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Load Flattening and Voltage Regulation using Plug-In Electric Vehicle's Storage capacity with Vehicle Prioritization using ANFIS

K Ramakrishna Reddy; Vellore Institute of Technology; Vellore; India; ramu.svce@gmail.com
S Meikandasivam; Vellore Institute of Technology; Vellore; India; meikandasivams@gmail.com

***Abstract*--Plug-In Electric Vehicle (PEV) storage capacity is limited and also it depends on battery energy level and trip timings. Hence, in order to effectively utilize PEVs storage capacity for grid support, smart charging and discharging control strategies are required. In this work, a new PEV control strategy is developed to achieve flat load profile and voltage regulation using PEV's storage capacity in an active residential distribution network. Both utility and PEV owner benefits (maximization of PEVs usage and customer revenue) are given equal importance while scheduling PEVs for grid support. PEVs prioritization is accomplished using Adaptive Neuro-Fuzzy Inference System (ANFIS) with five decision variables. It has been assumed that the PEVs are available as per the scheduled timings in and vehicle prioritization may cause marginal shift in pre-scheduled times but still target SoC is always ensured. During utilization of PEVs for load flattening, the voltage regulation at each bus where PEVs are connected is achieved by controlling active power transactions between the bus and PEVs. Multi-Objective Genetic Algorithm (MOGA) is used to decide optimal power transaction between grid and PEVs while maximizing PEV's storage exploitation without violating voltage limits. Proposed ANFIS prioritization (fixed rate) is compared with variable power rate strategy in order to investigate the advantages of proposed method.**

Keywords—PEVs, MOGA,ANFIS, Load flattening, Voltage Regulation, Cost of charging.

List of Variables and Indices

Indices

t	time interval
Δt	The time span of each interval
η	PEV Battery Efficiency
ΔP	Deviation in grid power
ΔV	Deviation in bus voltage
γ	Mileage of PEV (kWh/km)
L	The total length of a trip (km)

Variables

C_t^i	Cost of PEV charging at t^{th} interval
$C_{L,i}$	Cost of PEV battery replacement
$C_{t,c}^e$	Electricity price during t^{th} interval
DoD_i	Depth-of-Discharge if i^{th} PEV
$E_{pev}^{i,cap}$	PEV battery capacity
$C_{pev,i}^{bdc}$	Battery degradation cost
$C_{b,i}$	Cost of the battery
$L_{c,i}$	life cycles of PEV battery
$L_{pev}^{i,t}$	laxity of i^{th} PEV at t^{th} interval
P_{spec}^{grid}	Specified grid power
$P_{need}^{t,grid}$	Power need from grid during t^{th} interval
P_{solar}^{t}	Solar PV power during t^{th} interval
P_{load}^{t}	Load power during t^{th} interval
$P_{pev}^{t,ch}$	Charging requirement for all PEVs during t^{th} interval
$P_{rate}^{i,t}$	Power rate of i^{th} PEV during t^{th} interval
$P_{rate}^{i,t,ref}$	Reference power rate setting for PEV for voltage regulation
$PEV_{avail}^{t,i}$	Availability of i^{th} PEV at home during t^{th} interval
$P_{pev}^{T,t}$	Aggregate PEV power availability during t^{th} interval
P_1	Active power flow at bus 1
$SoC_{pev}^{i,t}$	SoC of i^{th} PEV at interval t^{th} interval
$SoC_{depart}^{i,t=t_d}$	*SoC* requirement before departure
$SoC_{i,pev}^{new}$	*SoC* after arrival from trip
$SoC_{i,pev}^{old}$	*SoC* before departure for s trip
t_d^i	Time of departure of i^{th}PEV
T_{ch}^i	Time required to charge PEV to maximum *SoC*
Q_1	Active power flow at bus 1

I. INTRODUCTION

The uncoordinated PEVs charging load on distribution network creates severe problems mainly by overloading the transformers and causing bus voltage deviations [1]. PEV's battery storage can be exploited for grid support that includes demand-side management, frequency regulation and voltage regulation. It has been reported that the probability of PEV staying at home during mid-day is 0.9 and that of staying at home is 0.5 during weekdays and weekends and hence PEV's storage can be exploited for grid support with the help of smart charging strategies [2]. However, Vehicle-to-Grid (V2G) and grid-to-vehicle (G2V) causes bi-directional power flow in electric networks that complicates the utility operation [3].

In distribution networks, voltage regulation can be done through on-load tap-changing transformers [4], solar PV's active power curtailment [5], reactive power management [6], and PEV's energy management via V2G and G2V

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functionalities [7]. The solar PV power curtailment and PVS's energy management are used in coordination for voltage regulation peak load shaving [8]. In [9], PEVs charging strategy is developed using Fuzzy-Genetic and Particle Swarm Optimization (PSO) aiming for flat load profile, line loss minimization with consideration of voltage regulation and transformer loading. PSO is used in [10] with static PEV mobility characteristics to obtain optimal power flow and to maximize customer revenue. An optimal PEV control strategy is developed for charging where *SoC*, battery lifetime degradation, the voltage at the bus and trip-schedule as the key parameters [11]. Battery lifetime and revenue maximization are given priority while using PEVs as mobile storages units [12].

PEV's storage is used for frequency regulation in an active distribution network with wind power plant while another objective is to minimize utility operating cost [13]. Electric vehicle's charging coordination for minimization of phase unbalance with consideration of vehicle uncertainty is proposed in [14]. PEVs storage has been used to mitigate wind power intermittency with consideration of vehicle trip requirements [15]. PEVs storage is exploited for voltage regulation of low voltage distribution network with solar PVs in [8]. Solar PV effect on bus voltage at midday period is mitigated with optimal usage of PEVs by adjusting charging rate [16]. Dynamic programming method is used in frequency regulation with PEVs support by taking *SoC* and customer profit as the key factors [17]. Fuzzy controller based grid frequency regulation is accomplished using PEVs storage (through charging and discharging). In this work only target SoC and voltage at the bus [18]. Droop control strategy is developed in [19] for frequency regulation of a two area interconnected grid using PEVs storage by ensuring target SoC level.

Most of the research works have concentrated on different ways of exploiting PEVs storage for both voltage and frequency regulation (other demand side management activities also). However, it has been less focused on the PEV's time of usage for grid support based on all the factors that affects both customer and utility benefits.

Revenue obtained by PEV owner through the participation in grid support is one of the key factors which encourages PEV owner to participate in grid support. In view of customer revenue maximization, it will be more economical if the PEV is charging during time zones of lower electricity prices [20]. Prioritizing PEVs while using for grid support is an important task to maximize exploitation of PEVs storage without creating inconvenience to the customer. In [21], authors have implemented PEVs prioritization where battery capacity and power rate are the decision variables but the customer revenue aspects are not taken into account. Cost of electricity along with target *SoC* is used for prioritization in [22] and in [23], *SoC* is taken as the key factor while deciding priority. The advantage of vehicle prioritization in effective utilization of PEV's storage is not much emphasized in the literature. In view of customer flexibility, prioritization plays a vital role when the laxity (PEV's flexible time duration for grid support) of each vehicle is known in prior (while scheduling/prioritizing).

In the existing literature, less focus has been dedicated on maximization of PEVs storage usage for grid support. Also, the prioritization of vehicles is not carried out based on both customer and utility perspectives simultaneously which creates a win-win situation between customer and utility. The impact of time of use of PEV's storage for grid support has not been much focused regarding to maximization of its usage for grid support and minimization of Cost-of-Charging (CoC).

In this work, an attempt is made to deal with the above-mentioned aspects in order to maximize PEVs storage exploitation and minimize CoC. Load flattening is considered to be the first objective and voltage regulation is the second objective. Here, maximizing PEVs storage exploitation directly reflects in load flattening as well. Along with this, customer satisfaction is considered through maximization of customer revenue (minimize CoC). The vehicle prioritization is carried out with consideration of both customer and utility perspectives simultaneously. Hence, both utility and customers are satisfied while PEVs are being exploited for grid support.

The proposed methodology focuses on the following aspects:

1. MOGA is used to achieve load fattening and voltage regulation by setting optimal power transaction (OPT) in-between bus and PEV for each interval of time '*t*'. Pareto-front obtained from MOGA provides different options from which utility operator can flexibly take a decision on PEV's scheduling.
2. Vehicle prioritization is accomplished using ANFIS in order to maximize the PEV power usage for grid support (load flattening and voltage regulation) and to maximize revenue (minimize CoC).
3. Here, both customer and utility benefits are given equal importance while exploiting PEVs for grid support.
4. Variable power rate strategy is accomplished instead of prioritization and the impact on load flattening, PEV power usage and CoC are investigated in comparison with ANFIS prioritization.

An active residential distribution system is considered in this work. It is assumed that local level Distribution Agent (DA) will take control over the local level system through implementing the instructions from the next higher level control agent. Each individual DA will take care of its local area and hence it reduces computational burden and requires localized communication only for information sharing and control. Here, only, the role of DA has been highlighted in achieving load flattening and voltage regulation with customer satisfaction. However the aggregated effect of all such distribution systems on the main grid will be substantially very high.

The whole day is sliced into uniform time intervals (15 minutes each) and zones of energy need and amount of energy need in each zone (charging/discharging) are identified. The available total PEV storage capacity in each zone is estimated

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using PEV mobility model. ANFIS based prioritization strategy is developed by considering both utility and customer satisfaction simultaneously. Battery capacity, SoC, Laxity, electricity price and cost of charging (-ve of revenue) are taken into account during the prioritization. The first three inputs comes under utility perspective whereas last two comes under customer perspective. Vehicle trip requirements are inherited in Laxity and hence the target *SoC* is ensured. The effectiveness of ANFIS prioritization in managing total PEV power availability ($\boldsymbol{P_{pev}^{T,t}}$) and its effect on load flattening is studied. ANFIS will assign a rank for each PEV in each interval of time based on which PEVs are allowed to participate in grid support.

The voltage at each bus where PEVs are connected is ensured to be within limits (0.9 -1.1 p.u) by regulating power transactions between PEVs and the bus. To set an OPT in a given interval, MOGA is used where voltage regulation and load flattening are the two objectives. However, voltage deviation is not allowed to cross ±10% from its nominal value (1 p.u) and hence power transaction is limited at each bus with voltage constraints. The effect of OPT on voltage deviations and load flattening is studied with the help of results obtained from MOGA Pareto-front.

In this work the following assumptions are made: 1.PEVs are available at home as per the scheduled time slots (actual PEV plugging time slots are adjusted/altered based on ANFIS prioritization); 2. Initial SoCs are assumed randomly; 3. The impact of PEV selection on network losses is ignored.

II. PEV AVAILABILITY FOR GRID SUPPORT

It is essential to estimate available number of PEVs accurately in order to schedule them for grid support. PEV mobility model provides information of PEVs availability for grid support and their readiness with required *SoC* level and laxity (available time in idle position). The probability analysis of vehicle availability is not presented in this paper due to page limitation. Data from National Travel Survey (NTS), Great Britain is used in this work for vehicle mobility modeling [24].

Let, $x + y + z = N$

Where, N=Total number of PEVs.

x=Number of PEVs getting charge for trip purpose.

y=Number of PEVs participating grid support.

z=Number of PEVs on trip.

Total power available from all PEVs during t^{th} interval ($P_{pev}^{t,T}$) is given by (1). The *SoC* and power rate constraints of PEV are given in Eq. (2) and (3).

$$\begin{aligned} P_{pev}^{t,T} &= \sum_{i=1}^{y} P_{rate}^{i,t} \text{ ---> Discharging zone} \\ P_{pev}^{t,T} &= \sum_{i=1}^{x+y} P_{rate}^{i,t} \text{ ---> Charging zone} \end{aligned} \tag{1}$$

$$0.2 \le SoC_t^i \le 0.8 \tag{2}$$

$$P_{rate}^{i,\min} \le P_{rate}^{i,t} \le P_{rate}^{i,\max} \tag{3}$$

Constraints based on Laxity, availability and type of zone are given in Eq. (4).

$$P_{rate}^{i,t} = \begin{cases} P_{rate}^{i,t} & \text{if } PEV_{avail}^{i,t} = 1 & & \text{Charg} \\ 0 & \text{if } PEV_{avail}^{i,t} = 1 \text{ and } L_{pev}^{i,t} < T_{ch}^{i} & & \text{Disch} \\ P_{rate}^{i,t} & \text{if } PEV_{avail}^{i,t} = 1 \text{ and } L_{pev}^{i,t} > T_{ch}^{i} & & \text{Disch} \\ 0 & \text{if } PEV_{avail}^{i,t} = 0 & & \text{Charg/ Disch} \end{cases} \tag{4}$$

The unavailability of PEV for grid support is denoted with the following constraints (Eq. (5) and (6)) which are pertaining to power rate and *SoC*.

$$P_{rate}^{i,t} = \begin{cases} P_{rate}^{i,t,ref} & \text{if } PEV_{avail}^{i,t} = 1 \\ 0 & \text{if } PEV_{avail}^{i,t} = 0 \end{cases} \tag{5}$$

The new SoC after the trip is estimated as follows.

$$SoC_{i,pev}^{new} = SoC_{i,pev}^{old} - \gamma L / E_{pev}^{i,cap} \tag{6}$$

The Laxity of PEV is given by Eq. (7) [25] and is denoted in terms of intervals. Higher the Laxity higher the vehicle flexibility for grid support band vice-versa.

$$L_{pev}^{i,t} = t_d^i - t - \frac{(SoC_{pev}^{i,t=t_d} - SoC_{pev}^{i,t})E_{pev}^{i,cap}}{\eta P_{rate}^{i,t}\Delta t} \tag{7}$$

Here, $T_{ch}^{i} = \frac{(SoC_{pev}^{i,t=t_d} - SoC_{pev}^{i,t})E_{pev}^{i,cap}}{\eta P_{rate}^{i,t}\Delta t}$ is the time need for PEV to get the charge to fill it up to target *SoC*.

III. FORMULATION OF OBJECTIVES

Here, in this work, three objectives are considered: load flattening, voltage regulation and minimizing cost of charging.

A. Load flattening

In this work, an active residential distribution network with house loads, small-scale solar PVs and PEVs with V2G functionality are considered. The sum of P_{load}^{t}, P_{solar}^{t}, and $P_{pev}^{t,ch}$ shapes the total power drawn from the grid (Eq. (8)).

$$p_{need}^{t,grid} = P_{solar}^{t} - P_{load}^{t} - P_{pev}^{t,ch} \tag{8}$$

The objective here is to achieve flat load profile throughout the day. This objective of load flattening is represented by Eq. (9) where *ΔP* is the difference between specified grid power and actual power drawn from the grid during t^{th} interval.

$$\min,\ \Delta P = \left| \left\{ \sum P_{solar}^{t} - \sum P_{load}^{t} \right\} + \left\{ \sum_{i=1}^{x} P_{rate}^{i,t} \pm \sum_{i=1}^{y} P_{rate}^{i,t} \right\} - P_{spec}^{grid} \right| \tag{9}$$

B. Voltage regulation

The second objective is to minimize ΔV at each bus using the PEV's active power transactions at each bus. This is ensure that the load flattening is not violating the voltage limits. The main focus of this work is on active power control and hence the voltage regulation is done using active power flow control between bus and PEVs.

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From the fig. 1, the voltage at bus '*2*' is given by Eq. (14) [26] and voltage rise because of PEV's power injection is given in Eq. (15) [2].

$$S_{pev}^{t} = V_{pev}^{t}(I_{pev}^{t})^{*} \tag{10}$$

$$I_{pev}^{t} = \frac{\overline{V_2} - \overline{V_1}}{r + jx} \tag{11}$$

$$S_{pev}^{t} = \frac{V_1 * V_2 \cos(\delta)}{x} + j\frac{V_2\left(V_2 - V_1\cos(\delta)\right)}{x} \tag{12}$$

$$V_2^2 = V_1^2 - 2\left(\left(P_{pev}^{t} r + Q_{pev}^{t} x\right) + \left(\frac{\left(P_{pev}^2 r + Q_{pev}^2\right)}{V_k^2}\right)\left(r^2 + x^2\right)\right) \tag{13}$$

$$V_2 = \sqrt{V_1^2 - 2\left(\left(P_{pev}^{t} r + Q_{pev}^{t} x\right) + \left(\frac{\left(P_{pev}^2 r + Q_{pev}^2\right)}{V_k^2}\right)\left(r^2 + x^2\right)\right)} \tag{14}$$

$$\Delta V_1 = \left(P_{pev}^{t} r + Q_{pev}^{t} x\right)/V_1 \tag{15}$$

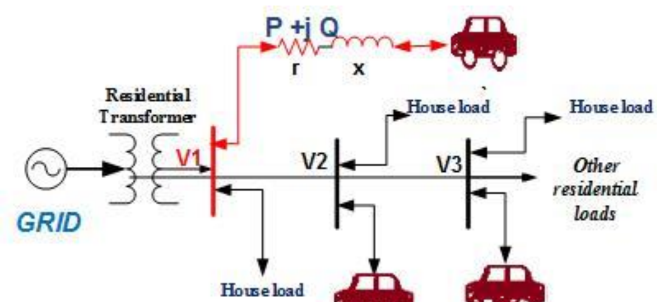

Fig. 1. Schematic of Residential PEVs connected in the distribution grid.

Here S_{pev}^{t}, P_{pev}^{t}, and Q_{pev}^{t} are PEV's apparent power, active power and reactive powers respectively that are injected by PEV during t^{th} interval. $\overline{V_1}$ *and* $\overline{V_2}$ are the voltage phasors at bus 1 and bus 2 respectively with the phase difference of δ. Objective 2 is formulated as shown in Eq. (16) for single bus and that of for b number of buses is given by Eq. (17). Here, $V_{bus}^{i,t}$ is i^{th} bus voltage at t^{th} interval and V_{bus}^{nom} is the nominal voltage of i^{th} bus (1 p.u).

$$\min,\ \Delta v = \min,\ \left|V_{bus}^{t} - V_{bus}^{i,nom}\right| \tag{16}$$

$$\min,\ \Delta V = \min,\ \left|\left\{\sum_{i=1}^{b} V_{bus}^{i,t} - \sum_{i=1}^{b} V_{bus}^{i,nom}\right\}\right| \tag{17}$$

C. Cost of PEV charging

Equation (18) represents cost of charging (C_t^i). Here, cost paid to customer for PEV discharging is equal to price of electricity, $C_{t,c}^{e}$). Equation (19) represents battery degradation cost ($C_{pev,i}^{bdc}$) of i^{th} PEV that depends on $C_{b,i}$, $E_{b,i}$, $C_{L,i}$, DoD_i and energy being charged or discharged (E_{pev}^{t}) during interval 't'. Smart pricing of electricity is taken from [27] which is shown in Eq. (20) where a1, a2 and α are pricing constants and are equal to 0.1, 0.2 and 10 respectively (see Fig. 2). Here, C_t^{reg} is the cost paid to owner due to participation in regulation (0.02$/kWh usage).

$$\min,\ C_t^i = \sum_{t=1}^{96}\left\{C_{t,c}^{e} + C_{pev,i}^{bdc} - C_t^{reg} - C_{t,d}^{e}\right\} * E_{pev}^{t,i} \tag{18}$$

$$C_{pev,i}^{bdc} = \left\{\left(C_{b,i} * E_{pev}^{i,cap} + C_{L,i}\right)/\left(L_{c,i} * E_{pev}^{i,cap} * DoD_i\right)\right\} \tag{19}$$

$$C_t^e = a1 + a2 * \alpha^{\left(P_{need}^{t,pev} - P_{spec}^{grid}\right)/P_{spec}^{grid}} \tag{20}$$

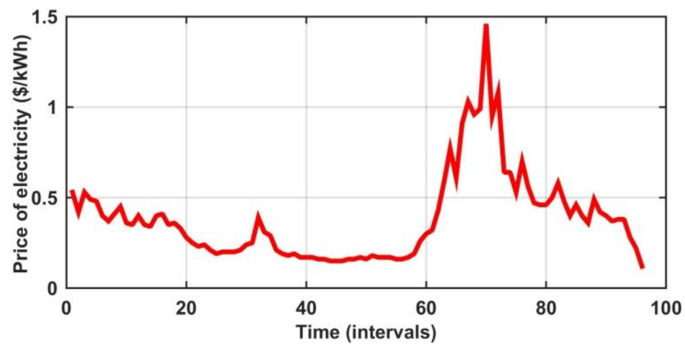

Fig. 2 Variation of the price of electricity during 24 hours

IV. PROPOSED CONTROL STRATEGY

In this work, utility and customers are given equal importance while PEVs are being exploited for grid support. Load flattening is achieved by ensuring voltage regulation and customer flexibility (with consideration of trip requirement). The above mentioned three objectives are dealt in two stages.

It is already mentioned that the PEVs are scheduled day-ahead (assumption). In the first stage, PEVs prioritization is carried out using ANFIS with the key objectives to maximize usage of battery storage and to minimize the cost of PEV charging. Here, the time of battery usage is one of the key factor that decides $P_{pev}^{T,t}$ during upcoming intervals. Though there is excess energy available at a given t, the power requirement may not be sufficient because of SoC constraints. As it is a very difficult task for utility operator to come up with a decision that which PEV has to be used first, ANFIS is trained to take a decision on vehicle prioritization.

In the second stage, voltage regulation is accomplished as part of load flattening through active power transactions between PEV and bus. In this work, MOGA is used to find an OPT in each interval to ensure voltage limits while using PEVs for load flattening.

A. ANFIS prioritization procedure

Adaptive neuro-fuzzy inference system or adaptive-network-based fuzzy inference system in short form ANFIS is developed in early 1990 by Jyh-Shing and Roger Jang [28]. It is the combination of artificial neural network (ANN) and fuzzy system. ANFIS uses learning capabilities of ANN and inference mechanism of the fizzy system in order achieve desired system output. In this work, the data for training is manfully prepared by mapping input parameters to output. Sugeno type fuzzy Inference System is used with five input membership (triangular) functions and with one output membership function (triangular). All the input and output

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parameters are converted into per unit values using Eq. (21) and (22) and the membership functions are designed between 0 and 1. Hybrid training method with 10 epochs and 0.5 error tolerance is used in this work.

Five variables are considered as inputs for ANFIS in prioritization. Two out of five comes under customer perspective (revenue and cost of electricity) and remaining three come under utility perspective (*SoC*, Battery capacity and Laxity). The impact of PEV usage time zone on $P_{pev}^{T,t}$ during upcoming intervals is explained in Fig. 3 which depicts three different PEV's batteries with different levels of SoCs. PEV-1 which is at 0.3 SoC level during 54th interval is participated in grid support by discharging its energy to the grid along with PEV-2 and PEV-3 which are at 0.5 and 0.8 SoC levels. At 61st interval PEV-1, 2 and 3 are reached to the SOC levels of 0.2, 0.3 and 0.7 respectively. It can be noted that, at 61st interval, PEV-1 is eliminated due to its SoC constraint limits which lead to $P_{pev}^{T,t}$ reduced by an amount of power equal to PEV-1's maximum power rate. The impact of prioritization on $P_{pev}^{T,t}$ and load profile are presented in section VII.

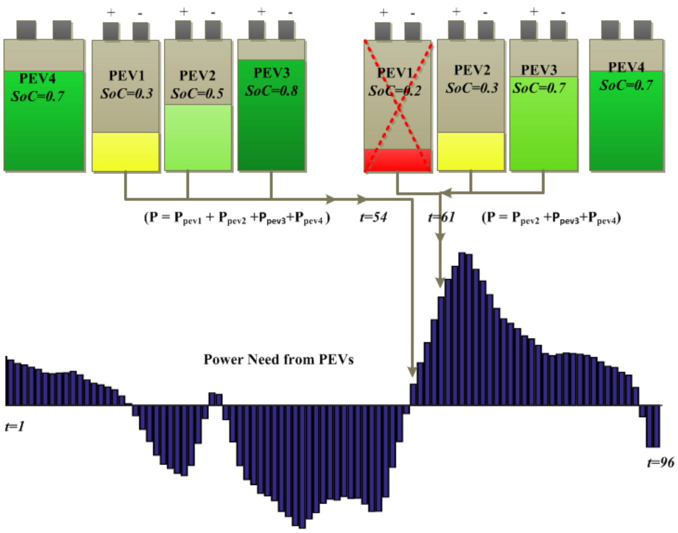

Fig. 3. Impact prioritization (or) time of PEV usage on $P_{pev}^{T,t}$.

B. Training data

The Training data is prepared manually by mapping five input variable to output (rank) for both charging and discharging cases. The prioritization is carried out by sorting ranks of PEVs ascending order. Higher the rank lower will be the priority and vice-versa. Suppose, in charging zone for a particular PEV, if *SoC* is high then rank should be high and vice versa (in utility perspective). Lower the Laxity, lower will be the flexibility of PEV usage for grid support and hence PEV is given lowest rank and vice-versa. When dealing with revenue, rank should be given based on C_{pev}^{t}, $C_{i}^{t}$and type of zone. In charging case, higher the value of C_{pev}^{t} and C_{i}^{t} lower should be the rank and vice-versa. It is because in charging case, if the PEV has high cost of charging (low revenue) it has to be charged when the price of electricity is less.

It is difficult to manually map the five inputs simultaneously as it may lead to misconception on the interdependency of decision variables too. To avoid complexity in preparing training data, it has been done in two stages. During the first stage, three inputs (utility perspective) alone are considered and rank is decided and then last two inputs (customer perspective) alone are considered to decide rank in the second stage. The average of these two ranks is taken as the actual rank of PEV. Hence, both customer and utility benefits are given equal importance while utilizing PEV for grid support. The whole training data is not shown here but only few sample cases are presented in Table. I (charging case). Discharging case has been dealt in opposite manner to that of charging case and is not included in this paper. In order to provide clear insight on prioritization, actual prioritization output (ranks assigned to PEVs) is presented in Table II for a specific time interval 't'

TABLE I
MAPPING OF INPUT VARIABLES TO OUTPUT (CHARGING ZONE)

S. No	E_{pev}^{cap}	SoC	L_x^t	C_e	Revenue	Rank
1	0.2	0.2	0.2	0.1	0.2	0.2
2	0.4	0.4	0.4	0.1	0.4	0.4
3	0.6	0.6	0.6	0.1	0.6	0.6
4	0.8	0.8	0.8	0.1	0.8	0.8
5	1.0	1.0	1.0	0.1	1.0	1
6	0.9	0.9	0.2	1.0	0.2	0.9
7	0.7	0.7	0.4	1.0	0.4	0.7
8	0.5	0.5	0.6	1.0	0.6	0.5
9	0.3	0.3	0.8	1.0	0.8	0.3
10	0.1	0.1	1.0	1.0	1.0	0.1

TABLE II
ACTUAL OUTPUT (RANK) OF ANFIS-CHARGING ZONE

PEV.id	E_cap	SoC	Li	C_e	Rev	Rank	Sorting
1	0.80	0.50	0.57	0.36	0.51	0.54	5
2	0.80	0.56	0.41	0.36	0.56	0.62	13
3	0.80	0.76	0.50	0.36	0.71	0.65	9
4	0.80	0.50	0.8	0.36	0.86	0.83	12
5	0.90	0.20	0.53	0.36	0.49	0.12	1
6	0.90	0.77	1.00	0.36	0.81	0.94	2
7	0.90	0.70	1.00	0.36	0.75	0.94	3
8	0.90	0.77	0.45	0.36	0.81	0.65	8
9	0.90	0.20	1.00	0.36	0.32	0.21	10
10	1.00	0.85	0.54	0.36	0.42	0.75	11
11	1.00	0.67	0.45	0.36	0.95	0.82	4
12	1.00	0.12	0.18	0.36	1.00	0.39	6
13	1.00	0.30	0.28	0.36	0.21	0.13	7

C. ANFIS Priority Matrix

Vehicle availability at home with required *SoC* level are allowed to participate in grid support. Also, the target *SoC* for trip purpose is ensured for each vehicle depending on its *SoC* and Laxity. Matrixes$\mathbf{V}_{avail}$, $\mathbf{V}_{\mathrm{L}}$and $\mathbf{V}_{SoC}$represents PEVs availability (1=available; 0= not available), Laxity and *SoC* respectively.

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$$\mathbf{V}_{avil} = \begin{bmatrix} 1 & 1 & . & . & . & . & 0 & 0 \\ 1 & 1 & . & . & . & . & 0 & 0 \\ 0 & 0 & . & . & . & . & 1 & 1 \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ 1 & 1 & . & . & . & . & 0 & 0 \\ 0 & 0 & . & . & . & . & 1 & 1 \\ 0 & 0 & . & . & . & . & 0 & 0 \end{bmatrix}_{N\times 96}$$

$$\mathbf{V}_{L} = \begin{bmatrix} L_{pev}^{1,1} & L_{pev}^{1,2} & . & . & . & . & L_{pev}^{1,95} & L_{pev}^{1,96} \\ L_{pev}^{2,1} & L_{pev}^{2,2} & . & . & . & . & L_{pev}^{2,95} & L_{pev}^{2,96} \\ . & . & L_{pev}^{3,3} & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & L_{pev}^{N-2,94} & . & . \\ . & . & . & . & . & . & L_{pev}^{N-1,95} & L_{pev}^{N-1,96} \\ L_{pev}^{N,1} & L_{pev}^{N,2} & . & . & . & . & L_{pev}^{N,95} & L_{pev}^{N,96} \end{bmatrix}_{N\times 96}$$

The SoC limits (Eq. (9)) are ensured to avoid PEVs from grid support (if not in the limits) and PEVs those are in trips are also eliminated from grid support.

$$\mathbf{V}_{SoC} = \begin{bmatrix} SoC_1^1 & SoC_2^1 & . & . & . & . & SoC_{95}^1 & SoC_{96}^1 \\ SoC_1^2 & SoC_2^2 & . & . & . & . & SoC_{95}^2 & SoC_{96}^2 \\ . & . & SoC_3^3 & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & SoC_{94}^{N-2} & . & . \\ . & . & . & . & . & . & SoC_{95}^{N-1} & SoC_{96}^{N-1} \\ SoC_1^N & SoC_2^N & . & . & . & . & SoC_{95}^N & SoC_{96}^N \end{bmatrix}_{N\times 96}$$

For each time interval t the five inputs to the ANFIS are given by vectors$\mathrm{I_1}$, $\mathrm{I_2}$,$\mathrm{I_3}$,$\mathrm{I_4}$and $\mathrm{I_5}$which represents $\mathrm{E_{pev}^{i,cap}}$, $\mathrm{L_{t,c}^{e}}$, $\mathrm{C_t^i}$, $\mathrm{L_{pev}^{i,t}}$ and $\mathrm{SoC_{pev}^{i,t}}$ respectively. The priority matrix $\mathrm{V_{pri}}$is obtained using priority vectors $\mathrm{V_{pri}^t}$ shown below through which priority matrix is formed by sorting PEVs according to their ranks (from rank vector $\mathrm{V_{rank}^t}$) in ascending order.

$$\mathbf{I}_1 = V_{cap} = \begin{bmatrix} E_{pev}^{1,cap} & E_{pev}^{2,cap} & . & . & . & . & E_{pev}^{N-1,cap} & E_{pev}^{N,cap} \end{bmatrix}_{1\times N}$$
$$\mathbf{I}_2 = E_{\cos t} = \begin{bmatrix} C_{1,c}^{e} & C_{2,c}^{e} & . & . & . & . & C_{95,c}^{e} & C_{96,c}^{e} \end{bmatrix}_{1\times 96}$$
$$\mathbf{I}_3 = C_{\cos t}^{pev,t} = \begin{bmatrix} C_t^1 & C_t^2 & . & . & . & . & C_t^{N-1} & C_t^N \end{bmatrix}_{1\times N}$$
$$\mathbf{I}_4 = V_L^t = \begin{bmatrix} L_{pev}^{1,t} & L_{pev}^{2,t} & . & . & . & . & L_{pev}^{N-1,t} & L_{pev}^{N,t} \end{bmatrix}_{1\times N}$$
$$\mathbf{I}_5 = V_{SoC}^t = \begin{bmatrix} SoC_1^t & SoC_2^t & . & . & . & . & SoC_{N-1}^t & SoC_N^t \end{bmatrix}_{1\times N}$$

The per unit quantities of the price of electricity and Laxity are calculated as given below for t^{th} interval of time.

$$\text{p.u of } C_{t,c}^{e} = \frac{C_{t,c}^{e}}{\max(I_1)} \tag{21}$$

$$\text{p.u of } L_{pev}^{1,t} = \frac{L_{pev}^{1,t}}{\max(I_3)} \tag{22}$$

The power rate of each PEV is set depending on voltage deviation at each bus where PEVs are connected. Interdependency of input variables in prioritization decision procedure will be taken care by ANFIS through training. Based on battery capacity, SoC and Laxity rank is assigned in utility perspective and then depending on the cost of charging and cost of electricity, the rank of each PEV is altered to maximize revenue or to reduce the cost of charging. Priority is assigned depending on rank assigned to each PEV. Higher the rank lesser will be the priority and vice-versa. Based on the priority matrix $\boldsymbol{V_{pri}^t}$, PEVs are allowed to participate in grid support.

$$\mathbf{V}_{rank}^t = \begin{bmatrix} 0.87 & 0.32 & . & . & . & . & 0.52 & 0.47 \end{bmatrix}_{1\times N}$$
$$\mathbf{V}_{pri}^t = \begin{bmatrix} N-5 & 8 & . & . & . & . & N-6 & 5 \end{bmatrix}_{1\times N}$$
$$\mathbf{V}_{pri} = \begin{bmatrix} V_{pri}^1 & V_{pri}^2 & . & . & . & . & V_{pri}^{N-1} & V_{pri}^N \end{bmatrix}_{N\times 96}^T$$

D. MOGA to set Optimal Power transaction

While dealing with multi objective optimization problems (MOOP), the classical methods follows deterministic transition rules and tries to secularize the objective functions. Also, the classical methods perform repeated applications while finding pareto-front (non-dominated set of solutions). Unlike, the classical (investigation of all possible solutions is not allowed), the evolutionary algorithms gives a set of best possible solutions (Pareto-front) out of all possible solutions. It is easy to select any one solution manually based on relative importance of the objectives [29]. From last decade, evolutionary algorithms (EA) have been explored and implemented for critical and complex MOOPs in real time world [30-32]. It is reported that 70% of meta-heuristic techniques used for MOOPs are based on EA approaches [33].

Among the EAs available in the literature, Genetic Algorithm (GA) based methods for MOOPs are more suitable due to their population based search. Especially, the crossover operation creates possibility to explore searching in unexplored ways. GA was initially developed by Holland and his students during 1960-1970 [34]. The very first GA based solution for MOOPs is known as vector evaluated GA [35]. Later, there has been a continuous exploration of different GA based solution methodologies were developed such as: Multi Objective GA [36], Niched Pareto Genetic Algorithm [37], Weight-based GA [38], Random Weighted GA [39] and Non-dominated Sorting GA [40].

In this work, MOGA has been used for the solution for the formulated MOOP. MATLAB optimization toolbox has been used here. However, the other GA based techniques for the solution of the proposed MOOP may vary in terms of their performance. MOGA is most suitable for MOOP because as it uses structures of the best solutions to bring out new Pareto-front in unexplored ways [39].

Minimization of ΔP and ΔV are taken as the two objectives in the MOOP formulated in this work. In general, MOOP will always lead to some conflict as anyone objective maximization or minimization will lead to degradation of another objective. Hence, there has to be a trade-off between

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the objectives to bring out one optimal solution from the Pareto-front. Here, MOGA is used to decide OPT with two objective functions given in Eq. (23) and (49) (these equations are designed for discharging case from which charging case can also be formulated). The tradeoff between these two objectives has to be done with compromising ΔP minimization in order to follow the voltage nominal voltage limits. Hence, the OPT has been decided and limited by voltage deviation and voltage limits respectively.

$$\min,\ \Delta P = \min, \left(\begin{array}{l} \left\{ \sum P^{t}_{solar} - \sum P^{t}_{load} + \sum_{i=1}^{x} P^{charge}_{pev,t,i} \right\} + \\ \left\{ \sum_{i=1}^{y} P^{charge}_{pev,t,i} - \sum_{i=1}^{y} P^{discharge}_{pev,t,i} \right\} - P^{spec}_{grid} \end{array} \right) \quad (23)$$

As the R/X ratio is high in distribution networks (especially in underground cables) is very high, the effect on voltage deviation will be majorly due to active power transactions at each bus [11]. From Eq. (15), it is clear that there will be a rise in bus voltage ($+\Delta V$) due to active power injection at that bus. The aggregate voltage deviation at all the buses where PEVs are connected is equated is given by Eq. (17) where $V^{i,t}_{bus}$is the i[th] bus voltage.

$$\text{RHS of (17)} = \left\{ \sum_{i=1}^{b} V^{i,t}_{bus} - \sum_{i=1}^{b} V^{nom}_{bus} \right\} \quad (24)$$

$$\text{RHS of (15)} = \left(P^{T,t}_{pev} br + Q^{T,t}_{pev} br \right) / \sum_{i=1}^{b} V^{nom}_{bus} \quad (25)$$

Equation (26) implies that the amount of deviation in voltage Eq. (24) should match with voltage rise due to power injection (Eq. (25)) for voltage regulation. Here, Eq. (26) is taken as the second objective function which is to minimize deviation in voltage at all buses (minimization of variance).

$$\min,\ \Delta V = \min,\ \sum_{i=1}^{b} \left\{ \left\{ V^{i,t}_{bus} - V^{nom}_{bus} \right\} - \frac{\left(\sum_{j=1}^{i_y} P^{disch}_{pev,t,j} r + Q^{disch}_{pev,t,j} x \right)}{V^{i,t}_{bus}} \right\}^2 \quad (26)$$

Here, $\sum_{i=1}^{y} P^{disch}_{pev,t,i} = P^{T,t}_{pev}$ for discharging case and i_y represents the number of PEVs participating in grid support which are connected to i^{th} bus. It has been assumed that the line impedance ($r+jx$) for all the PEVs connections to the buses are same. Now the objective 2 is to decide OPTto keep the voltage at all buses in between 0.1 and 0.9 p.u while achieving flat load profile. As our aim in this work is confined to active power management, the reactive power is assumed to constant with a constant power factor of 0.9. Now the only control variable is $P^{T,t}_{pev}$. The power constraints are given below.

$$-P^{i,rate}_{pev} \le P^{t,i,ref}_{pev} \le +P^{i,rate}_{pev} \quad (27)$$

$$P^{T,t}_{pev} \le P^{t}_{avail} \quad (28)$$

$$0.9(p.u) \le V^{t}_{bus} \le 1.1(p.u) \quad (29)$$

V DIRECT CONTROL ON PEV POWER RATE

In order to test the impact of the proposed ANFIS prioritization, a Direct PEV Power Control (DPPC) of each PEV is implemented in this section. Here, at starting of each interval, the power rates of all the PEVs are set uniformly based on OPT decided by the MOGA. The equations, (30) and (31) decides the initial power rate for charging zone and discharging zone respectively followed by the constraints given in (32) and (33). The flowchart shown in fig. 4 exhibits the way how the power rate of each PEV are adjusted based on OPT and voltages at all the buses. Fig. 4 represents the charging zone only and the same manner the discharging zone can also be understood easily.

$$\mathrm{P}^{t}_{rate} = \mathrm{OPT}/(x+y) ---> \text{Charging zone} \quad (30)$$

$$\mathrm{P}^{t}_{rate} = \mathrm{OPT}/(y) ---> \text{Disharging zone} \quad (31)$$

The constraints on OPT to be ensured at each interval while setting power rates are given below.

$$\sum_{i=1}^{(x+y)} \mathrm{p}^{i,t}_{rate} \le \mathrm{OPT}_t ---> \text{Charging zone} \quad (32)$$

$$\sum_{i=1}^{y} \mathrm{p}^{i,t}_{rate} \le \mathrm{OPT}_t ---> \text{Charging zone} \quad (33)$$

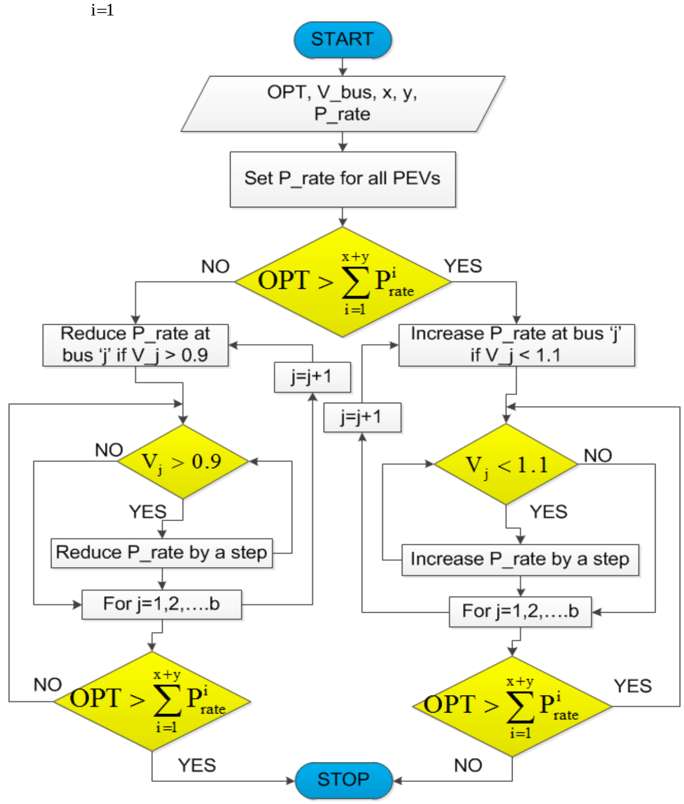

Fig. 4 PEV power rate adjustment based on OPT and bus voltages.

The other constraints on PEV battery usage are considered while adjusting power rate. Allowable rate of change in power

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rate (P_{rate}^{dif}) is given in Eq. (34) where $P_{rate}^{ref,t}$ is the reference power rate decided based on voltage regulation during interval 't'. Here, 200W is considered as the allowed $P_{rate}^{i,dif}$ at a stretch. Power rate constraints are accommodated as shown in Eq. (35) along with SoC limits.

$$P_{rate}^{t} = \begin{cases} P_{rate}^{t-1} - P_{rate}^{dif} & \text{if} \quad \left|P_{rate}^{ref,t} - P_{rate}^{t-1}\right| > P_{rate}^{diff} \\ P_{rate}^{t-1} + P_{rate}^{ref,t} & \text{if} \quad \left|P_{rate}^{ref,t} - P_{rate}^{t-1}\right| < P_{rate}^{diff} \end{cases} \qquad (34)$$

$$P_{rate}^{t} = \begin{cases} P_{rate}^{min} & \text{if} \quad 0.2 < SoC < 0.8 \quad \& \quad P_{rate}^{ref,t} < P_{rate}^{min} \\ P_{rate}^{max} & \text{if} \quad 0.2 < SoC < 0.8 \quad \& \quad P_{rate}^{ref,t} < P_{rate}^{max} \\ P_{rate}^{ref,t} & \text{if} \quad 0.2 < SoC < 0.8 \quad \& \, P_{rate}^{min} < P_{rate}^{ref,t} < P_{rate}^{max} \\ 0 & \text{if} \quad 0.2 < SoC < 0.8 \quad \& \, P_{rate}^{min} < P_{rate}^{ref,t} < P_{rate}^{max} \end{cases} \qquad (35)$$

The voltages at each bus are ensured to be within the limits while setting the power rate of PEVs connected to that particular bus. In charging zone, if $OPT < \sum_{i=1}^{x+y} P_{rate}^{i}$ then each bus is ensured to maintain voltage not less than 0.9 p.u and the power rate of PEVs at the particular bus ($V_j^t > 0.9\,p.u$) are reduced step by step. The same is accomplished at all the buses until the condition $OPT \geq \sum_{i=1}^{x+y} P_{rate}^{i}$ reaches. The opposite case is exhibited if $OPT > \sum_{i=1}^{x+y} P_{rate}^{i}$ for which PEV power rates are increased until the condition $OPT \leq \sum_{i=1}^{x+y} P_{rate}^{i}$ reaches. Here, the bus voltages are ensured to be less than 1.1 p.u ($V_j^t > 0.9\,p.u$) and power rates of PEVs are increased step by step. The comparison analysis on ANFIS prioritization and direct power rate control is presented in section VII.

VI SIMULATION SETUP

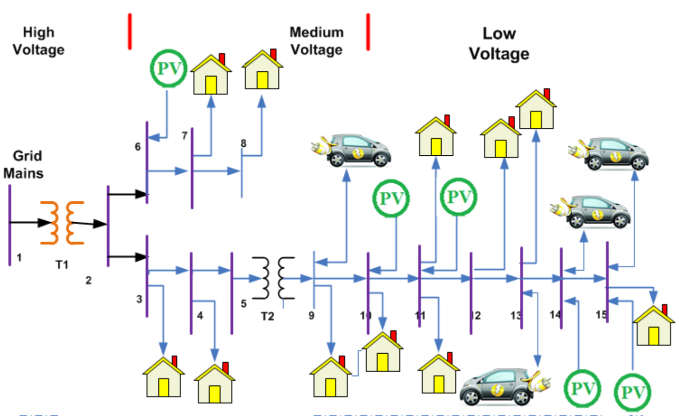

Fig. 5 Active residential distribution network with solar PVs and PEVs.

An active residential distribution network (Fig.5) consisting of 120 houses with 13 PEVs connected to bus 9-15.Four solar PV with 6kW of maximum power generation. The data needed for simulation is taken from DiSC (Matlab based smart grid simulation platform) [41]. Three different types of PEVs are considered for implementation and the technical specifications are given in Table III. PEV-1 is connected to bus 9, PEVs 2 to 4 connected to bus 13, PEVs 5 to 9 connected to bus 14 and PEVs 10 to 13 connected to bus 15.

TABLE III
PEV Technical Specifications

SPECIFICATION	BMW i3 REx	Chevrolet Volt	Citroen
Capacity (kWh)	22	16	16
Battery type	Li-ion	Li-ion	Li-ion
Charging rate	230V 6-8h	230V 7h	230V 7h
(kW/100Km)	13.5	16	13.5

VII RESULTS AND DISCUSSIONS

In the ANFIS prioritization process, consideration of SoC and Laxity plays a vital role in offsetting aggregate PEV power a for further usage in each zone. These two, decision variables helps in maximizing PEVs storage usage for grid ancillary service. Suppose, if the PEV of lower SoC has participated in grid support in a discharging zone at early intervals then sooner it will get empty and will no more be available for grid support as it reaches SoC limits. This case is explained using Fig. 3. On the other hand, PEV with higher Laxity should be given highest priority for grid support based on SoC. In contrast, decision based on laxity helps in both sides. While estimating Laxity, it accounts the target SoC and charging duration (see Eq. 6), the customer flexibility is ensured. And at the same time Laxity provides information regarding vehicle's flexible and critical time zones which helps the utility operator to take decision on time of storage usage. Hence, SoC and Laxity are the two key factors in deciding the time of PEV storage usage for grid support.

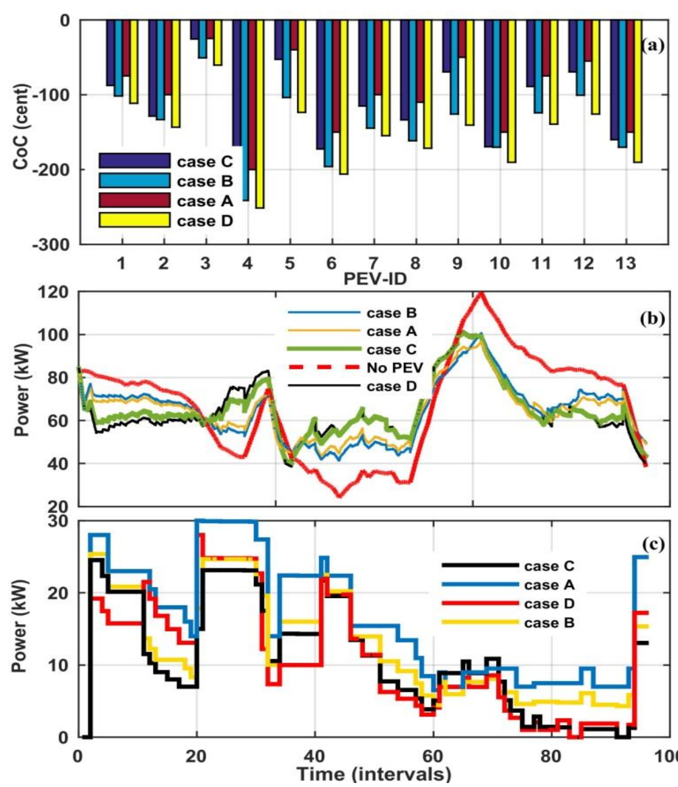

Fig. 6 Impact of ANFIS prioritization on (a) CoC (CoC is –ve equivalent of revenue) (b) Load flattening and (c) $P_{pev}^{T,t}$.

In view of customer satisfaction, revenue and price of

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electricity are the decision variables. Here, based on electricity price and revenue, the decision on priority is taken in such way that revenue of each individual owner is maximized. Here, for analysis purpose, four cases are considered in ANFIS prioritization and the effect of these scenarios on $P_{pev}^{T,t}$ for grid support is shown for all the four cases in Fig. 6(c).

Case A: Only Laxity and *SoC* are the decision variables.
Case B: All the five inputs to ANFIS are considered.
Case C: SoC is not taken into consideration.
Case D: Only electricity price and *CoC* are considered.

In Case A, customer revenue maximization is not taken into account while prioritizing PEVs. As discussed earlier, both Laxity and SoC are the key factors while deciding the time of PEV storage usage. Hence, in this case maximum power is available from PEVs during all the intervals (throughout the day). Case B represents the propped control strategy where all the five input decision variables are taken into consideration during PEVs prioritization. Here, in this case both customer and utility are satisfied and hence is said to be a win-win situation. However, $P_{pev}^{T,t}$ may be less than to that of the case A. In case C, only SoC is excluded from the decision inputs of ANFIS and the effect can be observed in terms of reduced $P_{pev}^{T,t}$. This indicates that the SoC is the key decision variable in maximizing $P_{pev}^{T,t}$. Finally, the case D, resembles the collective effect of the absence of Laxity and SoC on $P_{pev}^{T,t}$. In this case, ignoring Laxity in decision variables causes sudden PEV charging load (for trip purpose) and hence leads to deviations in ΔP even more. The effect of these four cases on ΔP can be seen from Fig. 6(b).

Cost of charging depends on Laxity, vehicle readiness (with required SoC level) and more importantly electricity price during availability. The type of zone (charging/discharging) during which the vehicle is available at plug point is another important factor that decides customer profit. The cost of charging is analyzed for cases A and B. Fig. 6(a) shows case A, B C and D. In case A, both customer revenue and price of electricity are not considered whereas in case D both customer revenue and price of electricity are only the decision variables. Case D gives maximum revenue in comparison with all the other three cases but fails in utility perspective in order to maximize the storage exploitation (maximize $P_{pev}^{T,t}$). Case B is only the dual perspective prioritization strategy through which both utility and the customer will get benefit through PEVs exploitation for grid support. Case C will not show any effect on customer revenue rather it will have an impact on power availability and ΔP.

The Pareto front obtained from MOGA gives a set of optimal power transactions from which utility operator can take a decision on setting amount of power transaction for a given time interval. Here, in Fig. 7, the Pareto front is shown for the discharging case from which it can be seen that 15kW power transaction will cause ΔV to reach zero whereas 25kW power transaction helps ΔP to reach zero. In this case, by ensuring voltage limits, the maximum power transaction that can be done in order to minimize ΔP at maximum extent is 24.6kW (where $\Delta P \approx 3$kW and $\Delta P \approx 0.1$) and let it be an OPT.

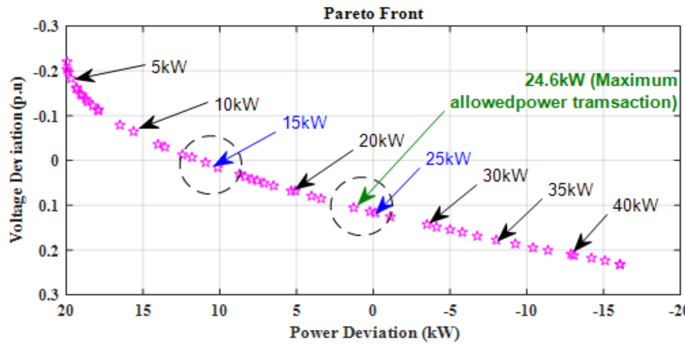

Fig. 7 Selection of OPT from MOGA Pareto-front

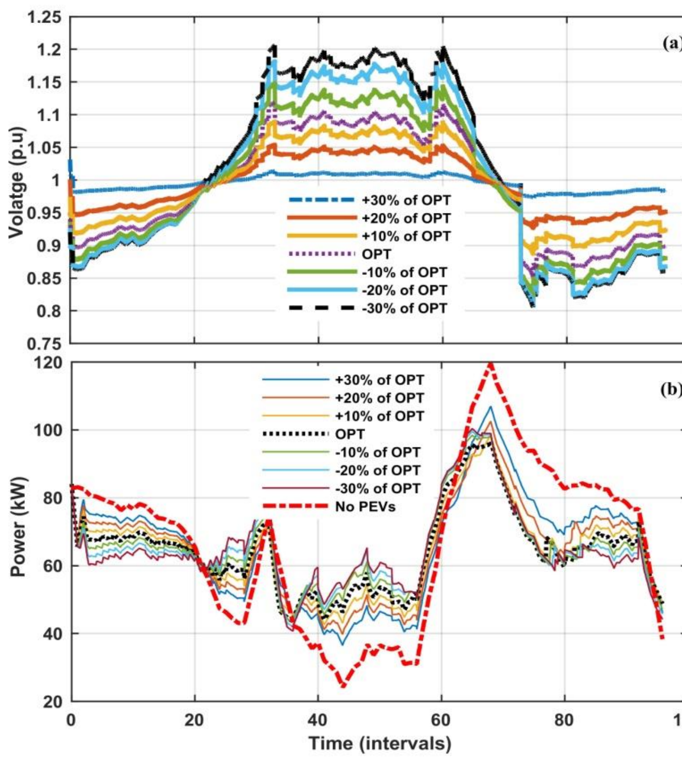

Fig. 8 Selection of OPT from MOGA (a) Impact on voltage regulation (c) impact on load flattening.

The effect of OPT selection will be mainly on voltage deviation (ΔV) and slack bus power deviation (ΔP) and the same is shown in Fig. 8(a) and 8(b) respectively. Here, ΔP and ΔV are analyzed by varying OPT by ±10% increment. Here, +0.1 deviation in voltage means that the voltage is lower than the nominal value (1 p.u) and in indicates discharging zone and -0.1 indicates charging zone. The maximum voltage limit can be touched at a given time interval for extreme minimization of ΔP (in Fig. 7, 1-0.9=0.1=ΔV). However, if the voltage goes beyond the limitations (i.e., ΔV > 1.1 or ΔV < 0.1), load flattening is to be compromised in order to ensure the bus voltages limits. In this case even though there is abundant PEV storage available that cannot be utilized for load flattening as it violates voltage limits. This scenario can

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be avoided by setting optimal energy usage for each interval in prior (day-ahead/hour-ahead).

In this work, fixed PEV power rates are considered in ANFIS prioritization. However, the impact of variable PEV power rate (DPPC) on ΔP, ΔV, CoC and $P_{pev}^{T,t}$ has been compared in table IV. In DPPC, SoC, laxity and battery capacity are not taken into consideration. However, the target SoC (for trip requirement, equal to 0.8) is ensured in each interval of time. In this case, due to the random usage of PEVs, i.e without considering laxity and SoC, the amount of $P_{pev}^{T,t}$ decreases. It is clear that this scenario is in contradiction to that of the proposed ANFIS prioritization (Fig. 9). This, directly effects load flattening which can be seen from Fig. 9(b). However, the bus voltages are maintained within the limits as OPT is ensured before each setting of power rate and in each interval 't' as well. Hence, there is no much difference between the two strategies when it comes to bus voltage regulation.

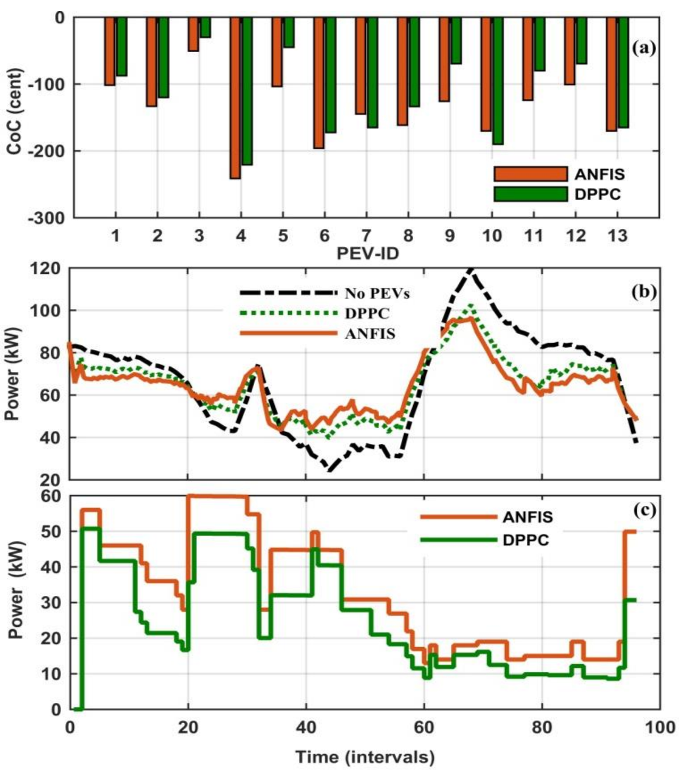

Fig. 9 Comparion of ANFIS prioritization and DPPC on: (a) CoC (b) ΔP and (c) $P_{pev}^{T,t}$.

TABLE IV
Comparison of DCCP over ANFIS prioritization

Comparison variable	ANFIS Prioritization	DPPC
ΔP	Minimized	Maximized
ΔV	Within the limits	Within the limits
CoC	minimized	Maximized/Unexpected
$P_{pev}^{T,t}$	Maximized	Minimized
Battery Degradation	Minimized	Maximized
Customer Flexibility	Good	Moderate

As in ANFIS prioritization, in DCCP, the electricity price and revenue are not taken into account while setting power rate. Hence, the CoC of each PEV is expected to be more that what it would be in prioritization case. However, in some cases DPPC may lead to reduce CoC. It may be due the coincidence of minimum price of electricity and charging given that SoC requirement for grid support if fulfilled. The unexpected cases of CoC reduction can be seen from Fig 9(a). Also, the battery degradation increase as the power rate is keep on changing. Hence, in this scenario of active distribution network, PEV prioritization is proven to be the better way in many aspects instead of variable power rate strategy. In some scenarios, variable power rate may help in effective energy management especially in charging fleets.

VIII CONCLUSION

In this work, both utility and customer perspectives are taken into consideration while scheduling PEVs for grid support. Prioritization of PEVs is carried out using ANFIS with five decision variables out of which three are pertaining to utility perspective and remaining two are customer perspective. The cost of charging is minimized and uniformity is maintained with all other vehicles per kWh capacity basis and also based on Laxity (vehicle flexibility). Load flattening is achieved by maximizing usage of PEVs storage while minimizing the cost of PEV charging. In order to achieve load flattening and voltage regulation simultaneously, MOGA is used to decide OPT in each interval of time. From the Pareto-front obtained by MOGA, the maximum usage of PEV power is decided in order to minimize deviation in slack bus power without violating voltage limits. From the results, the impact of prioritization using ANFIS can be seen in terms of maximizing aggregate PEV power availability and minimizing ΔP. The role of MOGA in optimal usage of PEV storage without violating voltage limits is examined and the impact of OPT on both ΔP and ΔV are analyzed. Also, the comparison analysis is done on fixed power rate (ANFIS prioritization) and variable power rate (DPPC) strategies as well.

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K Ramakrishna Reddy received his Bachelor degree in Electrical and Electronics Engineering from Sri Venkatesa perumal College of Engineering and Technology and Master degree in Electrical Power Systems from Sree Vidyanikethan Engineering College in 2008 and 2010 respectively. He is currently an internal full time research scholar in Vellore Institute of Technology, Vellore, India. His research interests include power system, smart grid, demand side management and Plug-In electric Vehicles.

S. Meikandasivam was received his Bachelor Degree in Electrical and Electronics Engineering in 2002 and Master Degree in Power Systems in 2005. He also worked as a Lecturer in Electrical and Electronics Engineering Department of Sri Chandra Sekharendra Saraswati Viswa Mahavidyalaya (Deemed University), Kanchipuram. He completed his PhD Degree at Maulana Azad National Institute of Technology (MANIT), Bhopal, India in 2010. Now he is working as an Associate Professor in Vellore Institute of Technology, Vellore.