

Minimizing power loss considering bulk uncoordinated charging station operation

S N Syed Nasir^a, R Ayop^b and J J Jamian^c

^{a,b,c}School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310, Skudai, Johor, Malaysia.
E-mail: ^asyednorazizul@utm.my, ^brazman.ayob@utm.my and ^cjasrul@fke.utm.my

Article History: : Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: The widespread usage of electric vehicles (EV) carries a negative impact on the distribution network. Higher penetration of uncoordinated charging station (CS) that used to charge the EV may boost the capacity of demand, especially during off-peak. Next, an increase in power loss may occur since the bulk operation of CS causes a higher power flow at existing networks. Furthermore, the CS varying demand usually challenging to handle, uniquely for the load that has various behaviour. From repetitious researchers, the CS operation often installs at the residency, parking lot and specific station. Then, the charging power requirement is different between EV's, which depend on battery size and characteristic. This research focuses on power loss parameters at the distribution network for uncoordinated CS operation. The analysis will be based on the 48-bus radial distribution system with two residential blocks using MATLAB environment. Then, suitable sizing and placement of multiple passive filters used to minimize power loss with assistance metaheuristic technique and multi-objective approach. From the result, propose method able to improve up to 8.03% compared to existing power loss after implement optimal sizing and placement of passive filter. The proposed method is useful to assist utility owner in reducing power loss issues at a distribution system that cause by extensive uncoordinated CS operation.

Keywords:

1. Introduction

The most reliable assurance of the environment and a pleasant assortment of sustainable energy sources have inflated the aggressive usage of EV [1–2]. Moreover, the International Energy Agency has foreseen a vital increase in EV demand up to 100 million each year by 2050 [3–4]. Besides, massive penetration of EV may raise power losses, lowering voltage profile, increase overall demands and diffusely degrade transformers and lines lifespan [5–9]. Hence, significant charging station infrastructure considering the impact to the power system, therefore, necessitated facilitating power system to allow greater penetration of EVs [9].

Since the rise of power loss become a significant concern when dealing with EV, broad researchers had focused with various method to reduce the impact such as installing the passive device which directly overcomes the power loss issue [10–16]. Next, to further enhance system efficiency and achieve approaching to optimal performance, real-time optimisation plans are crucial. Extensive research has proposed coordinating charging time which supports the utility owner strategy by offering cheap electricity tariff when charging at off-peak demand [15]. The speedy expansion of EV population requires continuous improvement on charging duration. Commonly, level 1 chargers recognise as low power chargers that require longer charging duration, which usually apply for EV user at residential areas. However, the customer at residential area also can apply level 2 chargers which extend better power level and duration but entail additional cost [9]. For level 3 charger offer faster-charging facility require at least one hour to charge the EV battery wholly, where usually established at the commercial area. Although level 3 charger allows fast charging duration, the charger incurs high cost and impact on the power system is significant, which can cause overloading and power loss issues [16–18]. Other than that, installing a passive filter to reduce the power loss in the system become the cheapest and practical application utilise [10–11, 16–18]. However, the sizing and placement of the passive filter become significant, particularly for the huger network. Furthermore, a single tune filter also acknowledged as a passive filter usually used to overcome the power loss issue as well as introduce reactive power. Although the active filter is the most forward-looking technology, the passive filter element is yet extensively applied because of the smooth implementation, economical cost and less maintenance cost [11–13].

Therefore, this research proposes the proper method for optimal sizing and placement of passive filters to minimise power losses with the assistance of meta-heuristic techniques. Additionally, the profile of load and CS will apply useful data from earlier research. Hence, in the means of optimising the most proper location and sizing, precise parameters necessitate being counted, such as the variation of CS's and loads. This article organised into five sections. The first section discusses the significance of EV and current research focus. Section 2 specifies in detail the fundamental parameters modelling such as distribution system, EV, passive filter and load characteristic. Next, section 3 directed on the methodology in determining the optimal sizing and placement based on the recommended metaheuristic method. In section 4, focus on results and the discussion on the results. Ultimately, the research conclusion manifested in Section 5.

2.System Modelling

These sections will concentrate on modelling the distribution system by considering CS locations. Next, to focus on the appropriate formula to determine battery SOC based on charging current and efficiency. Moreover, the passive filter, typical load profile and CS pattern design also presented.

2.1.Distribution system modelling

The distribution system is modelled based on typical load and CS operation. Toward showing the practical application, 48-bus radial distribution system applied for this research. The system consists of standard medium voltage IEEE 23 kV 10-bus radial distribution system with two 415 V low voltage residential block that has 19 buses each as per represented in figure 1. As the research focus on bulk EV usage, CS's located at every residential block buses, which add up 38 units as per figure 2.

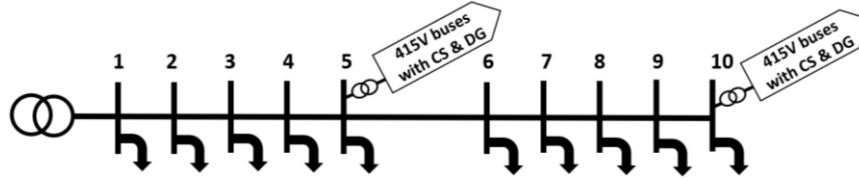


Figure 1. 23 kV IEEE 10-bus radial distribution system with residential block

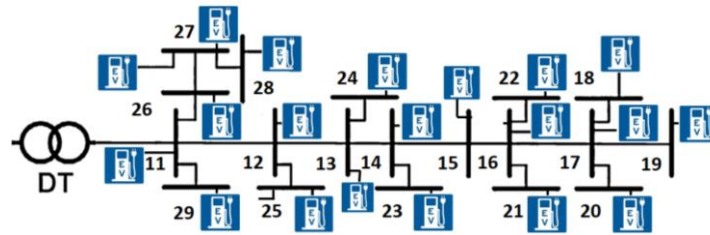


Figure 2. 0.415 kV 19-bus residential block

2.2.EV and battery modelling

Usually, EV contains a battery to store mass-energy depending on battery sizing. There are numerous battery sizes on the market based on customer interests. Besides, CS being design based on different output depends on customer demand such as low charging current if the customer has sufficient time (4-6 hours) to charge fully and slightly higher current if the customer needs faster charging (2-3 hours). Concerning this research, the charging current has fixed value by considering that CS does not have the facility to deviate the output current. Lithium iron phosphate batteries modelled as a typical battery model used for the analysis. The plug-in and plug-out battery SOC value depend on customer request while the current produced by CS to the EV battery is calculated based on that SOC state. General equation to identify SOC at the current state is as shown in equation (1).

$$SOC(\Delta t_{k+1}, i) = SOC(\Delta t_k, i) + \left(\frac{\Delta t}{Q_i}\right) I(\Delta t_k, i) \cdot 100 \quad (1)$$

where:

Q_i Rated battery ampere hour for the i^{th} PEV (Ah)

R_i Battery equivalent internal resistance for the i^{th} node (ohm)

$I(\Delta t_k, i)$ Charging current for the i^{th} PEV at current time slot(A)

$SOC(\Delta t_k, i)$ State of charge of the i^{th} PEV at kth time slot (%)

$SOC(\Delta t_{k+1}, i)$ State of charge of the i^{th} PEV at next kth time slot (%)

Δt_k Time interval

The value of battery SOC will also acknowledge internal resistance embedded in the battery, which will affect the efficiency of the battery. Hence, to correlate the impact, the power delivered from the source to the battery will influence battery efficiency (η) as per equations (2) and (3). Thus, the power consumed (P_{cs}) will have smaller energy due to the battery internal resistance (R_i) influence. Applying the quadratic equation as per (4), the current generated by CS can be computed using equation (5). Numerical a , b , and c are expressing numerical coefficient for quadratic equation (3). Thus, the SOC increment after a time interval can be collected based on all data.

$$P_{cs}(\Delta t_k, i) = \frac{P_{de}(\Delta t_k, i)}{\eta} \quad (2)$$

$$P_{de}(\Delta t_k, i) = V_{oc,i} \cdot I(\Delta t_k, i) + R_i I^2(\Delta t_k, i) \quad (3)$$

$$I(\Delta t_k, i) = \frac{\sqrt{b^2 - 4ac} - b}{2a} \quad (4)$$

$$I(\Delta t_k, i) = \frac{\sqrt{(V_{oc,i}^2 + 4 \cdot \Delta t \cdot R_i \cdot P_{cs}(\Delta t_k, i) \cdot \eta) - V_{oc,i}}}{2 \cdot R_i} \quad (5)$$

where:

- $V_{oc,i}$ Open circuit voltage for i^{th} node (V)
- $I(\Delta t_k, i)$ Charging current for the i^{th} PEV at current time slot(A)
- $P_{cs}(\Delta t_k, i)$ Consumed power for the i^{th} PEV (kW)
- $P_{de}(\Delta t_k, i)$ Delivered power for the i^{th} PEV (kW)
- η PEV efficiency

2.3.Passive filter modelling

One unit of the single tuned filter is considered as one set of the passive filter, as shown in figure 3. Equations utilised to determine capacitor, inductance and resistance elements are as per equations (6), (7) and (8), sequentially. The capacitor is determined based on injected reactive power and voltage at that bus. Quality factor (Q_u) plays a significant role in providing sharpness of tuning specified frequency. However, since this research does not focus on harmonic distortion, the quality factor set to 0.8. Three sets of passive filters will be put at the distribution system based on proper placement. Although there is no limit for the number of passive filters that can be installed in the distribution system, the increasing number of passive filter will also extend the complexity for obtaining an optimal placement and sizing due to the rise of parameters involved. Furthermore, it will boost the cost to place multiple passive filters in the distribution system practically. Although the sizing of passive filters that decided from the simulation in this research is not accessible in the market, it can be as an estimation value for practical implementation. This estimation can be used to pick the closes practical value of passive filter accessible in the market.

$$C_{Filter} = \frac{Q}{2\pi f V^2} \quad (6)$$

$$L_{Filter} = \frac{V^2}{2\pi f Q} \quad (7)$$

$$R_{Filter} = \frac{V^2}{Q_u Q} \quad (8)$$

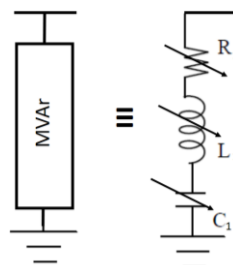


Figure 3. One set of passive filter

2.4.Load modelling

There are two types of loads involves which are EV load and customer load. Both loads are generated based on typical daily human behaviour. CS operation directly follow EV customer behaviour to charge while load consumption from CS depend on battery SOC, charging current used as well as CS efficiency. Figure 4 shows the load profile for normal load without EV and with EV for daily consumption. The power loss difference calculated based on power loss during system without EV and with EV. Basically, figure 4 design based on time which every

increment number represent 15 minutes different with the first time started at 9pm. Different power loss that cause by EV for every 15 minutes also recorded at figure 4. The CS operation designed to operate at night between 11pm until 9am where most of the CS based on level 1 or level 2 types.

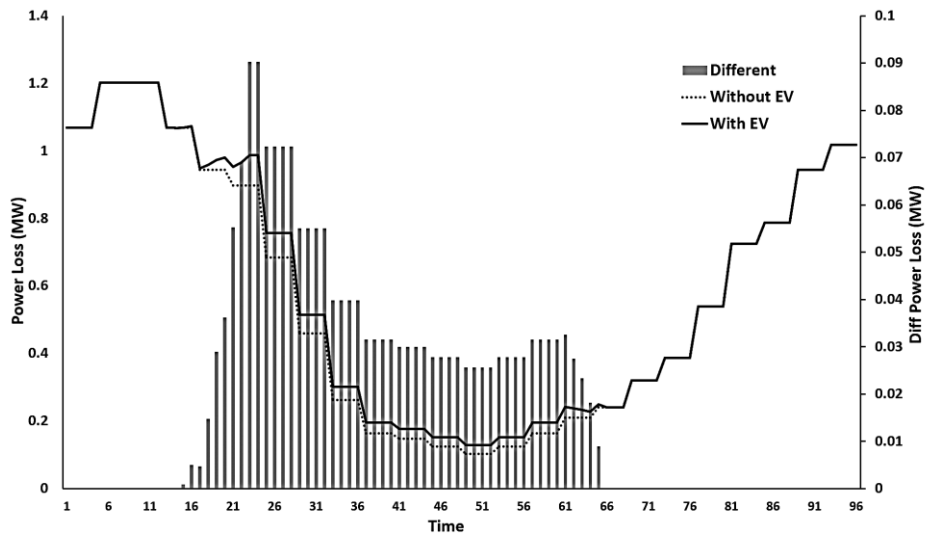


Figure 4. Load profile and power loss with and without EV for daily

3.Methodology

The simulation for finding placement and sizing of passive filters are not simulated together due to the load and CS operation variation. In the real application, only passive filter sizing can be changed while passive filter placement needs to be identified at the design stage. Typically, optimal placement and sizing of passive filter simulations in the distribution system can be divided into two stages, which are design and operational. The meta heuristic method will be used which is Modified Lightning Search Algorithm (MLSA) in this research. Design stage involves placement of passive filters in the distribution system, while the operation stage deals with optimal sizing only. Since optimal placement of passive filters involves large search space compared to the sizing of passive filters, the focus will only at the worst power loss recorded time only. The higher number of parameters with a wide range of choices becomes the major reason for longer computational time. Thus, the higher the number of buses and passive filters in the distribution system, the longer the computational time required to find optimal placement. Next, the operational stage in this research is to find the optimal sizing of passive filters. In this stage, the crucial part is to find the solution that provides improvement for objective functions. The flowchart in finding optimal placement and sizing are detailed in figure 5.

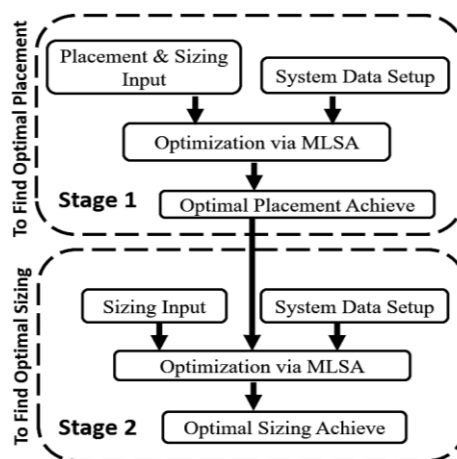


Figure 5. Flowchart in finding optimal placement and sizing

Moreover, propose concept that use in this research present at Figure 6. The process generally consists of customers, data centre and the distribution system. The process centralizes at the data aggregator (data centre) which will pool all data from the distribution system and customer EV data, which is then used to calculate sizing of all variable passive filters. The sizing of the variable passive filter depends on the current distribution system condition that will be assisted by MLSA and multi objective technique. The size of the passive filter will be

changed every 15 minutes. Customers will input their requested plug-out time and requested final SOC's at the time of plug-in. Once SOC reaches the requested SOC, CS will be switched to a standby mode. Since the time slot being set is 15 min (Δt), there will be a total of 96 slots per day. Furthermore, the aggregator (Data centre) has access to CS information including their bus locations, charger types, battery sizes, plug-in time and plug-out time. The CS's are controllable and have variable charging functions. During the charging process, each CS is assumed as a variable active load. In addition, the power used to charge the battery is based on the calculation done by the aggregator (Data Centre).

The total variables will become six, which are three locations and three optimal sizes. All these parameters will have its own constraints that needs to fulfil. In general, the parameters can be divided into 2 categories which are passive filter location and reactive value. The filter will be placed in low voltage bus to minimize any harmonic injection to medium voltage. Furthermore, only 3 passive filter will be placed at low voltage 415 buses system. The placement constraints are as (9) while reactive value range as per (10).

$$a_i \leq Filter_i \leq s_i, i = 11 \dots 48(9)$$

$$0kVar \leq Q_i \leq 50kVar, i = 1 \dots 3(10)$$

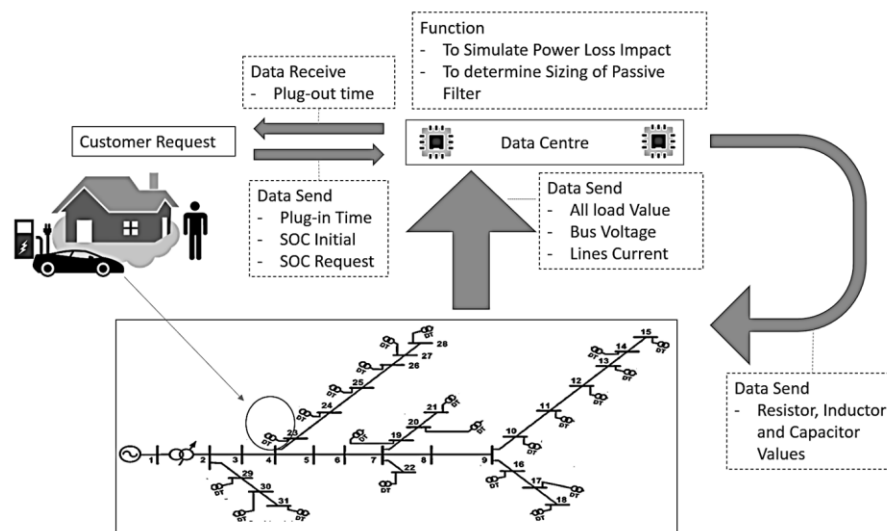


Figure 6. Basic concept of proposed process in practical system

4.Result and discussion

The simulation in this research arranged based on the plot where 38 units of CS simultaneously operated in low voltage 415 V buses with various types of CS characteristic and battery sizing. The analysis based on 24 hours which represent 96 sampling time, where one sampling time is equivalent to 15 minutes. The CS start operation occurs at night between midnight until noon the next day. Sampling time 23 (represent 1 am) decided due to the worst different power loss registered within 24 hours. From the result, without variable passive filter, power losses for sampling time 23 obtained to be 514.96 kW without CS and 582.21 kW with CS, respectively.

4.1.Stage 1: Optimal placement

Stage 1 concentrates on the best location to place the passive filter within low voltage bus. Thus, the metaheuristic technique, which is MLSA employed to find optimal placement for passive filters. Due to the higher parameter involved, the iteration use set at 200 to assure the effectiveness of the final solution. The population used at 50 and learning factor set at 2.0. Next, to find the best location, the worst scenario times, which is the time 23 chosen. Based on the simulation, optimal location for all passive filters for time 23 tabulated in Table 1. The sizing of passive filter is set at 10 kVar to ensure the minimum reactive can impact the total power loss value. From the results in Table 1, there is a significant reduction for maximum obtained the optimal placement for the variable passive filter.

Table 1. Optimal placement for different number of passive filters

Number of Passive Filter	Location Passive Filter (bus)				Total Power Loss (kW)
	1	2	3	4	

0	-	-	-	-	582.212
1	27	-	-	-	579.598
2	27	26	-	-	577.245
3	27	26	28	-	575.364
4	27	26	28	15	575.439

From the result, power loss value is decrease when the number of passive filter increase. The first stage, metaheuristic is employed to finding the best location for passive filter placement with focus on minimize the total system power loss. The crucial method is to choose place in the system that able to give impact to the system although the reactive injected is small which is 10 kVAr only. From Table 1, using one, two and three passive filter manage to reduce total power loss to 579.598 kW, 577.245 kW and 575.364 kW respectively. However, using four passive filter not give much difference on total power loss. Due to that, three passive filter at buses 26, 27 and 28 are choose for next stage. From the result, the increasing number of passive filters placed in the network, power losses improve. The optimal placement determined in this stage utilised for the optimal sizing based on time.

4.2.Stage 2: Optimal Sizing

Stage 2 focuses on the value of the passive filter element for every time, depending on the current load profile. The analysis involved in this part is only directing on filter sizing using MLSA while placement used as per previous stage result for three units of passive filters. The process of variations the passive filter value is based on explanation as per Figure 6. Hence, there is a total of 96 simulations done to identify optimal sizing for 96 times (represent 24 hours). Figure 7 displays the total power loss before and after installing the passive filter in the proposed network for 24 hours, while Table 2 presents the range of variable passive filter element reactive power for daily simulations. From the result in figure 7, the presence of passive filter improves the power loss between 0.89% to 8.03% for 24 hours, including the moment EV not present in the network. Even though the installation of a passive filter to reduce the losses during EV operation, the suggested approach also benefiting the existent load without EV. Next, the higher variance of power loss recorded during EV present, which satisfy the purpose of this research. Although the highest reactive power of passive filter is 50 kVAr, the optimal value of the passive filter at Table 2 shows that the highest value not the most suitable choice for all the time. Therefore, precise sizing is vital to get the optimal and productive value of power loss.

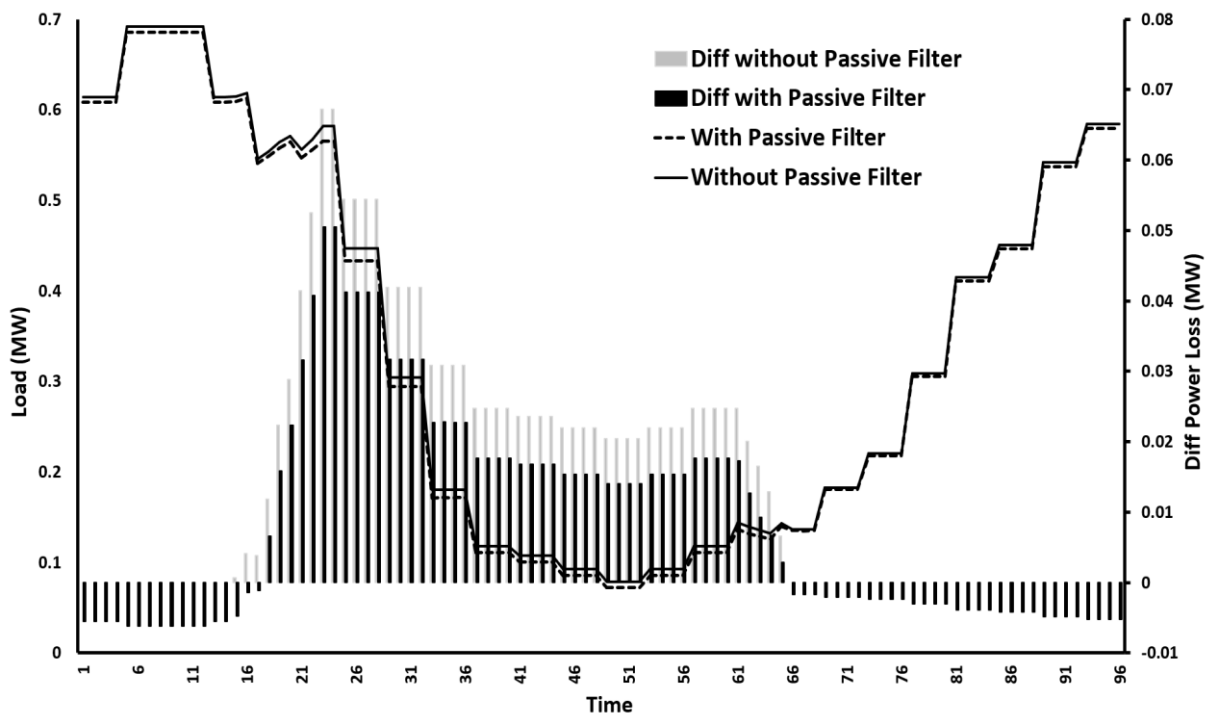


Figure 7. Total and difference power loss with and without passive filter installation for 24 hours

Table 2. Range of variable passive filter

Element		Minimum value	Maximum value
Passive Set 1	Filter	35.57 kVAr	50.00kVAr
Passive Set 2	Filter	49.76 kVAr	50.00 kVAr
Passive Set 3	Filter	1.00 kVAr	18.97kVAr

5. Conclusion

Optimal placement and sizing of the variable passive filter in the distribution system can decrease power losses. The proposed strategy has revealed that metaheuristic technique which is MLSA fitted of discovering the suitable passive filter placement and size to decrease power losses in the 48-bus system with 38 units of CS. Moreover, the placement of three sets of single tuned filters based on optimal placement method was able to reduce the power losses with a minimum number of passive filters. Furthermore, based on the simulation ran every 15 minutes for optimal sizing, the proposed technique observed to be able to improve up to 8.03% compared to existing power loss. The placement of variable passive filter for 24 hours also benefiting system during off operation of EV. The intended approach is essential to utility keeper for future distribution grid that might face the bulk of uncoordinated CS's in the network.

6. Acknowledgments

The researchers would like to express their appreciation to the Universiti Teknologi Malaysia (UTM) for supporting this work through UTMER Grant (17J76).

References

1. K Palmer, J E Tate, Z Wadud, and J Nellthorp 2018 Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan Applied energy 209 pp108-119.
2. S Wang, K Wang, F Teng, G Strbac, and L Wu 2018 An affine arithmetic-based multi-objective optimization method for energy storage systems operating in active distribution networks with uncertainties Applied energy 223 pp 215-228
3. S Falahati, SA Taher, and M Shahidehpour 2016 A new smart charging method for EVs for frequency control of smart grid International Journal of Electrical Power & Energy Systems 83 pp 458-469
4. P Cazzola, M Gorner, R Schuitmaker, and E Maroney 2017 Global EV outlook 2017: Two Million and Counting International Energy Agency France
5. NB Arias, JF Franco, M Lavorato, and R Romero 2017 Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation Electric Power Systems Research 142 pp 351-361
6. K Qian, C Zhou, M Allan, and Y Yuan 2010 Modeling of load demand due to EV battery charging in distribution systems. IEEE transactions on power systems 26(2) pp 802-810
7. S Shahidinejad, S Filizadeh, and E Bibeau 2011 Profile of charging load on the grid due to plug-in vehicles IEEE Transactions on Smart Grid 3(1) pp 135-141
8. E Sortomme, MM Hindi, SJ MacPherson, and SS Venkata 2010 Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. IEEE transactions on smart grid 2(1) pp 198-205
9. AG Boulanger, AC Chu, S Maxx, and DL Waltz 2011 Vehicle electrification: Status and issues Proceedings of the IEEE 99(6) pp 1116-1138
10. LR De Araujo, DRR Penido, S Carneiro Jr, and JLR Pereira 2018 Optimal unbalanced capacitor placement in distribution systems for voltage control and energy losses minimization Electric Power Systems Research 154 pp 110-121.
11. B Asadzadeh, and S Golshannavaz, 2017 Coordinated Wide-Area Regulation of Transmission System for Voltage Profile Improvement and Power Loss Reduction Trans. Electr. Electron. Mater.(TEEM) 18(5) pp 279-286
12. KL López, C Gagné, and MA Gardner, 2018 Demand-side management using deep learning for smart charging of electric vehicles IEEE Transactions on Smart Grid 10(3) pp 2683-2691

13. GR Bharati, and S Paudyal, 2016 Coordinated control of distribution grid and electric vehicle loads *Electric Power Systems Research* 140 pp 761-768.
14. A Londoño, and M Granada-Echeverri, 2019 Optimal placement of freight electric vehicles charging stations and their impact on the power distribution network *International Journal of Industrial Engineering Computations* 10(4) pp 535-556
15. S Limmer, and T Rodemann, 2019 Peak load reduction through dynamic pricing for electric vehicle charging *International Journal of Electrical Power & Energy Systems* 113 pp 117-128
16. SN Syed Nasir, JJ Jamian, and MW Mustafa 2018 Minimisation of harmonic distortion impact due to large-scale fast charging station using Modified Lightning Search Algorithm and Pareto-Fuzzy synergistic approach *IEEEJ Transactions on Electrical and Electronic Engineering* 13(6) pp 815-22
17. SN Syed Nasir, JJ Jamian, and MW Mustafa 2018 Minimising Harmonic Distortion Impact at Distribution System with Considering Large-Scale EV Load Behaviour Using Modified Lightning Search Algorithm and Pareto-Fuzzy Approach *Complexity* 2018
18. SN Syed Nasir, JJ Jamian, and MW Mustafa 2019 Minimising harmonic distortion impact cause by CS using meta heuristic technique *Telkonnika* 17(4)