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***Abstract*— The growing popularity of private vehicles' electrification will have a negative impact on the electric power system, especially on the distribution networks, if electric vehicles (EVs) charging is not managed properly. In this paper, a new technique for smart charging of EVs is proposed and tested with simulation. A fuzzy logic controller is used to control and manage the EV charging process to maximize electric utility and EV owner benefits. The electric utility's benefit is to mitigate the EV charging impacts on the distribution network by shifting EV charging to the off-peak period, while EV owners' benefit is to charge the EV at low cost. The controller regulates and controls the EV charging power depending on electricity price signal provided by the electric utility and EV battery state of charge (SoC). This controller needs basic communication with the electric utility to receive the electricity price signal every 1 hour. The objective of the controller is to charge EVs at low cost while keeping the normal operating conditions of the distribution network. MATLAB/SIMULINK is used to perform simulations and test the effectiveness of the proposed smart charging method. The results demonstrated that the proposed smart charging method reduced the impacts of EVs charging on the distribution network compared with uncontrolled charging.**

Keywords—Uncontrolled charging; smart charging; electric vehicles; fuzzy logic control.

I. Introduction

According to the International Energy Agency (IEA) global EV outlook of 2017 [1], there is a continuous decrease in the price of EVs which will result in the acceleration of EV deployment. The decline of battery cost is the reason for EVs prices reduction. Mass production in addition to research and development (R&D) results in rapid decay of battery costs. The continuous improvement of EVs and battery technology will narrow the price gap between EVs and conventional internal combustion engine (ICE) vehicles which will increase competitiveness. Evaluations of the countries' targets and equipment manufacturers' announcements seem to confirm these positive signals of the massive increase of the EVs stock market. EVs stock crossed 1 million in 2015 and surpassed 2 million in 2016. It is expected that the EVs stock market will be between 9 million and 20 million in 2020 and at 2025 will be between 40 million and 70 million.

Because this large number of EVs will be charged from the electric power grid, it is important to develop techniques for the optimal integration of EVs. There are three main types of EV charging; uncontrolled charging, delayed charging and smart charging. Uncontrolled charging is also called unregulated charging, uncoordinated charging, or dumb charging. Uncontrolled charging means that the cars start charging at the instant of arrival to home or workplace. This is the type of EV charging that is used nowadays. In this case, EV charging usually occurs at peak load hours which leads to severe grid impacts. Various studies found that uncontrolled EV charging may limit the acceptable penetration level of EVs in the distribution network [2]. The highest impacts on the distribution networks are expected if this charging technique is used. Usually, this happens when the utility has fixed tariff structure, so there are no incentives for EV owners to delay the charging.

In delayed charging, electricity utility companies use two tariff structures with high prices at peak period and lower prices at the off-peak period to motivate EV owners to charge at these times. With proper choice of the tariff structure, this can result in a flattened load profile and a decrease of the voltage drop caused by EV charging. If the off-peak and peak hours in the tariff structure are not set in an optimal way, the impact of EV charging may get worse [3]–[5]. This may occur since the low prices at off-peak period may motivate a huge number of EV owners to charge simultaneously which may result in higher voltage drop and load demand with the possibility of second peak formation at the first hours of off-peak hours.

Although the use of delayed charging can reduce the EV charging impacts on the distribution networks, it is observed that the network capacity is not used in an optimal manner. Various studies concluded that the controlling of charging start time and charging rates of EVs using a smart charging (controlled charging or coordinated charging) algorithm may use the power system in a more optimal and efficient way. Many studies presented coordinated charging algorithms [6]–[8] to control EV charging to maximize EV owners' benefits by reducing the charging cost or to maximize the electric utility benefits by shifting the EV charging to off-peak hours which reduces the impact on the electric power system. This is a part of the smart grid concept. In this type, the communication between EV and electric utility or Distribution System Operator (DSO) is continuous.

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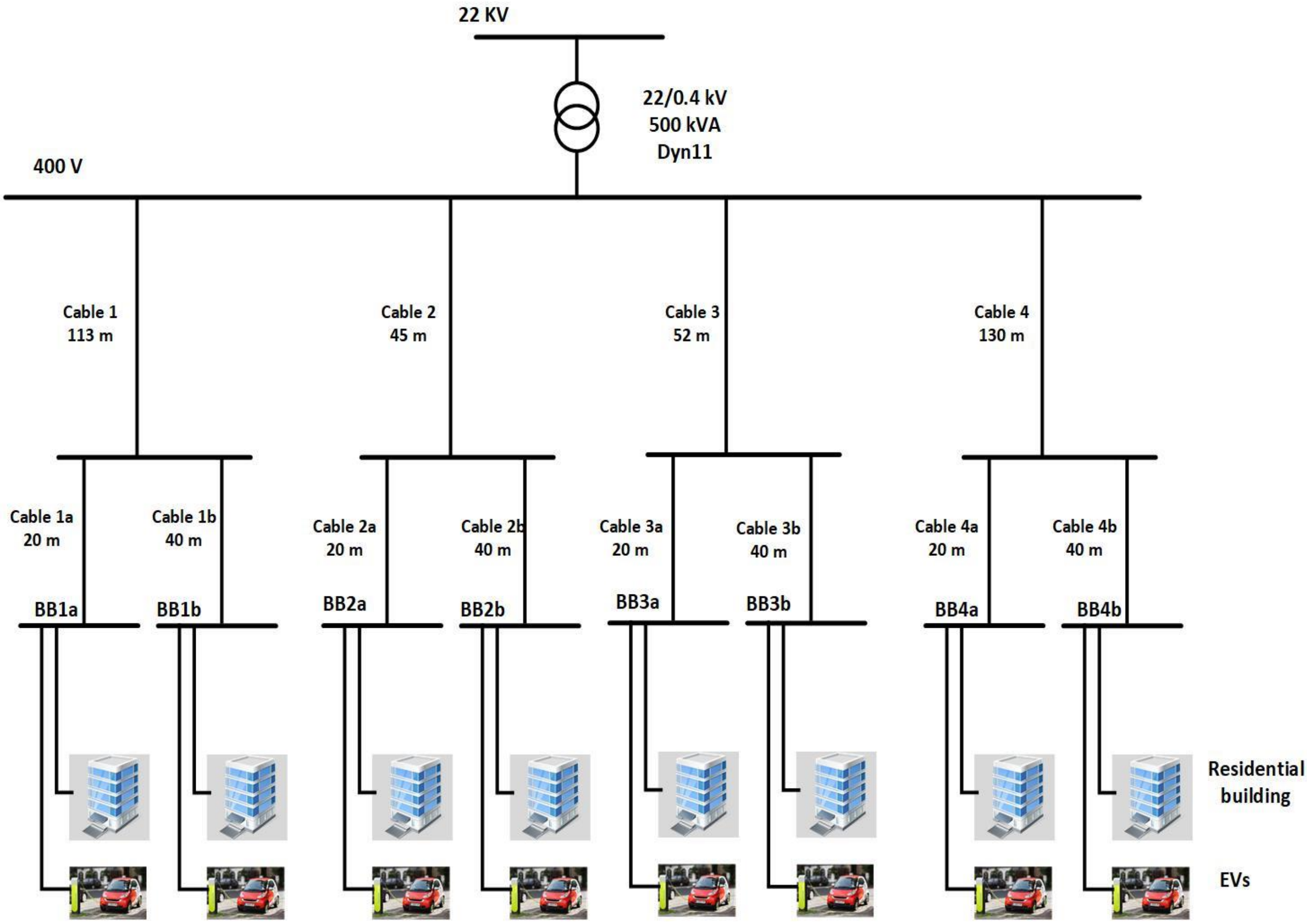

Fig. 1 LV distribution network one-line diagram.

In this paper, three operation scenarios are studied and compared. In the first scenario, the LV distribution network is supplying residential consumers only, and no EVs are plugged in for charging. In the second scenario, EVs with 50% penetration level are connected to the grid for charging. In this scenario, the EVs are charged in uncontrolled charging manner. In the third scenario, the EVs are charging based on the proposed smart charging method.

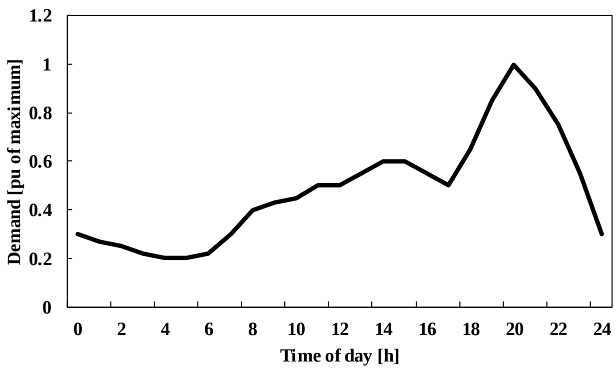

Fig. 2 Daily load curve of residential consumer.

II. Distribution Network Modeling and Simulation

A. Distribution Network

A 400 V LV distribution network is selected as a case study in this paper to execute simulations. It is a real distribution network located in New Toshka city, Aswan, Egypt. Fig. 1 shows the one-line diagram of the distribution network. It has a 500 kVA distribution transformer with 22 kV primary and 400 V secondary voltage. It supplies 96 residential consumers distributed equally at eight buildings. The system is assumed to be balanced, and the residential consumer's load is the same in all the 3 phases. All the system data is provided in [9]. Fig. 2 shows the load profile (power consumption variation) during the day for each consumer [10]. 1 p.u. is equivalent to 4 kVA which is the highest power consumption in the 24 hours. The load power factor is 0.9 lagging.

Nissan Leaf [11] is used to evaluate the impacts of its charging on the distribution network. It is a battery electric vehicle (BEV). This type of EVs is powered entirely by electricity and batteries are used as the electric power source, and it supplies an electric motor which drives the vehicle. No internal combustion engine (ICE) is used in this type of EVs. Its battery capacity is 24 kWh. The EVs are assumed to have 20% SoC when connected to the charger (initial SoC). A three-

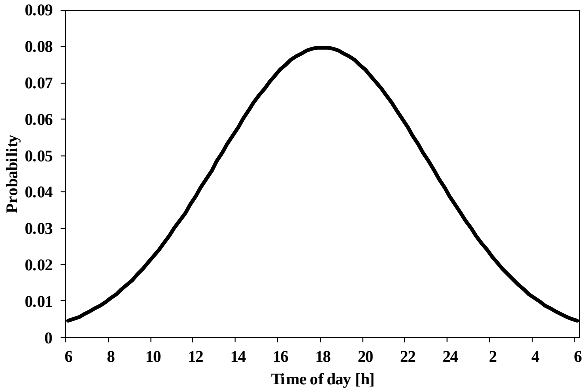

Fig. 3 Probability distribution of EVs charging start time.

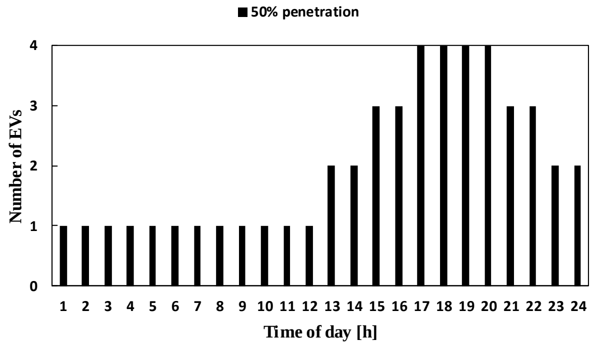

Fig. 4 EVs charging start time.

phase charger with 90% efficiency and 6.6 kW power rating is used to charge EVs.

B. *Uncontrolled Charging*

Three operation scenarios are studied; base case, uncontrolled charging, and smart charging. For uncontrolled charging, EVs start charging at the instant of home arrival (1) at the maximum charging power of the charger. This case has no coordination or management of EVs charging and the highest impacts is expected in this case. Fig. 3 shows that the start time of EVs charging follows a Gaussian distribution (2) with a mean (μ) equal to 18:00 and standard deviation(σ) equal to 5 hours [12]. The actual number of EVs that begin charging at each hour is shown in Fig. 4. A 50% penetration level of EVs is investigated which is equal to 48 EV. The penetration level of EVs can be calculated by (3).

$$t_{charging} = t_{arrival} \tag{1}$$

$$f(t,\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(t-\mu)^2 / (2\sigma^2)} \tag{2}$$

$$EVs\ Penetration\ Level[\%] = \frac{Number\ of\ EVs}{Number\ of\ Loads} \times 100 \tag{3}$$

C. *Smart Charging*

In this charging method, the EV charging is controlled by a fuzzy controller with electricity price signal and SoC as inputs and the charging power as an output. Most of the proposed smart charging techniques depend on the availability of sophisticated real-time communication between EVs and electric utility, but the proposed controller needs only basic communication to receive the energy price which is provided by the electric utility every 1 hour. The electricity price is

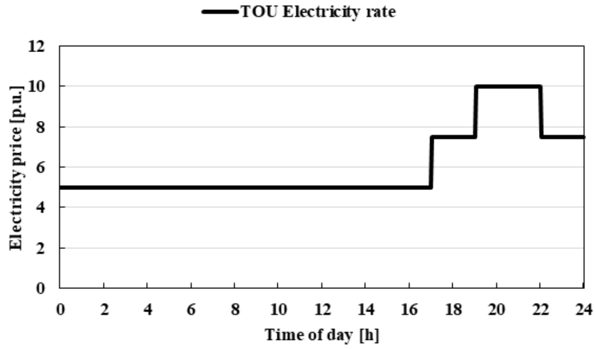

Fig. 5 Electricity tariff structure.

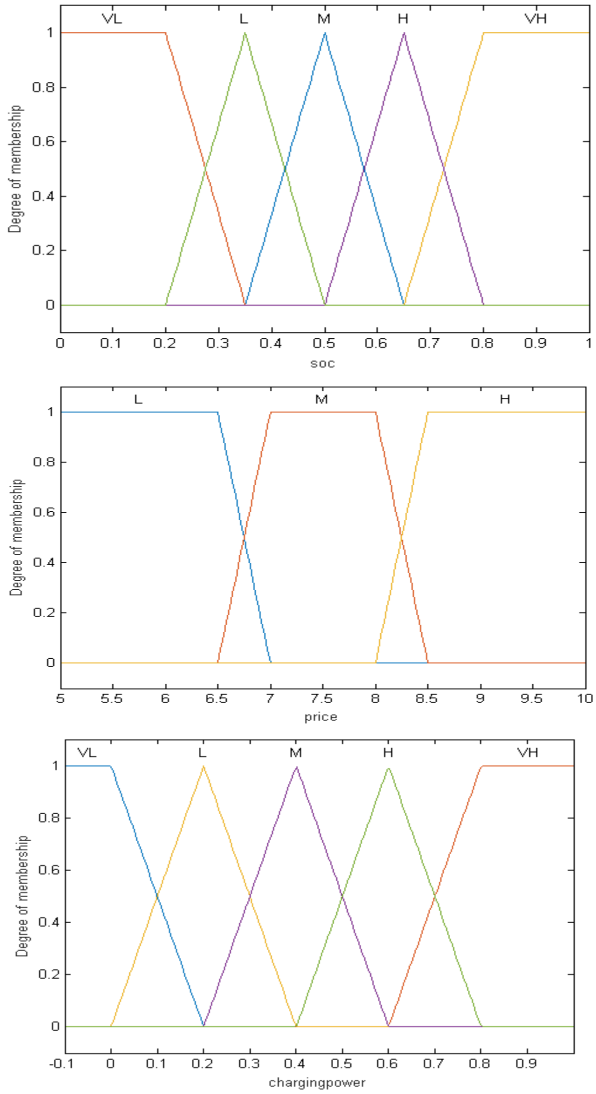

Fig. 6 Inputs and output membership functions.

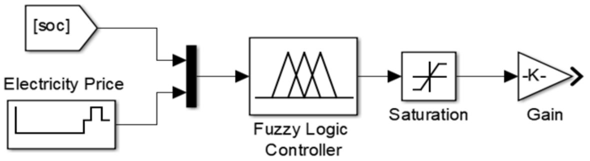

Fig. 7 MATLAB/SIMULINK model of fuzzy controller.

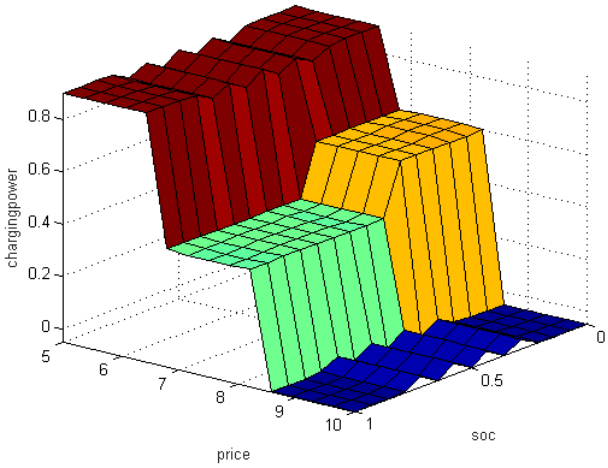

Fig.8 relation between inputs and output in 3-D.

assumed to vary during the day as in Fig. 5. The electricity price is 5 p.u. from 24:00 to 17:00, 7.5 p.u. from 17:00 to 19:00 and from 22:00 to 24:00, and 10 p.u. from 19:00 to 22:00. According to the controller design, the EV can charge at the maximum charging power when electricity price is low (5 p.u.). In addition, it charges at medium charging power depending on battery SoC when electricity price is medium (7.5 p.u.) and stop charging when electricity price is high (10 p.u.). The controller is designed to maximize EV owner benefit by charging the EV at low cost. Also, the electric utility benefits (operating the system within the acceptable limits) can be maximized by proper choice of electricity tariff structure. EV owners can be motivated to charge at off-peak hours which have low electricity prices and stop charging at peak hours which have high electricity price.

TABLE I. FUZZY CONTROLLER KNOWLEDGE BASE RULES

SoC \ Price	L	M	H
VL	VH	H	VL
L	VH	H	VL
M	VH	M	VL
H	VH	M	VL
VH	VH	M	VL

Fig. 6 shows that the universe of discourse of the output (charging power) and first input (SoC) is divided into five membership functions sets (three triangular and two trapezoidal); Very High (VH), High (H), Medium (M), Low (L), and Very Low (VL). Furthermore, the second input (energy price) is divided into three trapezoidal membership functions sets; Low (L), Medium (M) and High (H). Because the controller output signal is in p.u. so, it should be multiplied by EV charger rated charging power. A saturation limit block is added to the fuzzy controller output to guarantee the unidirectional flow of power from the power grid to the vehicle. Fig. 7 shows the MATLAB/SIMULINK fuzzy controller model with electricity price and SoC inputs and per unit charging power output which is multiplied by 6.6 kW gain. Table I shows the controller knowledge base rules. Fig. 8 illustrate a three-dimensional (3-D) visualization of the control space. The surface viewer shows the inputs and output relation.

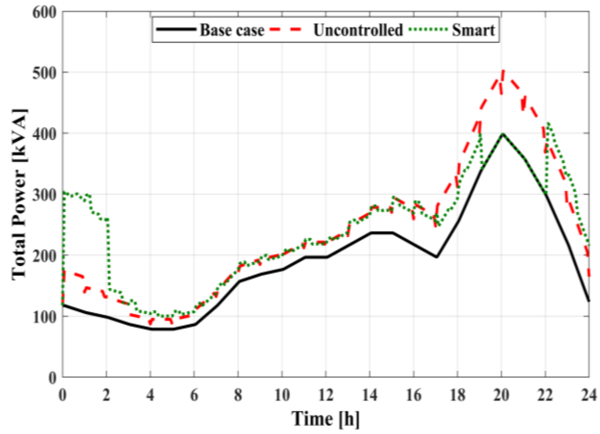

Fig. 9 Total power demand for the base case, uncontrolled charging, and smart charging.

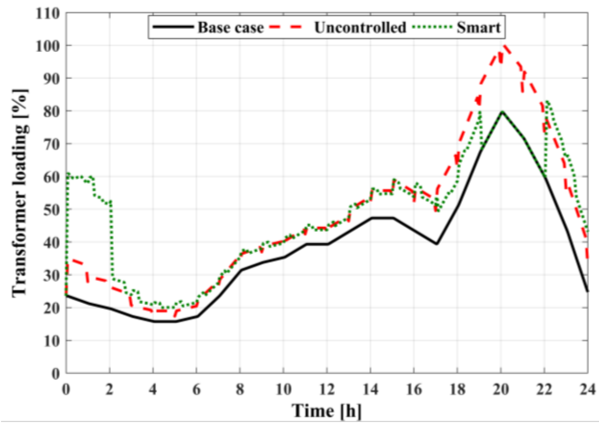

Fig. 10 Transformer loading for the base case, uncontrolled charging, and smart charging.

The proposed fuzzy controller can be easily extended to have more than two inputs or to include other distribution network parameters such as total power, transformer loading or feeders loading as well as EV owner preferences.

III. RESULTS AND DISCUSSION

A. Total Power Demand

For uncontrolled charging, the peak demand increased to 500 kVA with 100 kVA increase in peak demand at 20:00 compared with the base case. In opposition, for smart charging, the peak demand was almost the same as the base case because EVs stopped charging during the peak hours from 19:00 to

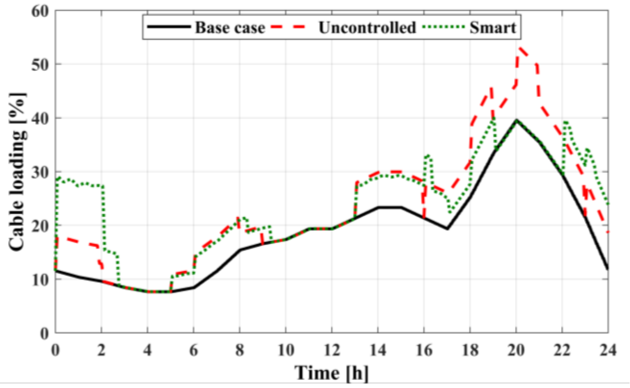

Fig. 11 Cable loading for the base case, uncontrolled charging, and smart charging.

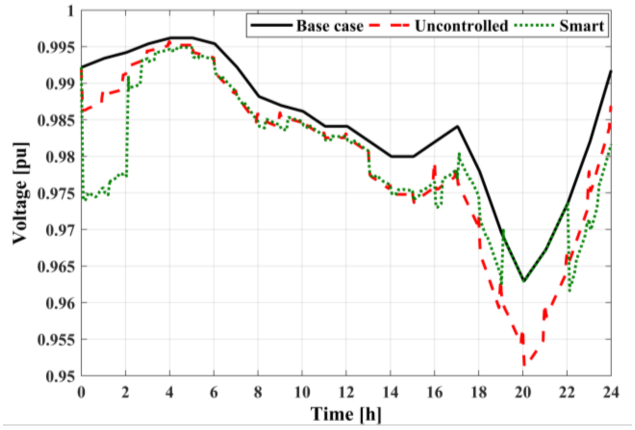

Fig. 12 Voltage profile for the base case, uncontrolled charging, and smart charging.

22:00 due to the high electricity price in these hours. EV charging was shifted to off-peak period as shown in Fig. 9 which is called valley filling.

B. Transformer Loading

The transformer loading increased with EV integration and reached 100% of its power rating at 20:00 as shown in Fig. 10 when uncontrolled charging was used to charge EVs. On the other hand, for smart charging, the transformer loading was limited to 80% of its power rating as in the base case. This means a 20% reduction in transformer loading compared with uncontrolled charging.

C. Cable Loading

The cable loading was very low during the whole day even at peak demand hours as shown in Fig. 11. The cable loading increased with uncontrolled EV charging and reached more than 50% of its capacity at 20:00. For smart charging, the highest loading recorded during the day was 40% of its power rating similar to the base case. This means more than 10% reduction in cable loading compared to uncontrolled charging.

D. Voltage at Cable Endpoint

Fig. 12 shows that uncontrolled charging of EVs results in a worse voltage profile compared with the base case. The voltage at the furthest point from the transformer reached the lower limit (0.95 p.u. according to ANSI standard [13]) of the acceptable operating conditions at peak time (20:00). On the contrary, smart charging improved the voltage profile because no EVs were charging during peak hours from 19:00 to 22:00 and the lowest voltage recorded was more than 0.96 p.u.

a.

IV. CONCLUSIONS

In this study, maximizing EV owners' benefit by controlling EV charging based on electricity price was executed. Fuzzy controller with electricity price and SoC inputs and charging power output was used to control EV charging. It was concluded that:

- Smart charging reduced the maximum power demand by 100 kVA which is a 20% reduction compared with uncontrolled charging. Apparently, the highest power demand recorded during the day was the same as in the base case. Smart charging resulted in valley filling.
- Smart charging reduced the maximum transformer loading during the day by 20% compared with uncontrolled charging. The highest transformer loading recorded for smart charging was 80% which was the same as the base case.
- Smart charging reduced the cable maximum loading by more than 10% compared with uncontrolled charging.
- Smart charging improved the voltage profile compared with uncontrolled charging and the lowest voltage recorded was higher than 0.96 p.u. similar to the base case.

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