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Review Paper on Load Demand Management Optimization for Accommodating Electric Vehicle

Authors: Km Seema Maurya[1], Dr. Imran Khan[2] , Dr Malik Rafi[3]

M. Tech Student, Azad Institute of Engineering & Technology, Lucknow[1]

Professor, Azad Institute of Engineering & Technology, Lucknow[2]

Professor, RR Institute of Engineering & Technology, Lucknow[3]

ABSTRACT

The shift of transportation technology from internal combustion engine (ICE) based vehicles to electric vehicles (EVs) in recent times due to their lower emissions, fuel costs, and greater efficiency has brought EV technology to the forefront of the electric power distribution systems due to their ability to interact with the grid through vehicle-to-grid (V2G) infrastructure. The greater adoption of EVs presents an ideal use-case scenario of EVs acting as power dispatch, storage, and ancillary service-providing units. This EV aspect can be utilized more in the current smart grid (SG) scenario by incorporating demand-side management (DSM) through EV integration. The integration of EVs with DSM techniques is hurdled with various issues and challenges addressed throughout this literature review. The various research conducted on EV-DSM programs has been surveyed. This review article focuses on the issues, solutions, and challenges, with suggestions on modeling the charging infrastructure to suit DSM applications, and optimization aspects of EV-DSM are addressed separately to enhance the EV-DSM operation. Gaps in current research and possible research directions have been discussed extensively to present a comprehensive insight into the current status of DSM programs employed with EV integration. This extensive review of EV-DSM will facilitate all the researchers to initiate research for superior and efficient energy management and EV scheduling strategies and mitigate the issues faced by system uncertainty modeling, variations, and constraints.

Keywords: FAME, DSM, electric vehicles(EV-DSM), smart grid (SG), CIAS based DSM

1. INTRODUCTION

The development of electric-powered motors for vehicles has a long history, dating back to before the commercialization of internal combustion engines (ICEs). The first electric vehicle was developed in 1828, using a basic electric motor assembly. However, the focus shifted to ICE vehicles due to their superior power delivery and lower fuel costs.

In recent years, there has been a renewed interest in electric vehicles (EVs) due to concerns about climate change, energy security, and the environmental impact of fossil fuels. EVs offer several benefits, including reduced greenhouse gas emissions, improved energy efficiency, and lower operating costs. The integration of EVs with the smart grid (SG) presents opportunities for demand-side management (DSM) and vehicle-to-grid (V2G) applications. EVs can participate in DSM programs by adjusting their charging schedules, providing frequency regulation, and offering spinning reserve. The benefits of EV adoption include:

- Reduced greenhouse gas emissions and improved air quality
- Improved energy efficiency and lower operating costs
- Enhanced grid stability and reliability

- Increased energy security and reduced dependence on fossil fuels.

The mass adoption of EVs can also provide several benefits, including:

- Support for the grid during contingencies and peak demand periods

- Provision of ancillary services such as voltage and frequency regulation

- Improved power quality and reduced transmission losses

- Enhanced consumer participation in energy markets and demand response programs

EVs can also play a crucial role in integrating renewable energy sources (RES) into the grid, by storing surplus energy and providing power during periods of shortfall. This can help to stabilize the grid and improve the overall efficiency of the energy system. Some key advantages of EVs include:

- Ability to store energy and provide power during peak demand periods

- Flexibility to adjust charging schedules and participate in DSM programs

- Potential to provide spinning reserve and frequency regulation services

- Enhanced grid stability and reliability

Overall, the adoption of EVs presents a significant opportunity to reduce greenhouse gas emissions, improve energy efficiency, and enhance grid stability and reliability.

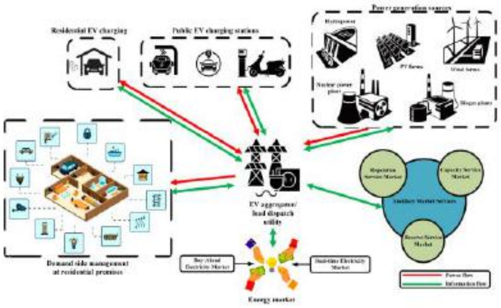

Fig. 1. EV operation in overall smart grid scenario with participation in electricity markets.

Demand-side management (DSM) programs are being implemented by utility operators to reduce energy consumption at the end-user level. These programs can benefit electric power markets by improving operational efficiency and profitability. This can be achieved through peak demand reduction strategies and managing spot-pricing volatility (Tronchin et al., 2018). DSM is a key component of smart grid (SG) infrastructure, and its implementation involves communication systems, sensor-based control devices, automated metering devices, and smart devices. Advanced information and communication technology (ICT) devices can improve grid operation efficiency and facilitate communication of tariff changes, benefiting DSM programs (Panda et al., 2022b). The integration of electric vehicles (EVs) can support DSM programs by providing energy storage and supply capabilities. EVs can operate as a load, supplier, or independent energy storage system, allowing distribution system operators (DSOs) to coordinate EV charging and implement DSM programs. Consumers can participate in DSM programs by modifying their energy usage patterns in three ways:

- Reducing energy consumption through load reduction techniques (Panda et al., 2021a)

- Shifting energy consumption to off-peak periods (Panda et al., 2021b)

- Using alternative energy sources to reduce dependence on the main utility supply

EVs can support DSM programs by:

- Acting as energy storage systems (ESS) and supplying energy during shortfalls

- Modifying charging/discharging patterns to level grid load consumption

- Providing regulation services to DSOs and supporting grid stability

- Offering different tariffs to motivate consumers to shift energy dependence from the utility gridThe coordinated operation of EVs can maximize business values in the energy market and optimize central control and charging processes (Ehsani et al., 2012).

1.2. EV-customer modeling parameters

The primary purpose of DSM can be realized through EV integration in two broad applications: (1) Energy efficiency and (2) Load shifting techniques. In general, power system operation, the fluctuation of load demand, and the fulfillment of supply–demand during peak usage are the primary issues and concerns.

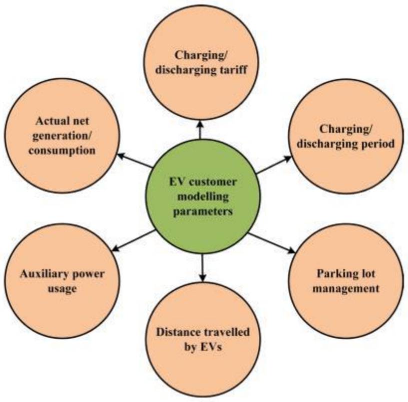

Fig. 2. The data to be collected to model EV in optimization problems.

On the contrary, when largescale adoption of EVs in the grid system is done without proper planning, these issues become more critical. If the flexible nature of EVs can be considered on the usage side of the end-user and they can be realized as shiftable loads, DSM-EV implementation can project itself as an excellent approach to address these issues (Yazdandoust and Golkar, 2020; Van der Meer et al., 2016). For proper implementation of DSM-EV techniques, specific data has to be aggregated, as illustrated in Fig. 3, which includes (Mohammad et al., 2020):

- Charging/discharging tariff
- Charging/discharging period
- Parking lot management
- Distance traveled by the EVs
- Auxiliary power usage during normal EV drive conditions

2. MATHEMATICAL MODEL FOR ENERGY CONSUMPTION

A thorough mathematical model that regulates energy consumption by distinguishing between flexible and non-flexible equipment is what makes dynamic energy management possible. This model also manages energy usage. The total energy consumption of the home is determined by calculating the energy consumption of each individual device based on its power rating, the amount of time it is operational, and the likelihood that it will be utilised. This is done in order to get the overall energy consumption of the home. Through the categorisation of home appliances as either flexible or non-flexible, this model offers a full knowledge of the dynamics inherent in the energy use of households. Because of this understanding, it is possible to optimise energy consumption in a way that corresponds with chances to save money and programs that are responsible for meeting demand.

In the case of flexible appliances, the model incorporates a degree of adaptability, which takes into account the likelihood that a particular item might be utilised during off-peak hours, which are times when the cost of energy is lower. The insertion of a binary choice variable into equation 1 is the theoretical representation of this concept in the context of flexible appliances. Et;Rshift is dependent on a set of parameters, which include the power rating Pr, which is a measurement of the amount of energy that an appliance consumes when it is in use; the operational hours Ht,r, which reflects the amount of time that the appliance is used within the selected time slot t; and a binary decision variable bt.r, which indicates whether the appliance is turned on or off. Et;Rshift is dependent on these parameters. This decision variable makes it possible for these appliances to have a flexible scheduling, which is especially important since it enables them to be turned on during off-peak energy hours, which can be done with the intention of lowering costs or when there is a strong supply of renewable energy. This is further improved by the consumption probability variable, Ut,r, which takes into account human conduct such as the tendency to leave dishwashing machines running overnight or automatic scheduling systems that optimise for energy savings. Furthermore, this variable takes into account the fact that human behaviour exists.

$$E_{t;Rshift} = \Sigma_{r \in Rshift} \left({}^{P}r \times {}^{H}{}_{t;r} \times {}^{b}{}_{t;r} \times {}^{U}{}_{t;r} \right) \qquad (1)$$

At the opposite end of the spectrum, in Equation 2, non-flexible appliances are those that have consumption patterns that are consistent throughout the year. The refrigerator and the security system are two examples of such equipment. Both of these appliances are essential to the operation of the household and often run continuously. The fact that these home appliances function in a consistent manner enables the model to incorporate them without the need for a binary classification variable. This is because the model is able to maintain consistency. Alternately, their energy consumption is a basic product of their power rating and operational hours, Et;Rnonshift, which shows the steady and predictable demand that they place on the energy system. This is an alternative to the traditional method of calculating energy consumption.

$$E_{t;Rnonshift} = \Sigma_{r} \,{}_{\in Rnonshift}\, (Pr\,^{x}\, H_{t;r}\,^{x}\, C_{r}) \qquad (2)$$

As a result of the model's classification of appliances into these two categories, it is possible to take a more targeted approach to the management of energy consumption [15]. It is conceivable, for example, to shift energy use away from flexible appliances during peak demand hours. This would result in a reduction in the strain placed on the grid and a reduction in the amount of money that people spend on energy. During this interim period, the consistent load of non-flexible appliances acts as a baseline for energy demand, so guaranteeing that essential services will continue to be uninterrupted.

$$R_{base}(t)\,{}^{=}\, E_{t;Rshift} + E_{t;Rnonshift} \qquad (3)$$

When calculating the home base load Rbase(t), the total amount of energy consumption from both flexible and non-flexible appliances is added together. The equation 3 is a representation of the entire energy consumption for the family at any given time, taking into consideration both the variable and the constant demands of the appliances.

$$R_{base}(t) = \Sigma_{r} \,{}_{\in Rshift}\, (Pr\,^{x}\, {}^{H}{}_{t;r}\,^{x}\, b_{t;r}\,^{x}\, U_{t;r}) + \Sigma_{r} \,{}_{\in Rnonshift}\, (Pr\,^{x}\, H_{t;r}\,^{x}\, C_{r}) \qquad (4)$$

When developing an energy model for a company operating in the information technology industry, it is important to take into account the ongoing demand from critical infrastructure. This need includes hardware such as servers and networking equipment. These components are not flexible because they are required to function continuously throughout the day and night. Because these components are essential to the continuous running of the business, they frequently do not have the possibility of being turned off or working at a reduced level. This is because they are required for the firm to continue to function. The power consumption of these non-flexible components can be represented using a notation known as PCD, which stands for power consumption. After that, the power consumption is multiplied by the number of hours that these components are operational. In the case of non-flexible loads, the number of hours that these components are operational remains the same throughout all intervals of time. In contrast, flexible loads in an information technology company may include workstations, particular office equipment, and possibly even the discretionary use of climate control systems. These loads are able to be varied according to the occupancy level and the requirements of the business. Flexible loads can be used to meet the needs of the business. These customisable loads make it possible to adopt energy management strategies, such as scheduling costly computing work during off-peak hours or modifying the air conditioning in areas of the office that are vacant. These strategies are examples of how energy management can be implemented. The equation that would be used to explain the base load of the IT sector company's Ibase(t) would be represented by Equation 5, which would be the numerical representation of the equation.

$$I_{base}(t) = \Sigma_{r} \,{}_{\in Cshift}\, (Pc\,^{x}\, {}^{H}{}_{t;c}\,^{x}\, b_{t;c}\,^{x}\, U_{t;c}) + \Sigma_{r} \,{}_{\in Cnonshift}\, (P_{c}\,^{x}\, H_{t;c}) \qquad (5)$$

Equation 6 depicts Ssolar(t), which examines the impact of renewable energy and solar implementation, taking into consideration both technology and the environment. This facilitates the formulation of the problem in a manner that is more practical. It takes into account the installed capacity of solar panels, denoted as Csolar, as well as their efficiency rate, denoted as ηsolar, in order to take into account the factors that are affecting energy output in the real world. In addition, the equation incorporates the variable St, which represents the availability of sunshine at different times, weather conditions, and seasons, and the variable Δt, which represents the amount of time required for the conversion of solar energy.

$$S_{solar}\ (t) = C_{solar}\ \text{X}\ Z_{solar}\ \text{X}\ S_t\ \text{X}\ \Delta t \qquad (6)$$

For the purpose of gaining a deeper comprehension of the expanding influence that electric cars (EVs) are exerting on the patterns of energy consumption in both the residential and commercial sectors, equation 7 is a representation of the charging load for electric vehicles (EVs). When it comes to understanding the ever-evolving picture of energy consumption in both the residential and commercial sectors, the EEV(t) equation is a crucial component that must be considered. A substantial contribution is made by it in the process of predicting the total charging demand for electric vehicles at a certain time.

$$E_{EV}(t) = \Sigma_{\text{EV=1 to NEV}}\ (P_{EV}\ \text{X}\ c_{t;EV})\ \ (7)$$

Equation (7) is formulated to calculate the total power demand of electric vehicles that are actively charging at a given time instant. In this formulation, the aggregate electric vehicle charging load at time t is represented by $RE(t)$. The equation accounts for all electric vehicles considered within the study, ranging from the first EV to the NEVNEV-th EV, where NEVNEV denotes the total number of electric vehicles that may be charging at that specific time. This parameter is particularly significant as it reflects the scale of EV adoption and charging infrastructure within the studied area, whether it is a residential neighborhood or a commercial parking facility.

3. MATHEMATICAL EXPRESSION FOR THE EV CHARGING RESCHEDULING

A set of non-peak hours is denoted by NP, the emergency scenario in which the vehicle has to be charged is denoted by E, and the set of peak hours during the day is defined by P according to Eq. 20, which is used to adjust the charging schedule of electric cars. E stands for the emergency scenario, by the way. Electric car charging schedules can be adjusted by defining the constraint as:

$$R_{EV}(t) = I_{EV}(t) = \begin{cases} 0 & \text{If } t \in P \qquad (20.1) \\ R^{sched}{}_{EV}(t) & \text{If } t \in E \qquad (20.2) \\ R^{sched}{}_{EV}(t) & \text{If } t \in NP \qquad (20.3) \end{cases}$$

Both RschedEV(t) and IEVsched(t) represent the scheduled charging rates for electric vehicles at times that are not considered to be peak hours. The amount of available charging time, the quantity of energy that electric vehicles require, and the capacity of the infrastructure that is used to charge electric vehicles are the factors that influence the charging rates for electric vehicles. Because of the execution of this objective function and the constraint, valley filling has been able to account for the peak demand that was expected to occur. Presented in Figure 6 is an illustration of the load curve that was obtained after the DSM approach was applied.

The development of the DSM with the updated restrictions has been accomplished through the application of a variety of optimisation strategies. Figure 7 is a flowchart that illustrates the various optimisation algorithms that were implemented for the DSM model. Additionally, the steps that were involved in the execution of the algorithm and the pseudocode that corresponded to it were described in detail as follows:

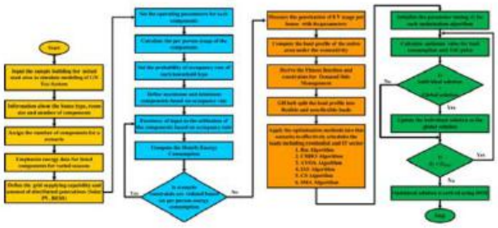

Fig 4.1. DSM optimization method implementation flowchart

4. FUTURE SCOPE AND RESEARCH DIRECTIONS

This literature survey examines the current state of research on electric vehicle (EV)-based demand-side management (DSM). The review identifies areas for improvement and suggests future research directions to enhance the existing technological advancements in EV-DSM. Key suggestions for future research include:

- Integrating virtual power plants to optimize smart loads and appliances for DSM, with EVs serving as energy hubs (Mohanty et al., 2022; Panda et al., 2022a)

- Developing hybrid financial models that combine incentive-based and tariff-based approaches to optimize load control features

- Applying meta-heuristic optimization techniques, such as particle swarm optimization (PSO) and genetic algorithms (GA), to improve DSM scheduling

- Implementing machine learning algorithms, such as k-map and fuzzy constrained algorithms, to extract insights from load consumption profiles

- Enhancing EV-DSM models to account for varying charging rates, standards, and battery swapping station methodologies

- Investigating price-sensitive scheduling and EV charging strategies based on price response and elasticity dynamics

- Addressing the lack of datasets for training machine learning models and developing more comprehensive EV-DSM models

- Exploring climate-based EV-DSM scheduling and its impact on renewable energy source (RES) generation

- Developing policies and regulations to promote EV adoption and participation in DSM programs

- Investigating the environmental impacts of EVs and opportunities for eco-friendly production and disposal

- Implementing simultaneous bidirectional power flow and individualized EV charge/discharge operation scheduling

- Examining the influence of plug-in hybrid electric vehicles (PHEVs) on charging/discharging patterns and DSM operations

- Developing communication protocols for IoT-based control strategies and smart device integration

5. CONCLUSION

The review concludes that EV-DSM has the potential to play a significant role in the future of energy management, and that further research is needed to address the existing challenges and opportunities.

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