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Multi-objective Optimal Scheduling of Electric Vehicles in Distribution System

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***Abstract*— In this paper we developed a multi-objective charging framework to optimally manage the real power dispatch of electric vehicles (EVs) incorporating vehicle to grid (V2G) approach. Objective function includes minimizing load variance and cost of charging associated with EVs present in residential area. Technique of order of preferences by similarity of ideal solution (TOPSIS) approach is used solve multi-objective scheduling problem. Scheduling optimization is carried out with grey wolf optimization (GWO). Comparative analysis of single and multi-objective scheduling is also presented in terms of losses, transformer peak load and line loading to illustrate the effectiveness of proposed approach. The proposed method is tested on 38-node distribution feeder and comprehensive analysis of simulation results is illustrated. Results show that with TOPSIS, solutions obtained are fairly favorable for both valley filling and cost minimization.**

Keywords— Vehicle to Grid (V2G), Multi-objective Model, TOPSIS.

I. INTRODUCTION

In recent years, role of EVs in transportation system has gained significant momentum as governments across the world are drawing out policies to regulate the imbalance in ecosystem. However, anticipated penetration of EVs raised concerns over their uncoordinated charging demands and subsequently, their impact on existing grid to efficiently serve the increased load demand. Uncoordinated charging of EVs may cause overloading of transformers and distribution lines, voltage limit violations, increased losses followed by network reinforcement in addition to higher operating costs at peak load [1]. Apart from technical and infrastructure challenges associated with integration of EVs, adoption among the customers poses a major barrier towards transportation electrification or e-mobility. Hence it is crucial to generate a pull among customers by creating an economical cost proposition, which will encourage them to invest in EVs. An efficacious solution to mitigate these issues is coordinated charging of EVs [2]. Through coordinated charging, EVs charging can be actively managed for better use of grid capacity and available generation. In addition, customers will easily consent to participate in coordinated EV charging if it favors their economic interest. These challenges motivate the need for multi-objective scheduling of EVs to consider the interest of both network operator and EV owner simultaneously.

Past literature has presented various aspects of EVs scheduling as multi-objective optimization with amalgamation of environmental, technical and economic concerns [3-13]. In [3] authors proposed to reduce CO_2 emissions from grid and vehicles simultaneously. A hierarchical EV charging to minimize load fluctuation, peak-valley difference and charging cost is presented in [4]. Comparison of EV charging from multiple stakeholder's perception including a coordination based charging strategy is discussed in [5]. The optimization in [6] aims to minimize fuel, electricity cost and battery degradation simultaneously. Authors established that battery contributes significant towards cost of EVs which tends to degrade over time hence battery health is crucial component of optimization problem. However, works in [3-6] did not consider any network for studying the impact of EV charging strategies.

Reference [7] proposed incentive program with lower off-peak electricity price to reduce revenue loss and load fluctuation of power supplier. The multi-objective problem is solved by using particle swarm optimization (PSO) based strategy. But arrival and departure time of all EVs are assumed to be same. Authors in [8] proposed optimal coordination of EVs in order to reduce the total cost of purchased energy and losses in the grid. Linear scalarization using weighing factors is employed to solve multi-objective problem. However, initial state of charge (SOC) is assumed to be fixed. Also, vehicle to grid (V2G) mode is not considered in above mentioned studies.

In [9] authors proposed a multi-objective framework for optimal operation of microgrids in presence of parking lot for EVs, grid and distribution generation (DGs). Each parking lot is modeled with aggregated EVs load facilitating active and reactive power support to augment power quality of microgrid. The multi-objective formulation is tackled using ε-constrained method. However, uncertainties associated with EVs are not considered. A multi-objective optimization to minimize load variance and cost is proposed in [10]. Optimal solutions to the problem is obtained by using weighted sum and fuzzy approach. The work in [11] also presented optimal coordination of EVs aiming reduction in operational cost and emissions. The multi-objective problem have been solved using ε-constrained optimization problem. The studies in [9-11] considered V2G mode of vehicles but did not include battery degradation cost model.

Authors in [12,13] investigated the dynamics of technical and economic interests for EVs charging with V2G approach. However, these papers used weighted and ε- constraints approach respectively. The optimal solution of weighted sum approaches shows high dependency on selected weights while in ε-constrained method one objective is considered as master objective and other is taken as slave [14]. Though fuzzification of objectives brings all the objectives on same scale and units, but it does not consider even distribution of pareto solutions [15].

TOPSIS is also an effective technique for multi-objective problem formulation that reduces the Euclidean distance of Pareto set from best solution of each objective and hence results in uniformly distributed pareto sets as compared to aforementioned approaches. TOPSIS approach is simple with good computational efficiency. This approach is adopted to solve complex, real-life, multi-objective engineering problems in diversified areas [14]. Recently, TOPSIS is used to solve multi-objective distributed energy resources (DER) planning problem [14-15].In [14] authors implemented TOPSIS to best compromising solution for multi-objective problem comprising different objectives as minimization of power real and reactive power loss, node voltage deviation and voltage stability index and voltage stability margin. In [15] TOSIS approach is integrated with metaheuristic technique to solve multi-objective problem.

This paper aims to explore multi-objective scheduling approach for EVs to determine optimal charging solutions to minimize 1) load variance and 2) total charging/discharging cost simultaneously. The TOPSIS approach is used to develop multi-objective model (MOM) for EVs scheduling. Comparative analysis of MOM is also carried out with single objective scheduling model for different penetration of EVs. The proposed scheduling strategy is implemented on 38-node distribution system and results are summarized through comprehensive evaluation of simulation results.

This paper is organized after this introduction section to have section II. In this section modeling of EV load demand is elaborated. In section III objective formulation and TOPSIS approach is explained. Optimization framework is presented in section IV. Section V summarizes outcomes of this work validated through simulation results. Finally, section VI concludes the work

II. MODELING ENERGY REQUIREMENT OF EVS

This paper aims to study scheduling of EVs parked in residential parking lot. All vehicles parked are assumed to be available in evening when the owners return from work until outset of next trip in the morning. The centralized control scheme is implemented by charging coordinator (CC) which performs optimal scheduling of EVs. Upon the arrival of EV in parking lot, EV owners submit SOC, EV specification (battery capacity, vehicle driving range known as AER) and departure time to CC. Based on the information furnished by EV owners, CC performs the optimization while fulfilling energy requirement of EVs.

Driving characteristics of EVs are modeled using probability density function which include arrival and departure time and daily distance driven. It is also assumed that PEV owners desire their battery to be fully charged before leaving the parking lot. So, charging requirement is determined by using total distance driven during the day, initial and departure SOC. Data regarding the above mentioned attributes (spatial and temporal characteristics) of EVs is adopted from [16].

A. Initial SOC

In this work SOC refers to amount of energy remained in battery when EV reaches parking lot. In order to extend the battery life, minimum 20% SOC is set in this work. Initial SOC is estimated by considering the total distance driven by EV. Accordingly, for EV having distance travelled D and AER of D_r, arrival SOC_awould be:

$$SOC_a = 1 - \frac{D}{D_r} \tag{1}$$

EV owner is required to submit the information regarding the initial SOC to CC (same as fuel-based vehicle furnish information of required of its fuel) and it assumed that departure SOC required is 100%.

B. Energy Requirement to Charge EVs Battery

The energy requirement of EV depends upon its arrival SOC. This energy is drawn from utility to fully charge the battery and is expressed as:

$$E_r = \frac{(1 - SOC_a)B_c}{\eta} \tag{2}$$

where E_r is energy required to fully charge the battery, B_c is battey capacity and η is efficiency of charging of EV. When EV is in charging mode, efficiency is $\frac{1}{\eta_c}$ and when EV is in discharging mode, efficiency is η_d.

III. MULTI-OBJECTIVE PROBLEM FORMULATION

This section defines the objective function, constraints and multi-objective formulation using TOPSIS under proposed scheduling strategy.

A. Objective Functions and Constraints

1. Valley Filling model (VFM): The increasing losses in distribution system remains a major concern of power sector. Addition of EV load can further worsen the situation. Valley filling leads to shifting of load demand and results in improved load variance. Authors in [17] established that improvement in load variance results in loss reduction. Mathematically, load variations i.e. to reduce the difference between instantaneous load and average load is expressed as:

$$f_1 = \sum_{t=1}^{24} \left(S_{sys}^t - S_{avg}\right)^2 \tag{3}$$

where

$$S_{sys}^t = \sqrt{\left(L_{sys}^t\right)^2 + (Q_{res}^t)^2} \tag{4}$$

$$L_{sys}^t = L_{res}^t + \sum_{i=1}^{N_v} L_{i,EV}^t \Delta t \tag{5}$$

where N_v is total number of vehicles and S_{avg} is average apparent load of system. Here, equation (4) represents the total apparent power of the system i.e.S_{sys}^t and equation (5) represents total active power demand (L_{sys}^t) which is composed of residential load (L_{res}^t) and total EVs load (L_{EV}^t) at any time instant t. A time step one hour represented by ‘t’ is considered in this work.

2. Minimum Charging/Discharging Cost Model (MCM): Cost of charging / discharging implicate the total cost incurred by CC. The total cost will include charging cost, revenues earned through discharging and battery degradation cost. The charging/discharging cost is expressed as:

$$C_{charge} = \sum_{i=1}^{N_v} \sum_{t=1}^{t_{i,p}} \lambda^t . x \tag{6}$$

where λ^t is electricity price at time t and x is charging/discharging rate at time t as define below:

$$x = \begin{cases} x_{ch}^t . \eta_c & charging\ mode \\ \dfrac{x_{dch}^t}{\eta_d} & discharging\ mode \end{cases} \tag{7}$$

Here $x > 0$ represents charging mode while $x < 0$ signifies discharging mode. $t_{i,p}$ is parking duration of i^{th} EV. Battery degradation cost is expressed as [12], [13],18]:

$$C_{deg} = \sum_{i=1}^{N_v} \frac{C_{bat}.B_{c,i} + C_l}{B_l.B_{c,i}.\ DOD} . E_{dis}^{\Delta t} \tag{8}$$

Here C_{bat} is cost of battery, $B_{c,i}$ battery capacity of i^{th} vehicle, C_l is cost of labor for battery replacement and DOD is depth of discharge. In this study, $C_{bat} = 300\$/kWh$, $C_l = 240\$$ and $B_l = 5000$ at 80% discharge [18]. Thus, the total charging/discharging cost incurred by CC can be expressed as:

$$f_2 = C_{charge} + C_{deg} \tag{9}$$

3. MultiObjective Model (MOM): The objective function in this model is designed to simultaneously optimize load variance and total cost incurred by CC. Thus, the objective function is formulated as:

$$f_3 = \min(f_1 + f_2) \tag{10}$$

The objective function presented in (3), (9) and (10) is subjected to following constraints:

$$P_{ch}^{min} \leq x_{ch}^t \leq P_{ch}^{max} \tag{11}$$

$$P_{dch}^{min} \leq x_{dch}^t \leq P_{dch}^{max} \tag{12}$$

$$SOC_{min}^t \leq SOC_{avg}^t \leq SOC_{max}^t \tag{13}$$

$$\sum_{t=1}^{t_{i,p}} \left(x_{i,ch}^t . \eta_c - \frac{x_{i,dch}^t}{\eta_d} \right) \Delta t = E_{i,r} \tag{14}$$

where $E_{i,r}$ represents the energy required by i^{th} EV. Equation (11) and (12) defines maximum and minimum charging and discharging power limits. Constraint of average SOC is expressed in equation (13). The values of SOC_{min}^t and SOC_{max}^t are considered as 0.2 and 1 respectively. Constraint (14) ensures that battery is fully charged at the end of parking period.

B. Multiobjective Formulation Using TOPSIS approach

TOPSIS was introduced by Hwang and Yoon in 1981[19]. This technique is based on Euclidean distance of each solution from best solution set known as positive ideal solution (PIS), while simultaneously minimizing it from the worst solution knowns as negative ideal solution (NIS). Mathematically, multiobjective problem can be expressed as:

optimize $[f_1(x), f_2(x), f_3(x) \ldots \ldots \ldots \ldots . f_n(x)]$

subjected to x ϵ F, where $f_j(x): \Re^n \to \Re$ is j^{th} objective function, $j = 1,2,3 \ldots \ldots . . n, n > 1$, and F is feasible search space. Following are sequence of steps to find compromising solution for proposed multi-objective problem:

Step 1 (Calculate a normalized decision matrix): In this step all dimensional attributes are transformed into non-dimensional attributes. The normalized value of matrix elements n_{ij} is calculated as follows:

$$n_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}} \ \forall\ i \in m\ and\ j \in n \tag{15}$$

where m and f_{ij} are number of alternatives and j^{th} objective value corresponding to i^{th} alternative, respectively.

Step 2 (Calculate weighted normalized matrix): The weighted normalized value is calculated in following way.

$$v_{ij} = w_j . n_{ij} \quad \forall\ i \in m\ and\ j \in n \tag{16}$$

here, w_j is weight corresponding to normalized element. Although this step can be skipped if all the objectives are equally important.

Step 3 (Determine positive and negative ideal solutions): PIS maximizes the benefit criteria and minimizes the cost criterion and NIS minimizes the benefit criterion and maximizes cost.

$$PIS = (v_1^+ , v_2^+ , \ldots \ldots . . v_n^+) \tag{17}$$

$$NIS = (v_1^- , v_2^- \ldots \ldots \ldots v_n^-) \tag{18}$$

where

$$v_j^+ = \begin{cases} \max(v_{ij})\ \forall\ i\ , if\ objective\ represents\ benefit \\ \min\ (v_{ij}) \forall\ i, if\ objective\ represents\ cost \end{cases}$$

$$v_j^- = \begin{cases} \min\ (v_{ij})\ \forall\ i, if\ objective\ represents\ benefit \\ \max\ (v_{ij})\ \forall, if\ objective\ represents\ cost \end{cases}$$

Step 4 (Determine Euclidean distance): Euclidean distance $d_j^+\ and\ d_j^-$ from PIS and NIS is calculated as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{19}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{20}$$

Step 5 (Calculate the relative closeness index to PIS): Relative closeness index (RCI) of each alternative is calculated as given below:

$$RCI_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \tag{21}$$

The alternative with highest value of RCI will be taken as most compromising solution.

IV. OPTIMIZATION FRAMEWORK

All optimizations in this work are carried out using GWO. GWO proposed by Mirjalili [20] is inspired by hunting technique of grey wolves. The hunting process of grey wolves is governed by information provided by leaders alpha (α), beta (β) and delta (δ) in terms of position of each other. Each wolf tries to get prey according to information provided by α, β and δ. Mathematically, the best solution is α while β and δ are second and third optimal solutions respectively. Equation (22) and (23) are used to update the positions of wolf:

$$\vec{X}(k+1) = \overrightarrow{X_p}(k) - \vec{A}\cdot\vec{D} \tag{22}$$

$$\vec{D} = \left|\vec{C}\,.\overrightarrow{X_p}\,(k) - \vec{X}\,(k)\right| \tag{23}$$

where k represents current iteration, $\vec{X}$ is grey wolf position and $\overrightarrow{X}_p$ is prey position and $\vec{D}$ is distance from prey. The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2a\cdot\overrightarrow{r_1} - a \tag{24}$$

$$C = 2\overrightarrow{r_2} \tag{25}$$

where r_1 and r_2 are random vectors in range [0,1] and value of a is linearly reduced from 2 to 0 over the course of iterations. Position of each wolf is updated as follows:

$$\vec{X}(k+1) = \frac{1}{length(p)}\sum_{i\in p} X_p(+1),\;\; p[\alpha,\beta,\delta] \tag{26}$$

Procedure of GWO for EVs scheduling is given as:

1. Initialization
   - Set number of searching wolves, iteration number etc.
   - Initialize particle of dimension $N_v \times T$ where N_v is number of vehicles in a given time period.
   - Calculated fitness of each wolf α, β and δ corresponding to objective of each model. In case of MOM fitness is calculated on the basis of RCI values obtained from TOPSIS approach.
2. Current position of wolf is updated according to (22)-(26).
3. If any of the constraints is violated then make corrections.
4. Compare and update the position of wolves.
5. Terminate if stopping criterion is reached otherwise increase iteration and go to step 2.

V. SIMULATION RESULTS AND DISCUSSIONS

In this section, 38-node bus system as shown in Fig.1 is studied for optimal integration of EVs in distribution system. In this work EVs are assumed to be present only on residential lateral. The parameters for 38 node bus system and residential load profile is taken from [21]. The power factor corresponding to residential load profile is assumed to be 0.9. A transformer of 1000 KVA capacity is assumed to supply residential lateral. For this study 3-tier pricing system information and five types of EVs and residential charger with 3.33 kW capacity is considered for charging and discharging of vehicles. Assuming maximum consumption of household to be 4 kW total of 230 houses can be observed on residential lateral [13]. Average number of vehicles per house are assumed to be 2.12 [22]. Therefore, total number of vehicles in the residential lateral are found out to be 488, whose driving profile is adopted from [16]. EVs are assumed to be uniformly distributed over the residential nodes.

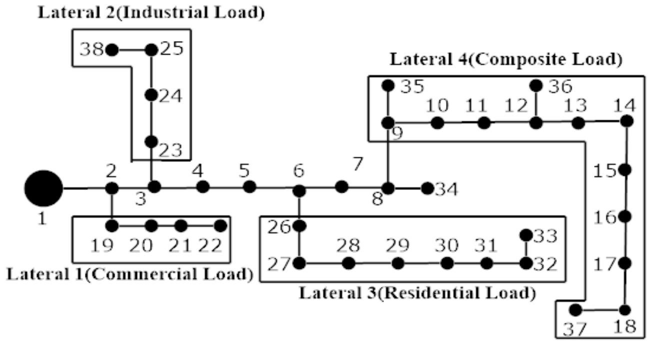

Fig.1: Line diagram of 38 node bus distribution system

In this work scheduling of EVs is obtained with MOM using TOPSIS approach. To illustrate the effectiveness of TOPSIS, the scheduling results obtained with TOPSIS is compared with scheduling results obtained with VFM and MCM. Comparative analysis is carried out for different penetration of EVs. EVs penetration here refers to total number of EVs present in residential lateral. EVs penetration is discretized into 4 levels (20%, 40%,60%, 80%)to determine the maximum penetration for each charging strategy. Maximum penetration here refers to number of EVs that can be accommodated by distribution infrastructure without violating the distribution infrastructure constraints such as transformer limits, distribution line limits and voltage limits. Table I shows the voltage, transformer and line loading limits respectively [12].

The impact of different objectives under different EVs penetration on line capacity, peak load and losses is shown in Table II. It can be observed that maximum allowable penetration is different in case of VFM, MCM and MOM respectively. It is evident from Table II that residential lateral can easily accommodate 80% penetration of EVs in case of VFM while MCM can easily accommodate 40% of EVs penetration. In case of MCM when EVs penetration is 60% transformer limits and line 19 loading limits are violated. It is worth to note that when MOM scheduling is adopted 60% of EV penetration can be accommodated by the distribution network without violating infrastructural limits. In case of VFM the peak load is always less than the peak load of base case (without EVs) i.e., 952.17 kVA, while for MCM the peak load is lower than base case when EVs penetration is

20% and 40% respectively. On further increasing the EVs penetration with MCM, the peak load violates the transformer limit. The peak load in case of MOM always lie between the peak load values obtained from VFM and MCM due to its multi-objective formulation. It is also to be noted that the network losses increase on increasing EVs penetration. However, when EVs penetration is low the difference between losses in case of VFM and MCM is less but when

TABLE I. VOLTAGE,TRANSFORMER LOADING AND LINE LOADING LIMITS

Voltage Limits	Transformer Loading Limit	Line Loading Limits
Upper Limit 1p.u.	1000KVA	Line 14(6-26) 1.5 p.u.
Lower Limit 0.93p.u		Line 19 (30-31) 0.5p.u.

TABLE II. IMPACT OF DIFFERENT OBJECTIVES UNDER DIFFERENT PENETRATION

Penetration Level	**Charging Strategy**	**Line Capacity**		**Peak Load (KVA)**	**Losses (MW)**
		Line 14	**Line 19**		
0	Base Case	64.6%	67.8%	952.17	1.83
20%	VFM	57.9%	62%	854.53	1.84
	MCM	61.4%	66.4%	910.62	1.85
	MOM	**61.1%**	**64.2%**	**901.38**	**1.85**
40%	VFM	54.6%	67.8%	806	1.87
	MCM	62.9%	66%	927.17	1.89
	MOM	**61.1%**	**64.2%**	**901.38**	**1.88**
60%	VFM	54.7%	52.6%	809.46	1.92
	MCM	70%	112%	**1032**	1.97
	TOM	**62.4%**	**94.6%**	**923.32**	**1.95**
80%	VFM	57.6%	67.4%	849.69	1.96
	MCM	88%	141.2%	1294.7	2.05
	MOM	**66.9%**	**102.6%**	**989.84**	**1.99**

EVs penetration increases, losses in case of MCM increases sharply. Also, the losses in case of MOM are found to be lie between VFM and MCM.

Fig.2 shows the transformer load profiles corresponding to each of the objectives under different EV penetration. It can be observed that for VFM, EV scheduling assists in both peak shaving and valley filling. Thus, peak to valley difference is reduced and a flat load profile is obtained under all the penetration when VFM for scheduling is considered. In case of MCM also EVs demand help to fill valley and shave peak load until low penetration of EVs. However, when EVs penetration is high MCM results in new peak. For example, in 60% and 80% penetration a new peak demand can be observed for MCM. The reason is that MCM objective minimizes total charging/discharging cost which causes all available EVs to simultaneously charge and discharge at low and high prices respectively. It can be seen from Fig. 2 that EVs scheduling profile obtained under MOM from TOPSIS approach found to be tradeoff between other two objectives. It can be observed from Fig. 2 that obtained load profile reduces the peak to valley difference as well as peak load demand in the early morning such that not to exceed the transformer loading limit of 1000 kVA.

Table III shows the comparison of different scheduling models in terms charging/discharging cost and load variance. According to results, load variance is significantly better with VFM as compared to MCM for any particular penetration of EVs. Similarly, the charging/discharging cost in case of MCM is better than in case of VFM, because in MCM, EVs

Penetration Level	Charging Strategy	Total Daily Charging cost	Load Variance
20%	VFM	58.58	3.053×10^5
	MCM	37.86	4.46×10^5
	MOM	**45.5**	**4.0 ×10^5**
40%	VFM	144.07	6.71×10^4
	MCM	99.27	2.77 ×10^5
	MOM	**131.65**	**2.0 ×10^5**
60%	VFM	285.55	6.43×10^4
	MCM	163.85	5×10^5
	MOM	**239.09**	**1.9 ×10^5**
80%	VFM	434.26	9.22×10^4
	MCM	207.25	1×10^6
	MOM	**346.52**	**2.8410^5**

TABLE III. COMPARISION OF DIFFERENT OBJECTIVES

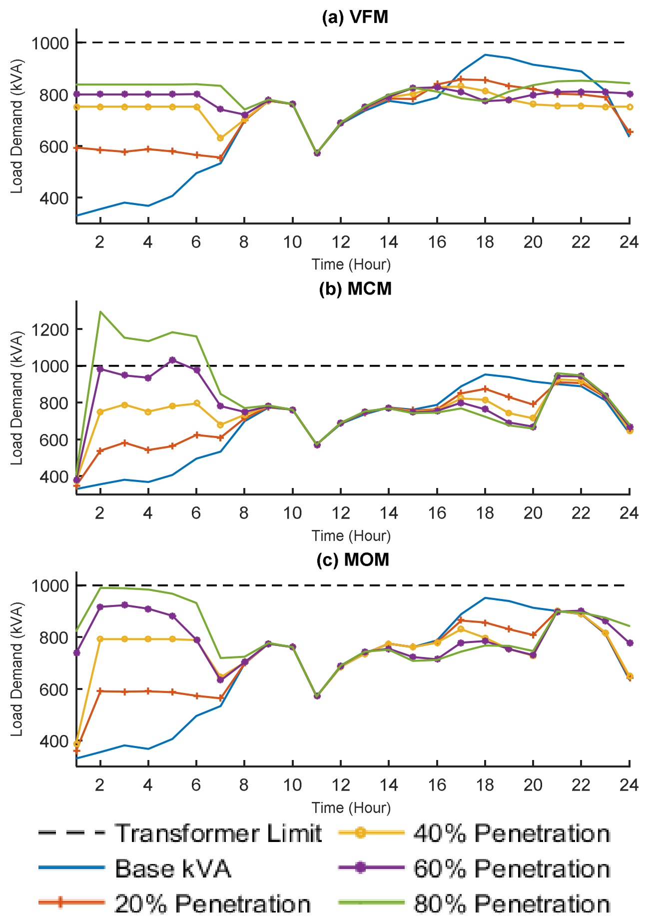

Figure 2: Load profiles for different charging models

discharge when prices are high and charge when prices are low so as to achieve maximum benefit. However, in case of MOM, the CC optimizes the EVs such that both flat load profile and minimum charging cost is achieved. For any particular EV penetration, as a tradeoff, MOM results in improved load variance in comparison to MCM and less charging/discharging cost in comparison to VFM. Therefore, with TOPSIS, solutions obtained are fairly favorable for both valley filling and cost minimization. Hence, with this approach significant penetration of EVs can be achieved while keeping an edge over load variance and cost of charging.

VI. CONCLUSION

In this work multi-objective optimization framework is investigated for optimal scheduling of EVs using TOPSIS approach. Scheduling optimization is handled using GWO. Moreover, effectiveness of adopting multi-objective scheduling is established by comparing it with single objective optimization approach. Results show that VFM is superior in minimizing load variance whereas MCM gives better charging/discharging cost. But TOPSIS approach gives fairly compensated results while combining benefits of both the objectives. This approach ascertains a compromised solution while achieving substantial penetration with favorable results for both the objectives. Application of this methodology to a test case demonstrates effectiveness of proposed approach.

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