D_k^i - C_j^i)P_{\text{PEV}}^i \Delta t - BDC_k^i \tag{4}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

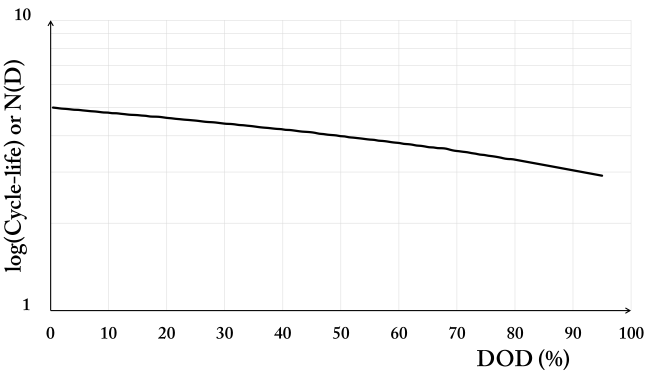


Fig. 1: Variation of $\log(cycle\text{–}life)$ with $\%DOD$

where C_j^i and D_k^i are the prices of electricity per kWh for charging and discharging of PEV in the intervals j and k respectively, R_i is the revenue per charge-discharge cycle of i^{th} PEV in cents and H_i is the profit gained per cycle by i^{th} PEV in cents. From (4), it can be observed that higher differences between C_j^i and D_k^i results in higher DOD up to which V2G is viable. Therefore, the revenue gained from charge-discharge cycles of PEVs must compensate the corresponding BDC_k^i to make V2G viable.

In competitive electricity markets, price varies with supply and demand. This variation cannot be predicted accurately if the intermittent sources of energy have greater share in the generation. When PEVs with V2G are integrated as one of the resources into such scenarios, the energy mismatches tend to reduce. Also, the price of electricity becomes stable or less varying. Although this practice is quite successful in reducing the energy mismatches, its sustainability in the long run cannot be guaranteed as the revenue gained by PEVs from lower price variation may not break-even the BDC. Therefore, PEVs must be included strategically into such scenarios to make their integration economically viable. In this paper, two energy management strategies for integrating PEVs into microgrids are proposed.

The former strategy is suitable when the day-ahead forecast on energy generation and consumption is not accurate whereas the latter one is used when accurate day-ahead forecast is available. The selection of the strategy to be followed is based on the accuracy of the day-ahead forecast data during intervals prior to the decision making carried out by vehicle aggregator. The vehicle aggregator initially assumes that the day-ahead forecast is accurate and schedules the charging and discharging activities of PEVs by respecting their economical and operating preferences using the optimisation model described in Section III-B. The outcome of the optimisation is based on the forecast information and is prone to forecast errors. However, the supply demand deviation in the system caused from forecast errors during an interval are addressed by the operating reserve capacity maintained by the system. For a system like microgrid with renewable energy sources, this operating reserve can be 15% of the connected load [19]. Therefore, the forecast errors upto 15% are offset by the operating reserve capacity of microgrid. The reserve capacity is offered by either an energy storage system or the utility grid. Based on the the average error observed over the intervals, the vehicle aggregator switches between the strategies. If the average error is greater than 15% then the vehicle aggregator follows spot market strategy described in Section III-A (Strategy I) otherwise it follows the schedule prepared based on the forecast.

1) Energy management strategy for V2G without accurate forecast data in microgrids: When the day-ahead energy generation and demand forecast in microgrids is not accurate then the charging and discharging scheduling of PEVs is decided by following real-time generation and demand data (5 or 15 min prior) presented by DGs and loads. Based on the mismatch calculated from real-time information the charging and discharging schedule of PEVs is scheduled in decentralised manner. In case of energy shortage in microgrids, the PEVs will be used as the sources to fill the shortage. In this case PEVs submit bids to PEV aggregator to provide energy through V2G. The bids submitted by PEVs include offer price which is the summation of cost of stored energy and the expected cost of battery degradation. The bids by PEVs are calculated based on the assumption that there will be no charging or discharging before they leave the parking station, as if there is no knowledge of forecast. Based on the bids submitted by PEVs, the aggregator chooses PEVs with lowest offer prices till the energy shortage is bridged. The shortage beyond the available PEVs capacity will be assigned to the utility grid.

In case of excess energy in microgrids, PEVs will be charged by the aggregator. The selection of PEVs for charging is based on the State of Charge in kWh (SOC) of their batteries, i.e. the PEV with SOC less than the minimum required value to travel after leaving the parking station will be given high priority to charge. A more detailed description of this strategy is given in section III-A.

2) Energy management strategy for V2G with accurate forecast data in microgrids: If the forecast on energy generation and consumption in a microgrid is accurate on day-ahead or half-day ahead basis then the charging and discharging schedules of PEVs are centrally decided by the aggregator. The aggregator generates a schedule for charging and discharging of PEVs by simultaneously optimising the following goals without violating the desire operational preferences of PEV owners and the network constraints.

a) Minimising the supply-demand mismatch in the microgrid by using V2G and G2V capability of PEVs
b) Minimising the overall charging cost of PEVs
c) Maximising the revenue of PEVs through V2G by offsetting their BDC

The proposed energy management strategies are implemented using a MAS setup suitable for microgrids and is as shown in Fig. 2. In this MAS the proposed strategies are implemented by separately managing PEVs from the primary market which is a market within the microgrid in which DGs trade the energy with loads. In Fig. 2, Distributed Generation Agents (DGAs) and Point Load Agents (PLAs) represent DGs and loads connected in the microgrid respectively. Auction Supervising Agent (ASA) is the market organising agent for primary market and follows first price Continuous Double

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

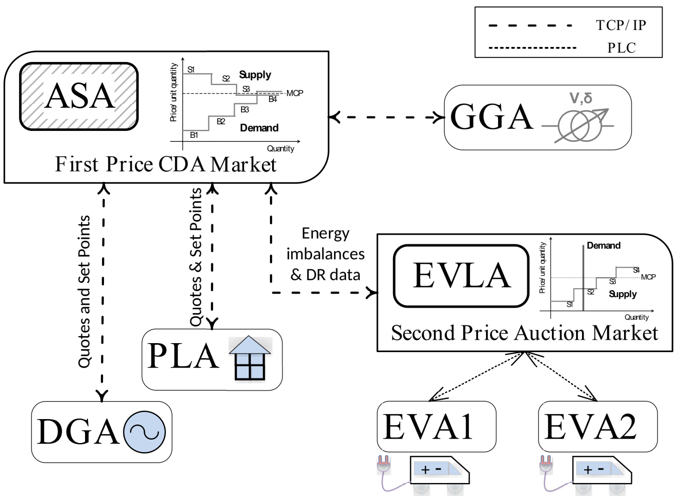


Fig. 2: MAS architecture for energy management in smart microgrids with V2G

Auction (CDA) mechanism to conduct auction among DGAs and PLAs. A detailed description on CDA market mechanism is available in [4]. ASA also suggests vehicle aggregator on selection of the strategy to be followed based on the deviation between day-ahead forecast data and real-time data. In this market bids placed by DGs and loads are limited to the range [Grid Buying Price (GBP), Grid Selling Price (GSP)], as the bids beyond this range are undercut by the utility grid. Global Grid Agent (GGA) represents the utility grid to address the residual demand and excess supply beyond the PEVs capacity. Residual demand in a microgrid connotes the power demand that cannot be met using the available energy sources. Similarly the excess energy is the superfluous or surplus energy available in the microgrid in any interval. PEVs in the microgrid are represented by Eelctric Vehicle Agents (EVAs) whereas Electric Vehicle Load Aggregator (EVLA) represents the energy aggregator for PEVs. The communication links shown in Fig. 2 represent the type of communication required among various agents in the architecture. EVAs submit their desired operational preferences to EVLA which follows them as guideline for scheduling the charging and discharging of PEVs. The preferences include Starting Interval (SI), Leaving Interval (LI), desired minimum SOC to be maintained with PEVs by the end of LI ($SOC_{\text{LI}}|_{min}$), SOC_{max}, SOC_{SI} and rated kW.

The proposed MAS treats PEVs as adjustable loads and their charging and discharging schedules are decided by EVLA based on the energy supply and demand forecast information. The type of strategy to be used to manage V2G is chosen by the MAS based on the accuracy of forecast information as described in the later parts of this section.

III. Optimal V2G Management Model for Microgrids

A. Energy management strategy for V2G without accurate forecast data in microgrids

In case of inaccurate forecast, ASA suggests EVLA to follow this strategy. Based on the real-time energy supply and demand information, ASA calculates the energy mismatch (ΔP). If the mismatch during a Demand Interval (DI) is non-zero then PEVs will be called for addressing the mismatch. The value of ΔP sets the directions for managing the energy and the role of PEVs as sources or sinks.

Case I - $\Delta P < 0$: ASA requests EVLA to provide the energy support which in turn invites quotes from EVAs. Each quote includes the price per kWh at which a PEV is willing to sell and the power in kW. EVLA follows Second Price Auction (SPA) mechanism to choose the set of PEVs to address the energy shortage. The trader who submits the lowest offer price will be chosen as winner if the offer is less than GSP and the price he receives is the second lowest price. Thus, it ensures profit to the winner. If the lowest among the offer prices submitted by EVAs is more than GSP then the shortage will be assigned to the utility grid. Alternatively, if the lowest offer price is less than GSP and the second lowest price is more than GSP then the price to be offered to the winner is GSP. In SPA, the bids submitted by traders reflect their true valuation (τ) since submitting a bid higher or lower than the true valuation does not merit their profit. The true valuation of energy connotes the cost of energy below which it is not economically feasible to sell. The rationale behind applying SPA is its quick market clearing capability and transparency. A more detailed description of SPA can be found in [20] and [21]. EVLA conducts SPA among EVAs and sends the outcome to ASA.

Evaluating true valuation of energy by EVAs: If the energy demand is more than supply then EVLA notifies EVAs to submit the quotes. EVAs calculate the offer price by taking the BDC correspond to the expected DOD after travelling EDD. For a PEV, the minimum SOC to be maintained at the end of LI can be expressed as,

$$SOC_{\text{LI}|min} = SOC_{min} + SOC_{\text{edd}} \tag{5}$$

where,

$$SOC_{\text{edd}} = \text{ECR} \times \text{EDD} \tag{6}$$

In an interval j, if the PEV is not used for V2G service (not discharged) then the expected SOC at the end of EDD will be calculated by assuming a worst-case scenario in which the PEV will not be charged till the end of LI. This is valid when there is no accurate forecast on energy surplus or shortage in the microgrid. Therefore,

$$SOC_j^{\text{edd}+} = SOC_{j-1} - SOC_{\text{edd}} \tag{7}$$

If PEV is used for V2G service in the interval j then SOC_j is less than SOC_{j-1} by ($P_{\text{PEV}} \times \Delta t$). In such cases, SOC at the end of EDD is given by,

$$SOC_j^{\text{V2G, edd}+} = (SOC_{j-1} - (P_{\text{PEV}} \times \Delta t)) - SOC_{\text{edd}} \tag{8}$$

Eq. (8) is also based on the assumptions as (7). From (7) and (8), it can be observed that $SOC_j^{\text{V2G,edd+}}$ is lower than $SOC_j^{\text{edd+}}$ and hence causes higher depth of discharge at the end of the EDD. This leads to higher BDC due to extra degradation of the cycle-life. Therefore, while calculating the true valuation of energy in interval j, the BDC corresponding to the change in DOD from $DOD_j^{\text{edd+}}$ to $DOD_j^{\text{V2G,edd+}}$ must

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

be incorporated. Here, $DOD_j^{\text{edd}+}$ and $DOD_j^{\text{V2G,edd}+}$ are DODs corresponding to $SOC_j^{\text{edd}+}$ and $SOC_j^{\text{V2G,edd}+}$ respectively. As per (1), the BDC to be considered in the interval 'j' is calculated as follows.

$$BDC_j = \left(\frac{1}{f(DOD_j^{\text{V2G,edd+}})} - \frac{1}{f(DOD_j^{\text{edd+}})}\right) \times CB \quad (9)$$

τ of a PEV in interval j is calculated using BDC and the Cost of Stored Energy (CSE) as,

$$\tau_j = CSE_{(j-1)} + \alpha_j \quad (10)$$

where, $CSE_{(j-1)}$ is the cumulative price of stored energy at the end of interval $(j-1)$ and is calculated by taking the weighted average of charging and discharging prices of the energy from SI to $(j-1)$.

$$\alpha_j = BDC_j/(P_{\text{PEV}}\Delta t) \quad (11)$$

In (11), α_j connotes the extra revenue to be recovered per unit energy (or additional value of the quote to be place) in order to breakeven the BDC corresponding to discharging of the PEV in interval j.

Case II - $\Delta P > 0$: In this case ASA sends ΔP and Market Clearing Price (MCP) information to EVLA which chooses EVAs to charge based on their SOC in the corresponding interval. If SOC_j of a PEV is less than its $SOC_{\text{LI}}|_{min}$ then the PEV will be given higher priority to charge. If there are multiple PEVs with $SOC_j < SOC_{\text{LI}}|_{min}$ then they are selected to charge in the increasing order of their SOC. Also, if PEVs are charged to $SOC_{\text{LI}}|_{min}$ then they will be chosen on the order of their arrival. After identifying the required number of PEVs, EVLA updates the corresponding EVAs with the price of electricity. EVAs use this price to update their CSE. At the end of the DI, the excess energy beyond PEVs capacity will be assigned to GGA.

B. Energy management strategy for V2G with accurate energy supply and demand forecast data in microgrids

DGAs and PLAs submit their respective forecast(day or half-day ahead) information to ASA which notifies EVLA with the energy imbalances calculated based on the forecasts. ASA sends the estimated prices of electricity for the corresponding energy imbalances in the market to EVLA. EVAs submit their status and preferences about charging and discharging to EVLA on their arrival. EVLA generates a schedule for PEVs by optimising the objectives described in section II-2 without violating the operational preferences of PEVs.

Optimisation model for optimal V2G management: The primary objective of the proposed V2G management strategy under the presence of accurate forecast data is minimising the supply demand mismatch in the microgrid by scheduling charging or discharging of PEVs. This can be represented as,

$$f1 : Min \sum_{j \in y(t_s,t_e)} \left(\Delta P_j + \sum_{i=1}^{M} x_j^i P_{\text{PEV}}^i a_j^i\right) \quad (12)$$

where x_j^i is a decision variable whose value represents the state (+1 for charging, -1 for discharging and 0 for idle) of i^{th} PEV in interval j. a_j^i is availability indicator to represent the availability of i^{th} PEV in interval j and it is equal to 1 if $j <$ LI, 0 otherwise. The second objective (minimising the overall charging cost of PEVs and maximizing the revenue from V2G while offsetting the BDC) is modelled as,

$$\begin{aligned} f2 : Min \sum_{j \in y(t_s,t_e)} \Bigg\{ & \left(C_j^i \sum_{i=1}^{M} \frac{(x_j^i + |x_j^i|)}{2} P_{\text{PEV}}^i a_j^i \Delta t\right) \\ & - \sum_{i=1}^{M} \left(D_j^i \frac{(|x_j^i| - x_j^i)}{2} P_{\text{PEV}}^i a_j^i \Delta t + BDC_j^i\right) \Bigg\} \end{aligned} \quad (13)$$

where C_j^i and D_j^i are the prices of electricity per kWh for charging and discharging of PEVs in the interval j respectively and are equal to the prices forecasted by ASA for the interval. The objective functions (12) and (13) need to be solved simultaneously, subject to the constraints given in (14), to obtain the optimal charging and discharging schedule of PEVs. The schedule minimises the estimated mismatches in the microgrid while making V2G integration economically viable.

$$SOC_{max} \geq SOC_{\text{LI}} \geq SOC_{\text{LI}}|_{min} \quad (14)$$

During the discharging of PEVs, if SOC becomes less than the SOC with which they arrived then CSE corresponding to the initial SOC will be taken into account while deciding the cost of V2G. The objective function shown in (13) is non-linear which demands a non-linear multi-objective technique such as evolutionary algorithms based approaches [22].

In this work, a modified Artificial Bee Colony (ABC) algorithm, called Artificial Bee Colony-Rate of Change (ABC-ROC) [23], is used to optimize the overall objective function formulated as,

$$\begin{aligned} Min \Bigg\{ & \left(\sum_{j \in y(t_s,t_e)} \gamma(j) f1\right) + \gamma_2 f2 \\ & + \gamma_3 \left(S_{\text{LI}}|_{min} - SOC_{\text{LI}}\right) \\ & + \gamma_4 \left(SOC_{\text{LI}} - SOC_{max}\right) + \gamma_5 \Bigg\} \end{aligned} \quad (15)$$

where γ, γ_2, γ_3, γ_4 and γ_5 are the parameters to be tuned while solving (15). The weight factors $\gamma 3$ and $\gamma 4$ are chosen such a way that they are relatively high compared to the product of $\gamma 2 * f2$ so that the members of the population which violate SOC constraints are heavily penalised. In the present work, the values of γ_2, γ_3, γ_4 and γ_5 are taken as $1, 1e3, 1e3$ and $1e3$ respectively. The value $1e3$ for γ_3 and γ_4 is arrived by increasing the value starting from 100. The value of γ is case dependent and is chosen as follows:

$$\gamma(j) = \begin{cases} 1e3 & \text{if } |\Delta P_j| < \sum_{i=1}^{M} |(x_j^i)^*| P_{\text{PEV}}^i \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

where, $(x_j^i)^*$ is the value of x_j^i in the current population generated by ABC. The value of $\gamma(j)$ is also chosen to be $1e3$ (case 1 of $\gamma(j)$ given in (16)) to equally penalise

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

it unless there is violation in SOC constraints. The ABC-ROC algorithm parameters used for solving the proposed optimization problem are colony size 200, maximum ROC 0.6, maximum flag 40, maximum trace 60 and maximum cycles 500. The generated schedule is submitted to ASA which obtains binding contracts with DGAs and PLAs for charging and discharging respectively to make the generated schedule certain and independent of deviations in the forecasted information. The contracts are made for the quantum of energy needed for charging of PEVs or delivered from discharging of PEVs at forecasted prices. In energy surplus intervals, the contracts are made between the PEVs that are scheduled to charge and DGAs with relatively higher energy cost. This is due to the fact that the bids placed by such DGs are undercut by the bids of DGAs with lower energy cost per kWh. Therefore, DGs with higher energy cost per kWh are assigned to the utility grid to sell the excess energy at GBP which is usually less than the proposed contract price. This gives motivation to such DGs to have binding contracts in excess energy intervals.

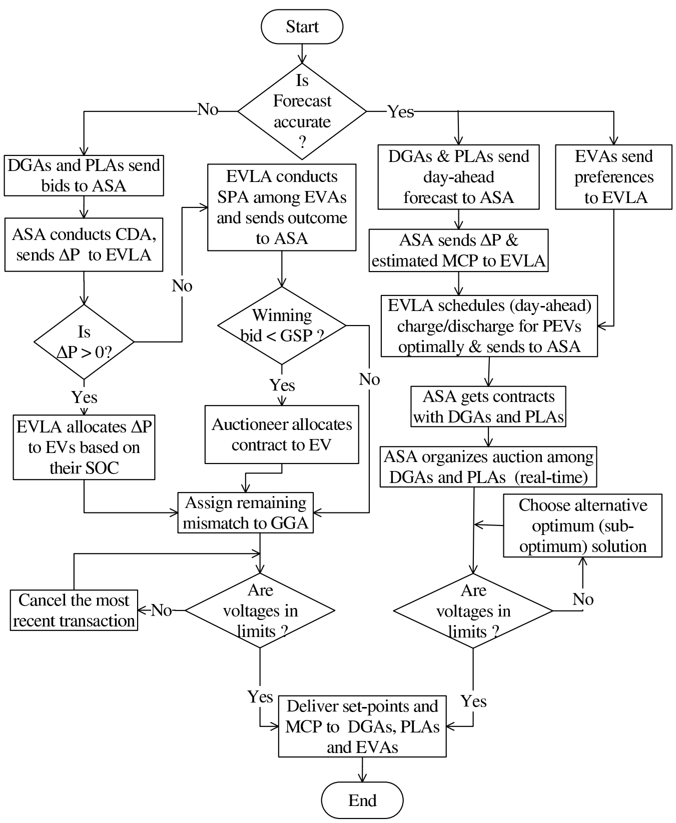


Fig. 3: Flowchart of the proposed energy management system

Similarly, during the energy shortage intervals ASA makes binding contracts between the PEVs scheduled for discharging and PLAs with higher profit motivation (type-1 loads, example commercial buildings). This is due to the fact that these loads submit lower bids which are undercut by the bids placed by the loads with relatively less profit motivation (type-2 loads, example residential units). Therefore, type-1 loads will be left out in the primary market and buy energy from the utility grid for meeting the residual demand at GSP which is usually higher than the binding contract price. This gives motivation for type-1 loads to have binding contracts during the power shortage intervals. If the profit motivation behaviour of loads is not known then ASA chooses loads randomly to make the binding contracts. In the beginning of each DI in primary market, DGAs and PLAs submit real-time generation and demand for the immediate next DI to ASA. After receiving the information ASA conducts auction (CDA mechanism) among DGAs and PLAs by excluding the quantum of energy specified in binding contracts for the corresponding DI. The submitted information by DGAs and PLAs may not be the same as day-ahead or half-day ahead forecast information. In such cases, the excess supply or the residual demand will be assigned to the utility grid.

Figure 3 showcases the underlying mechanism of the proposed energy management strategies. The obtained schedule may cause voltage violations or line limit violations which must be verified before finalizing the set points. The limit violations are verified with Open Distribution System simulator (OpenDSS) [24], which is an open source software to simulate distribution systems with DGs and Storage elements. It has a powerful component library covering different DG types and storage systems which helps the systems operators to quickly build systems for simulation. In addition to this, OpenDSS provides a graphical representation of the system status upon solving the power flow, which can be used to quickly assess the systems status. The linking between the proposed agent based energy management system to OpenDSS is done using the COM service of OpenDSS.

In case of auction based scheduling of PEVs (case without accurate forecast), the most recent contract obtained between PEVs and DGs/Loads will be canceled if voltages are violated. In case of optimisation based scheduling (case with accurate forecast), the obtained schedule will be sent to OpenDSS platform where it will be executed. If there are any voltage violations observed, then ASA requests EVLA to provide an alternative solution (sub-optimal) which will be again verified for voltage limit violations.

IV. Case Study: Simulation, Results & Discussion

The modelling presented in section III suggests that V2G is economically viable for the systems with large price variations. In case of distribution systems, due to the high penetration of DGs and other energy resources such as demand response, the variations in price of electricity may not be enough to attract large scale integration of V2G unless the utility provides special incentives to the EV owners to offset the degradation costs. Alternatively, such EVs can be integrated into the system operation through microgrids by localizing the electricity trading process to microgrid. Therefore in this case study, a modified IEEE-37 bus system with a grid-connected microgrid is taken as a case study and is shown in Fig. 4.

The ratings of loads connected outside the microgrid are same as the specified values of the standard IEEE-37 bus distribution system [25]. The ratings of DGs and loads connected in the microgrid are as shown in the Fig. 4. In order to apply the proposed energy management strategies on the case study

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

system, two scenarios are considered. In the first scenario, no forecast information is taken into account and the scheduling of PEVs is done by following the strategy described in section III-A. In second scenario, the forecast information is taken into consideration and the scheduling of PEVs is done by following the strategy described in section III-A.

In both the scenarios, energy selling price of the utility grid is taken as 13.5 cents per kWh and buying price as 9 cents per kWh. These prices set the limits on quotes and energy clearing prices in primary market.

Scenario I - Without accurate forecast: For this scenario, it is taken that three PEVs are available in the microgrid for V2G management. The ratings, cycle-life and ECR of the PEVs are given in Table A1. The desired operational preferences and status of PEVs on their arrival to the parking lot are as given in Table A2. The vehicles V1, V2 and V3 are represented by agents EVA-1, EVA-2 and EVA-3 respectively. At this point, it is assumed that PEVs arrive to the parking lot by 8 a.m. and submit their information to EVLA on their arrival.

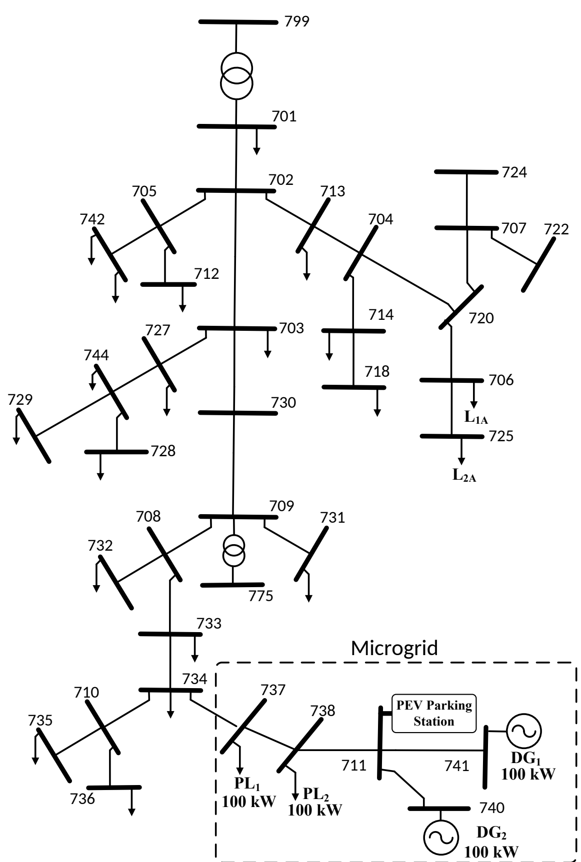


Fig. 4: Modified IEEE 37 bus distribution network with a grid connected microgrid

Assuming that the forecast available with ASA is not accurate, DGAs and PLAs submit their real-time supply and demand information along with the initial quote in the preceding DI to ASA. Table I shows supply and and demand information of DGs and loads respectively for 16 DIs each of 15 minitues duration. After receiving the information, ASA organizes CDA market for settling the energy requirements with local energy producers and sends MCP along with residual demand or excess supply (ΔP) information to EVLA. The last two columns of the table show mismatch between supply and demand and MCP in the corresponding DI.

TABLE I: Real-time generation, demand and MCP data

DI	Generation (kW)		Demand (kW)		ΔP	MCP
	DG1	DG2	PL1	PL2	(kW)	(¢/kWh)
1	50	50	70	80	-50	12.13
2	50	50	80	80	-60	12.28
3	50	50	70	80	-50	12.13
4	50	50	70	80	-50	12.13
5	90	90	60	60	60	10.47
6	90	80	60	60	50	10.59
7	90	90	60	60	60	10.47
8	90	90	60	60	60	10.47
9	50	50	70	80	-50	12.13
10	50	50	70	80	-50	12.13
11	50	50	80	80	-60	12.28
12	50	50	80	80	-60	12.28
13	90	90	60	60	60	10.47
14	90	90	60	60	60	10.47
15	90	90	60	60	60	10.47
16	90	90	60	60	60	10.47

Based on ΔP value, EVLA either invites bids from EVAs to address the residual demand or chooses PEVs to charge using the excess supply by following the procedure detailed in Section III-A. As shown in Table I, during the intervals 1 to 4 and 9 to 12 the onsite energy is inadequate to serve the loads in microgrid whereas in rest of the intervals excess supply is available. During the energy shortage intervals, EVAs submit bids to discharge if their SOC is more than $SOC_{\text{LI}}|_{min}$. Tables II, III and IV present the trading activities of PEVs in the market organised by EVLA. Each table shows, how the bids by PEVs are calculated and the corresponding clearing prices in the market. Table II provides more details on the bidding strategy whereas other two provide only required information.

Table II shows the detailed calculation for V1 in each interval with τ, α and the quotes placed. In Table II, the entries under SOC column has two values for each DI to indicate SOC of V1 in the beginning (S_{I}) and ending (S_{II}) of the corresponding interval if it is charged or discharged. Also, BDC has two entries in each interval viz. PT (*Present*) and FT (*Future*). The present BDC values indicate degradation cost of batteries corresponding to the change in SOC from S_{I} to S_{II} whereas the future BDC values indicate degradation cost corresponding to the change in SOC after travelling EDD, i.e. from$(\text{S}_{\text{I}} - SOC_{\text{EDD}})$ to $(\text{S}_{\text{II}} - SOC_{\text{EDD}})$, assuming no further charging of batteries till LI. Similarly, PT and FT values of α and τ indicate the additional bid and true valuation of energy by V1 corresponding to the present and future values of BDC respectively.

During the interval-1 energy is inadequate to meet the demand and EVLA requests bids from EVAs. While calculating the bids, EVAs choose future BDC values corresponding to the expected change in DOD after traveling EDD. For example, during interval-1 the present and future BDC values of V1 are 2.57 cents and 7.02 cents respectively. The rise in future BDC is attributed to the uncertainty associated with SOC_{LI} in case of no forecast on energy supply and demand. This drives EVAs to consider future BDC values than the present BDC, thus EVA-1 places a bid (true valuation) at a price 12.81 cents per kWh which is calculated using (10). Similarly, during all the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

TABLE II: Bids and schedule of EVA-1

Interval	SOC# variation		BDC#		additional bid, $\alpha^{\#}$		Cost of stored energy#	Bid	PEV Schedule	
	Begin	End	Present	Future	Present	Future		(Price, Quantity)	Clearing Price #	Quantity@
1	57.5	55	2.57	7.02	1.03	2.81	10	(12.81,10)	13.44	-10
2	55	52.5	3.14	8.59	1.26	3.44	10	(13.44,10)	13.5	-10
3	52.5	50	3.84	10.51	1.54	4.20	10	(14.2,10)	-	
4	52.5	50	4.69	12.86	1.88	5.14	10	(15.14,10)	-	
5	52.5	55	-	-	-	-	10	-	10.47	10
6	55	57.5	-	-	-	-	10.02	-	10.59	10
7	57.5	60	-	-	-	-	10.05	-	10.47	10
8	60	60	-	-	-	-	10.06	- -	-	
9	60	57.5	2.30	5.74	0.92	2.30	10.06	(12.36,10)	13.49	-10
10	57.5	55	2.57	7.02	1.03	2.81	10.06	(12.87,10)	13.5	-10
11	55	52.5	3.14	8.59	1.26	3.44	10.06	(13.5,10)	13.5	-10
12	52.5	50	3.84	10.51	1.54	4.20	10.06	(14.27,10)	-	
13	52.5	55	-	-	-	-	10.06	-	10.47	10
14	55	57.5	-	-	-	-	10.08	-	10.47	10
15	57.5	60	-	-	-	-	10.10	-	10.47	10
16	60	60	-	-	-	-	10.11	-	-	

#: Units of SOC in kWh, BDC in ¢ and the rest are in ¢ per kWh; @: (+) and (-) represent charging and discharging respectively

energy shortage intervals EVAs submit their bids along with quantum of power. Tables III and IV show the bids placed by EVA-2 and EVA-3 respectively.

TABLE III: Bids and schedule of EVA-2

DI	SOC# variation		BDC# part of bid	CSE#	Bid (Price,Quantity)	PEV Schedule	
	Begin	End				Price#	kW@
1	55	52.5	3.44	10	(13.44,10)	13.5	-10
2	52.5	50	4.20	10	(14.2,10)	-	
3	52.5	50	4.20	10	(14.2,10)	-	
4	52.5	50	4.20	10	(14.2,10)	-	
5	52.5	55	-	10	-	10.47	10
6	55	57.5	-	10.02	-	10.59	10
7	57.5	60	-	10.05	-	10.47	10
8	60	60	-	10.06	-	-	
9	60	57.5	2.30	10.06	(12.36,10)	13.49	-10
10	57.5	55	2.81	10.06	(12.87,10)	13.5	-10
11	55	52.5	3.44	10.06	(13.5,10)	13.5	-10
12	52.5	50	4.20	10.06	(14.27,10)	-	
13	52.5	55	-	10.06	-	10.47	10
14	55	57.5	-	10.08	-	10.47	10
15	57.5	60	-	10.10	-	10.47	10
16	60	60	-	10.11	-	-	

#: Units of SOC in kWh, BDC in ¢ and the rest are in ¢ per kWh
@: (+) and (-) represent charging and discharging respectively

During the energy shortage intervals, EVLA conducts SPA market to identify set of PEVs for addressing the shortage and to finalize the price at which shortage is met. In interval-1 EVA-1, EVA-2 and EVA-3 submitted 12.81 cents per kWh, 13.44 cents per kWh and 14.69 cents per kWh respectively as bids to sell 10 kW of power. Therefore, EVA-1 is chosen primarily as the winner and the price offered is 13.44 cents per kWh which is the second lowest. Moreover, the second lowest bid, submitted by EVA-2, is less than GSP and hence EVA-2 is also chosen to meet the shortage. The price offered to EVA-2 is 13.5, as the next lowest bid (14.49 cents per kWh) is higher than GSP. However, during the interval-2 EVA-1 alone is operating in V2G as the second lowest bid (submitted by EVA-2) is more than GSP. At this point, if the market price range is extended beyond 13.5 cents per kWh (e.g. 15 cents per kWh) then more V2G participation by PEVs can be observed.

During the energy surplus intervals, EVLA chooses EVAs to charge by following the procedure given in Section III-A. From Tables II, III and IV , it can be observed that during the intervals 5 to 7 EVA-1 and EVA-2 are charged till the SOC reaches SOC_{max} whereas EVA-3 is charged to maximum during the intervals 5 and 6. Although SOC of PEVs is more than $SOC_{\text{LI}}|_{min}$, the motivation for PEVs to get charged beyond the required SOC can be explained as: a) if they depart with lower SOC, but greater than $SOC_{\text{LI}}|_{min}$, then the degradation cost corresponding to the DOD after traveling EDD is relatively high, b) profit made through V2G.

From Tables II, III and IV, it can be noted that the number of charge-discharge cycles undergone by V3 are less compared to the charge-discharge cycles of V1 and V2 due to higher CSE of V3 than V1 and V2. Also, the number of charge/discharge cycles undergone by V1 is more compared to that of V2 and V3 due to higher initial SOC of V1 causing lower BDC costs and hence lower bids than V2 and V3.

The obtained schedule of PEVs is executed on the case study network simulated in OpenDSS environment and verified that voltages are within the limits (0.95 p.u.). In this strategy, the time required to generate PEV schedule varies from 1 to 3 minutes depending on the number of vehicles handled by EVLA.

TABLE IV: Bids and schedule of EVA-3

DI	SOC# variation		BDC# part of bid	CSE#	Bid (Price,Quantity)	PEV Schedule	
	Begin	End				Price#	kW@
1	55	52.5	3.44	11.25	(14.69,10)	-	
2	55	52.5	4.20	11.25	(15.45,10)	-	
3	55	52.5	4.20	11.25	(15.45,10)	-	
4	55	52.5	4.20	11.25	(15.45,10)	-	
5	55	57.5	-	11.25	-	10.47	10
6	57.5	60	-	11.22	-	10.59	10
7	60	62.5	-	11.19	-	-	
8	60	60	-	11.19	-	-	
9	60	57.5	2.30	11.19	(13.49,10)	13.5	-10
10	57.5	55	2.81	11.19	(14,10)	-	
11	57.5	55	3.44	11.19	(14.63,10)	-	
12	57.5	55	4.20	11.19	(15.39,10)	-	
13	57.5	60	-	11.19	-	10.47	10
14	60	60	-	11.16	-	-	
15	60	60	-	11.16	-	-	
16	60	60	-	11.16	-	-	

#: Units of SOC in kWh, BDC in ¢ and the rest are in ¢ per kWh
@: (+) and (-) represent charging and discharging respectively

Scenario II - With accurate forecast: At this point of case study, it is assumed that the real-time generation and demand information given in Table I is available a priori with DGs

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

and loads and is submitted to ASA on day-ahead basis by the respective DGAs and PLAs. For the given forecast of supply and demand, it is assumed that ASA estimated the market clearing prices and forwarded to EVLA along with the supply-demand mismatch. In this scenario, three cases are studied to analyze the performance of the proposed energy management strategy. In the first case, three PEVs are taken into consideration with ratings as given in Table A1. Table V shows the optimal charging and discharging schedule of PEVs obtained by EVLA adhering to the desired operational preferences given in Table A2. The values given in the last two column of the Table V refers the charging or discharging price, and the resulting mismatch after adding the V2G. The charging and discharging schedule of PEVs is forwarded to ASA which creates binding contracts with DGs and loads to make the obtained schedule certain.

The schedule given in Table V is obtained by taking the degradation cost corresponding to the change in SOC between consecutive intervals, i.e. the present value of BDC, as the charging and discharging schedules of PEVs till their respective LIs are known. This allows the operators to use PEVs to higher DOD for the given price range. If the obtained charge/discharge schedule of PEV is such that SOC_{LI} is less than SOC_{SI} then the cost of discharging would be CSE. The prices given in Table V refer to the charging and discharging price of PEVs.

By comparing the discharging (V2G) prices of PEVs given in Tables II, III, IV and V, it can be observed that the price of energy from V2G is minimum if the available forecast on energy supply and demand is accurate. This is due to the certainty of SOC_{LI} in Secnario-II (with accurate forecast information) whereas it is unpredictable in Scenario-I.

TABLE V: Charging and Discharging schedule of V2G (3 PEVs) with accurate forecast scenario

Interval	PEVs Schedule ^{a}			Charging/Discharging Price in ¢/kWh	Resulting mismatch after V2G in kW
	V1	V2	V3		
1	-10	0	0	12.13	-40
2	-10	-10	-10	12.28	-30
3	-10	-10	0	12.13	-30
4	0	0	-10	12.13	-40
5	10	10	10	10.47	30
6	10	10	10	10.59	20
7	10	10	10	10.47	30
8	10	10	10	10.47	30
9	-10	-10	-10	12.13	-20
10	-10	-10	-10	12.13	-20
11	-10	-10	-10	12.28	-30
12	-10	-10	-10	12.28	-30
13	10	10	10	10.47	30
14	10	10	10	10.47	30
15	10	10	10	10.47	30
16	10	10	10	10.47	30

a: (+)&(-) represent charging & discharging in kW respectively

Fig. 5 shows the power mismatch in two cases compared with the actual mismatch in the system. As shown in graph, the residual demand and excess supply are diminished with inclusion of V2G. Although it is an expected outcome of V2G integration, the effect of forecast of energy supply and demand on the effective utilisation of V2G is one of the important aspects of proposed V2G integration strategy. From the graph, it can be observed that V2G service is better utilised when the forecast information is accurate compared to the scenario when it is not.

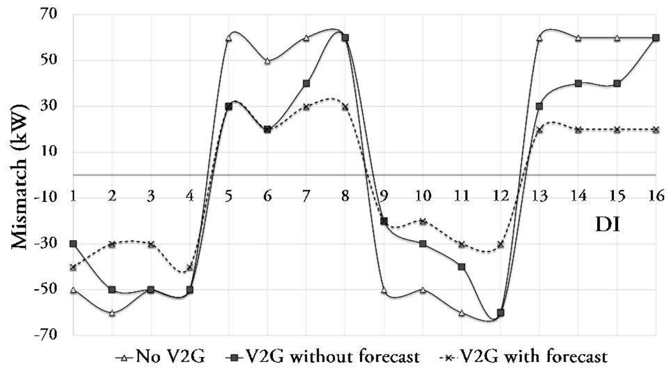


Fig. 5: Comparing ΔP in Case-I and II with reference to actual mismatch

TABLE VI: Charging and Discharging schedule of V2G (10 PEVs) with accurate forecast scenario

DI	PEV Schedule*										ΔP^a after scheduling
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	
1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-5
2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
3	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-5
4	0	-1	-1	-1	-1	-1	0	-1	-1	-1	-10
5	1	1	1	1	1	1	0	1	1	1	15
6	0	1	1	1	1	0	1	1	1	1	10
7	1	1	1	1	1	1	1	1	1	1	10
8	1	0	1	1	1	1	1	1	1	1	15
9	-1	-1	-1	-1	0	0	-1	-1	0	0	-20
10	-1	-1	0	0	-1	-1	-1	0	-1	-1	-15
11	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
13	1	1	1	1	0	1	1	1	1	1	15
14	1	1	1	0	1	1	1	1	1	0	20
15	1	1	1	1	1	1	1	1	1	1	10
16	1	1	0	1	1	0	1	0	0	1	30

a: (+)&(-) represent charging & discharging in kW respectively; *: the status of PEV as given in (12) and (13)

In order to verify the scalability of the proposed approach, the same case study is reconsidered with 10 PEVs and 25 PEVs. In case of 10 PEVs, the rating of each PEV is taken as 5kW with all other parameters given in Table A1 are unchanged whereas in latter case the rating is chosen as 2kW. Table VI and VII show the obtained optimal schedule for the forecast data given in Table I. The mismatch values given in the tables represent the modified ΔP after incorporating the optimal schedule generated by EVLA. By comparing the mismatches in Tables I, VI and VII, it can be observed that the mismatches in the microgrid are reduced by engaging the V2G potential and flexible demand capability of PEVs. The time taken for solving the optimization in case of 10 PEVs is approximately 7.7 minutes and in case of 25 PEVs it is 18.53 minutes on a computer with Intel i5, 2.6 GHz processor with 4GB RAM. If the number of vehicles are increased then the convergence time increases significantly due to the nonlinear nature of BDC in the the objective function.

In the proposed energy management system, it is assumed that PEVs submit their preferences and status at least one hour (T_{Max}) before the schedule commences (say at 8 a.m.). This time duration sets the limit on the number of vehicles

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

TABLE VII: Charging and Discharging schedule of V2G (25 PEVs) with accurate forecast scenario

	PEV Schedule*																									ΔP^a after
DI	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	scheduling
1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	0	-10
2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
3	0	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	-1	0	-1	-10
4	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	-1	-1	0	-1	-1	-1	0	0	-1	-1	-10
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	16
6	0	1	1	0	1	1	0	1	1	0	1	1	0	0	1	1	1	1	0	1	1	1	1	0	1	16
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	14
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	14
9	0	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-10
10	-1	-1	-1	0	-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	0	-10
11	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-10
13	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	14
14	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	14
15	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	16
16	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	16

a: (+)&(-) represent charging & discharging in kW respectively; *: the status of PEV as given in (12) and (13)

managed by an aggregator. For example, in the present case study when the number of PEVs are 25 the time required to converge the optimization problem is 18.53 min, which is close to one third of T_{max}. And, for the given time limitation EVLA can manage approximately 75 PEVs. In order to accommodate more EVs, EVLA can increase T_{Max} from 1 hour to 1.5 hours which allows it to accommodate approximately 100 EVs. Alternatively, using multiple EVLAs in the system more EVs can be managed. In such cases, overall mismatch in the microgrid is apportioned, similar to [15] using line limits, among all EVLAs and each EVLA targets to minimize assigned portion of the mismatch using the proposed approach. The post-schedule mismatch information of each aggregator will be shared to other EVLAs which may pick up the additional mismatch to address from the information shared by other EVLAs without violating the feeder limits and adjust the EVs schedule. For this, each aggregator agent informs the concerned other aggregator about the additional support that it can provide. The financial model for exchanging the apportioned mismatches among the multiple aggregators is currently not covered by the scope of the paper.

The proposed V2G strategy is also applied to another set of case study data with forecast for 36 intervals, i.e. from 9 a.m. to 6 p.m. In this case study the operational preferences of PEVs are same as in previous case study except the LI of PEVs, which is taken as 36. The graph given in Fig. 8 shows the charging and discharging schedule along with the forecasted mismatches and market clearing prices. From the graph, it can be seen that the PEVs are discharged only during intervals 17 to 20 due to higher battery degradation costs that cannot be off-set at other market prices.

The obtained optimal schedule in all three cases is executed in OpenDSS environment on the case study system shown in Fig. 4. It is found that no voltages are violating the limit (0.95 p.u.). Figure 6 depicts the convergence progress of the optimization algorithm, i.e. ABC, with number of iterations when 8 PEVs are participating in a scenario with the same forecast data. The graph also shows the convergence progress of ABC-ROC , ABC algorithm with colony size 500, limit value 200 and maximum cycles are 1000, and Genetic Algorithm (GA) with elitism 10%, crossover 10% and mutation 1% for solving *f2*. By comparing the convergence process of the three algorithms it can be observed that ABC-ROC approach converges quickly, i.e. in 302 iterations, when compared to other two algorithms.

Figure 7 shows the cumulative convergence probability functions of the proposed ABC-ROC based optimization approach, ABC based approach and GA based approach for the same case study with 8 PEVs. The graphs show that the ABC-ROC based approach is able to converge to overall optimum at higher cumulative probability (0.82), than other two approaches. This indicates that ABC-ROC based approach is more reliable than ABC and GA based approaches to solve the proposed optimization problem.

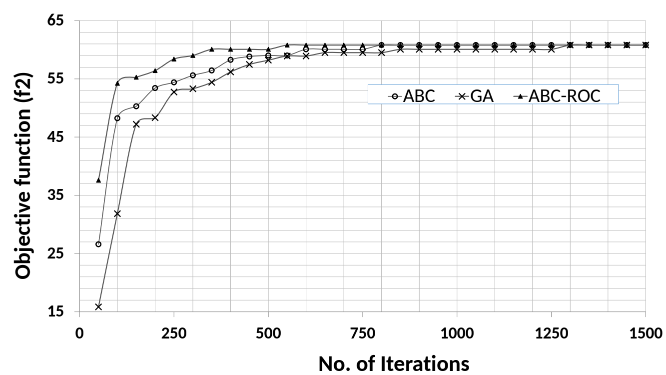


Fig. 6: Convergence of the objective function $f2$ using ABC, GA and ABC-ROC algorithms

A. Discussion

From the simulation results and modelling presented in Section-II, it can be understood that the effective utilization of V2G (to higher DOD levels) can be achieved in economically viable way in the systems with large electricity price variations. In breif, to make V2G viable for higher values of DOD the difference between cost of discharging and charging must be high .

Another important factor that effects the economic viability of V2G is the battery cost. If the battery cost of a PEV is high then its BDC will be more. This demands a large difference between discharging and charging costs to offset the higher

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

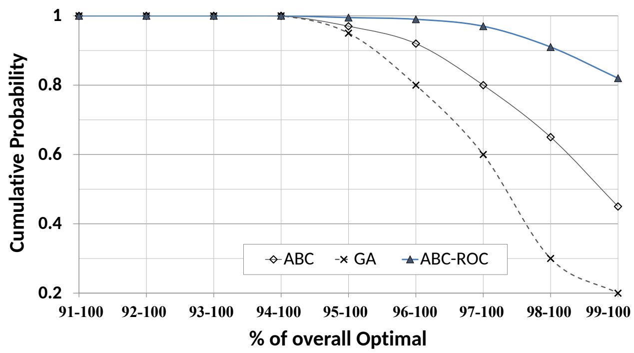


Fig. 7: Cumulative convergence probability distribution of the ABC-ROC, ABC and GA based optimization approaches

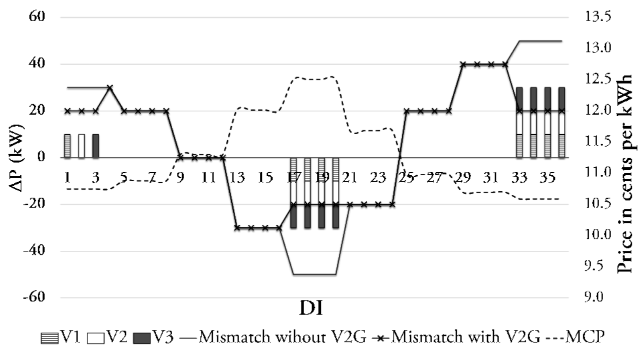


Fig. 8: Scheduling of PEVs with forecast data for 36 intervals

BDC values. Figure 9 shows the dependency of % of DOD on price difference and cost of battery. The graph represents maximum limits on DOD up to which V2G is viable for different battery costs and for a given range of price difference. For the market price range taken in the case study (i.e., 4.5 = 13.5 cents per kWh − 9 cents per kWh), the discharging of PEVs (V2G) is economically viable only for the region marked in blue. Therefore, from Fig. 9 it can be deduced that V2G service upto higher DOD levels is feasible for PEVs with lower battery cost and in the scenarios with higher electricity price variations in the system.

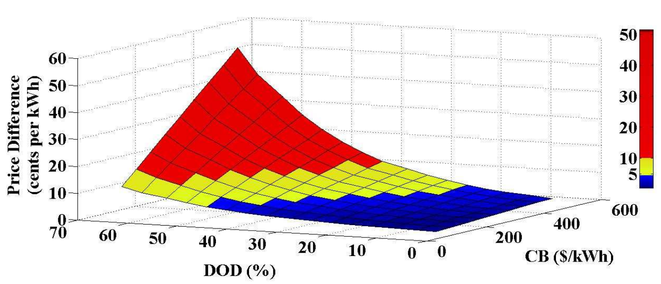


Fig. 9: The effect of charging and discharging price difference on DOD for different battery cost values

V. Conclusions

In this paper, novel energy management strategies for integration of PEVs with V2G into the operation of grid connected microgrids with and without accurate forecast information are proposed. If the forecast is not accurate then PEVs are encouraged to participate in V2G by forming a separate market following SPA mechanism. Also, a bidding strategy that uses BDC corresponding to expected DOD after travelling EDD is proposed for PEVs to bid in SPA market. If the forecast is accurate then an optimal study is carried out to schedule the charging and discharging of PEVs.

The proposed strategy is implemented using a MAS framework on JADE and applied to a microgrid case study system with two sets of data. From the simulation results and relevant analysis it is observed that if forecast on energy supply and demand in microgrids is not accurate then the future value of BDC of PEVs decides the discharging price which makes the cost of electricity from V2G higher in this scenario. Therefore, for a given market price range V2G to higher DOD levels at lower price can be realised if the forecast information is accurate. It is also observed that V2G is economically viable for PEVs with lower battery cost and in the scenarios with large difference between discharging and charging costs. The simulation results and analysis show that the proposed strategy together with MAS framework is successful in managing V2G in microgrids.

Appendix

TABLE A1: PEV Details

Parameter	Value
Make/Model	Tesla Model S
Battery technology	Li-ion (NCA)
Battery capacity (SOC_{max})	60 kWh
Charge/discharge rating	10 kW
SOC_{min}	5%
Life cycles	600 at 95% DOD
Battery cost	$ 10,000
ECR	0.38 kWh/mile

TABLE A2: PEVs arrival status and operational preferences

Parameter (units)	V1	V2	V3
SOC_{SI} (kWh)	57.5	55	55
CSE (cents per kWh)	10	10	11.25
SI	1	1	1
LI	16	16	16
EDD (miles)	32	32	32
SOC_{min} (kWh)	3	3	3
$SOC_{\mathrm{LI}}\vert_{min}^{\#}$ (kWh)	15.16	15.16	15.16

References

[1] H. Roh and J. Lee, "Residential demand response scheduling with multiclass appliances in the smart grid," *IEEE Trans. Smart Grid*, Jul. 2015, Available Online.

[2] N. Hassan, Y. Khalid, C. Yuen, S. Huang, M. Pasha, K. Wood, and S. Kerk, "Framework for minimum user participation rate determination to achieve specific demand response management objectives in residential smart grids," *International Journal of Electrical Power and Energy Systems*, vol. 74, pp. 91–103, Jan. 2016.

[3] E. C. Kara, J. S. Macdonald, D. Black, M. Brges, G. Hug, and S. Kiliccote, "Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach," *Applied Energy*, vol. 155, pp. 515 – 525, Mar. 2015.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2646779, IEEE Transactions on Smart Grid

[4] H. Nunna and S. Doolla, “Demand response in smart distribution system with multiple microgrids,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1641–1649, Dec. 2012.

[5] F. Islam and H. Pota, “V2g technology to improve wind power quality and stability,” in *2011 Australian Control Conference (AUCC)*, Nov 2011, pp. 452–457.

[6] F. Rassaei, W. Soh, and K. Chua, “Demand response for residential electric vehicles with random usage patterns in smart grids,” *IEEE Transactions on Sustainable Energy*, Jun. 2015, *A*vailable Online.

[7] M. Musio, M. Porru, A. Serpi, I. Marongiu, and A. Damiano, “Optimal electric vehicle charging strategy for energy management in microgrids,” in *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, 2014, pp. 1–8.

[8] A. Hoke, A. Brissette, D. Maksimović, A. Pratt, and K. Smith, “Electric vehicle charge optimization including effects of lithium-ion battery degradation,” *2011 IEEE Vehicle Power and Propulsion Conference (VPPC)*, pp. 1–8, Sep. 2011.

[9] A. Hoke, A. Brissette, K. Smith, A. Pratt, and D. Maksimovic, “Accounting for lithium-ion battery degradation in electric vehicle charging optimization,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 2, no. 3, pp. 691–700, Jul. 2014.

[10] M. Ortega-Vazquez, “Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty,” *IET Generation, Transmission & Distribution*, vol. 8, no. 6, pp. 1007–1016, Jun. 2014.

[11] L. Igualada, C. Corchero, M. Cruz-Zambrano, F. Heredia *et al.*, “Optimal energy management for a residential microgrid including a vehicle-to-grid system,” *IEEE Trans. on Smart Grid*, vol. 5, no. 4, pp. 2163–2172, 2014.

[12] M. Zhang and J. Chen, “The energy management and optimized operation of electric vehicles based on microgrid,” *Power Delivery, IEEE Transactions on*, vol. 29, no. 3, pp. 1427–1435, 2014.

[13] S. Misra, S. Bera, and T. Ojha, “D2p: Distributed dynamic pricing policy in smart grid for phevs management,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 3, pp. 702–712, 2015.

[14] M. H. Tushar, C. Assi, and M. Maier, “Distributed real-time electricity allocation mechanism for large residential microgrid,” *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1353–1363, 2015.

[15] C.-K. Wen, J.-C. Chen, J.-H. Teng, and P. Ting, “Decentralized energy management system for charging and discharging of plug-in electric vehicles,” in *Wireless Communications & Signal Processing (WCSP), 2012 International Conference on*. IEEE, 2012, pp. 1–6.

[16] S. I. Vagropoulos, D. K. Kyriazidis, and A. G. Bakirtzis, “Real-time charging management framework for electric vehicle aggregators in a market environment,” 2015.

[17] S. Gao, K. Chau, C. Liu, D. Wu, and C. Chan, “Integrated energy management of plug-in electric vehicles in power grid with renewables,” *Vehicular Technology, IEEE Transactions on*, vol. 63, no. 7, pp. 3019–3027, 2014.

[18] L. Ottaway, “What makes tesla’s batteries so great? - torque news,” 2015. [Online]. Available: http://www.torquenews.com/2250/what-makes-tesla-s-batteries-so-great

[19] J. P. P. et.al., *Resource Adequacy Requirements: Reliability and Economic Implications*, 2013. [Online]. Available: https://www.ferc.gov/legal/staff-reports/2014/02-07-14-consultant-report.pdf

[20] Z. Suli, M. Zhongjing, and L. Xiangdong, “Optimal microgrid economic operations under progressive second price auction mechanisms,” in *2013 32nd Chinese Control Conference (CCC)*, July 2013, pp. 8891–8896.

[21] H. K. Nunna, S. Battula, A. Sesetti, and S. Doolla, “Impact of incentive mechanism on demand response programs in smart microgrids with electric vehicles,” *Intelligent Ind. Syst.*, vol. 1, no. 3, pp. 245–254, 2015.

[22] E. K. Burke and G. Kendall, *Search Methodologies*. Springer, 2014.

[23] S. Anuar, A. Selamat, and R. Sallehuddin, “A modified scout bee for artificial bee colony algorithm and its performance on optimization problems,” *Journal of King Saud University - Computer and Information Sciences*, vol. 28, no. 4, pp. 395 – 406, 2016.

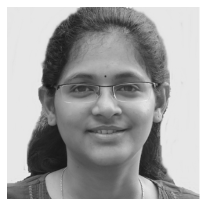
[24] “OpenDSS documentation.” [Online]. Available: http://sourceforge.net/projects/electricdss/

[25] IEEE PES Distribution System Analysis Subcommittee’s Distribution Test Feeder Working Group, “Distribution Test Feeders,” http://http://ewh.ieee.org/soc/pes/dsacom/testfeeders/, 2013, [Online; accessed 03-November-2014].

H. S. V. S. Kumar Nunna (S’11–M’14) received the M. Tech and PhD degrees from National Institute of Technology Calicut, Kerala, India and Indian Institute of Technology Bombay (IITB), Mumbai, India in 2010 and 2014 respectively.

He is currently working as a Postdoctoral Research Fellow at the Center for Green Energy Management and Smart Grid (GEMS) research of the Department of Electrical and Computer Engineering, National University of Singapore. His research interests include smart distribution systems, demand side management, microgrids, electricity markets, multi-agent system applications in smart grids, power system security and resiliency.

Dr. Kumar received the “Award for Excellence in Thesis Work” from IIT Bombay in 2015 for the research contributions made during the doctoral work, and Best Research Poster Award in 1st IITB-NUS joint Research Symposium in 2014.



Swathi Battula (S’09) received the B.Tech degree in Electrical and Electronics Engineering from National Institute of Technology Warangal, Telangana, India in 2011. She worked with Tata Power Co. Ltd as a Lead Engineer during 2011-13. She also received M.Tech degree in Energy Systems and Engineering from Indian Institute of Technology Bombay, Maharashtra, India in 2015. She is currently working as a Research Engineer at the Center for Green Energy Management and Smart Grid (GEMS) research of the Department of Electrical and Computer Engineering, National University of Singapore. Her current research interests include multi agent system applications for power systems, resource scheduling of virtual power plants and demand side management.

Suryanarayana Doolla (SM’15) received the Ph.D. degree in power systems from the Indian Institute of Technology, Delhi, India, in 2007, and the M.Tech. degree in energy systems and engineering from the Indian Institute of Technology, Bombay, India, in 2002. He is currently working as an Associate Professor at the Indian Institute of Technology Bombay, where he teaches and directs research in power electronics and power systems application in smart microgrids as a faculty member of the Energy Science and Engineering Department. He joined the department as Assistant Professor in 2009. He was with Power Research and Development Consultants (2009), Bangalore and Machine 2 Machine (2006-2008), Hyderabad before joining IIT Bombay.

He is currently serving as an Associate Editor for Electric Power Components and Systems, IEEE Transactions on Industrial Applications and IEEE Electrification Magazine. He is also editorial Board Member for International Journal of Sustainable Energy (Taylor & Francis Journals), Electrical Power Components and Systems, IEEE Electrification Magazine. Dr. Doolla is Member of Board of Studies of several technical Universities in the Country. He served as publication chair for several IEEE International Conferences.

Dipti Srinivasan (SM’02) received the M.Eng. and Ph.D. degrees in electrical engineering from the National University of Singapore (NUS), Singapore, in 1991 and 1994, respectively.

She worked at the University of California at Berkeleys Computer Science Division as a Postdoctoral Researcher from 1994 to 1995. In June 1995, she joined the faculty of the Electrical & Computer Engineering department at the National University of Singapore, where she is an Associate Professor. From 1998 to 1999 she was a Visiting Faculty in the Department of Electrical & Computer Engineering at the Indian Institute of Science, Bangalore, India. Her research interest is in the development of hybrid neural network architectures, learning methods, and their practical applications for large complex engineered systems, such as the electric power system and urban transportation systems.

Dr. Srinivasan is currently serving as an Associate Editor of the IEEE TRANSACTIONS ON NEURAL NETWORKS and the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS. She was awarded the IEEE PES Outstanding Engineer award in 2010.