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Research paper

Demand side management of electric vehicles in smart grids: A survey on strategies, challenges, modeling, and optimization

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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.

1. Introduction

The history of electric-powered motors to drive passenger and commercial vehicles dates back a long and profound history, even before the internal combustion engine's (ICE) commercialization. The first motor vehicle powered by electricity was in 1828, using a crude but feasible electric motor assembly fitted to propel a car. Since then, rapid advancements took place until the early 1900s globally due to the non-availability of crude oil refining techniques and the eventual development of ICE vehicles (Situ, 2009). The suitability of ICE vehicles to provide for more excellent power delivery and their cheap fuel tariff favored the ICE vehicles more than their electric vehicle (EV) counterparts. The golden age of the automotive industry thus put a greater emphasis on developing and deploying ICE vehicles until now, when the disadvantages of higher emissions and decreasing crude oil reserves have outweighed the economic viability of running and maintaining fossil fuel-consuming engines. The focus on the further development and advancement of EV technologies has been given utmost priority to combat the environmental, financial, and sustainability problems (Chan, 1999). The initial hesitations while

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Abbreviations

ICE	Internal Combustion Engine
DSM	Demand Side Management
ESS	Energy Storage System
RES	Renewable Energy Sources
ICT	Information and Communication Technology
EE	Energy Efficiency
DLC	Direct Load Control
DSB	Demand Side Bidding
RTP	Real-time Pricing
BESS	Battery Energy Storage System
G2V	Grid to Vehicle
EVCS	Electric Vehicle Charging Station
ISO	Independent System Operator
ADR	Automated Demand Response
UC	Unit Commitment
ANN	Artificial Neural Network
LP	Linear Programming
ACO	Ant Colony Optimization
DE	Differential Evolution
EMS	Energy Management System
IPGA	Improved Partheno-Genetic Algorithm
MPC	Model Predictive Control
RMILP	Robust Mixed-integer Linear Programming
CVaR	Conditional Value at Risk
MPSOPF	Multi-period Security Constraint Optimal Power Flow
DL	Deep Learning
RL	Reinforcement Learning
PA	Pursuit Algorithm
MRS2R	Multi-EV Reference and Single-EV Real-time Response
MILP	Mixed Integer Linear Programming
TSO	Transmission System Operator
ABC	Artificial Bee Colony
EV	Electric Vehicle
DR	Demand Response
V2G	Vehicle to Grid
SG	Smart Grid
DSO	Distribution System Operator
ToU	Time of Use
CL	Curtailable Load
CPP	Critical Peak Pricing
SoC	State of Charge
SoH	State of Health
DoD	Depth of Discharge
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
PEV	Plug-in Electric Vehicle
DG	Distributed Generation
DP	Dynamic Programming
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
FL	Fuzzy Logic
PAR	Peak-to-Average Ratio
VCS	Virus Colony Search
NLP	Nonlinear Programming
RMIQP	Robust Mixed-integer Quadratic Programming
DER	Distributed Energy Resource
SBP	Stochastic Dynamic Programming
RARL	Robust Adversarial Reinforcement Learning
HRL	Hierarchical Reinforcement Learning
ADMM	Alternating Direction Method of Multipliers
KKT	Karush–Kuhn–Tucker
NILE	Non-intrusive Load Extracting
GSM	Global System for Mobiles
COA	Correlation Optimization Algorithm

opting for EVs compared to ICE vehicles were due to the infrastructure related to charging and the range anxiety issues. With the gradual advancements in the field of semiconductors, battery technologies, efficient motor designs, and energy management systems, all the issues that used to exist in significant proportions have reduced to mere inconvenience but present themselves as more economically viable in the long run.

Recent advancements in the grid infrastructure and the eventual smart grid (SG) setup have allowed for seamless integration of EVs as active and passive participation in the grid infrastructure in individual and clustered/coordinated setups (Shaukat et al., 2018; Tan et al., 2016). The capability of the EVs in their unidirectional control, bidirectional control, and power flow has allowed the grids to maximize their potential in offering more efficient usage patterns and their support in grid services (Mal et al., 2013). Various motivational factors to incorporate EVs on a mass scale and their efficient utilization have been mentioned as follows:

- Electrification of the vehicular transportation sector presents a viable resolution to issues faced by climate change, energy security, and the geographical availability of carbon-based fossil fuels (Tran et al., 2012).
- Most vehicles remain parked at their respective premises of charging infrastructure up to 90% of the total time (Razipour et al., 2019), so they can remain connected to the grid infrastructure and participate in energy flow programs using their batteries as energy storage systems (ESS) using the concept of the vehicle to grid (V2G).
- EVs in mass-scale can support the grid in case of contingencies and deliver ancillary services to the grid entities in the form of peak shaving, voltage, and frequency regulations, and behaving like a spinning reserve whenever required (Saldaña et al., 2019).
- The mass-scale adoption of EVs, when undertaken in a coordinated and organized manner from the technical standpoint, dramatically enhances the operational and economic evaluation of the smart grid in the areas of performance, efficiency, and power quality mitigation capability (Farhoodnea et al., 2013).
- The aggregated coordination of EVs can enable active participation of the consumers in the energy market by providing support to the electric grid in facilitating regulatory activities and system management (Shafie-Khah et al., 2016b).
- The EVs can store the surplus generated energy obtained by renewable energy sources (RES) by deploying different charging topologies or be able to provide power during shortfalls in generation and provide a more levelized grid load consumption/supply curve using V2G programs. This would allow EVs to act as energy-buffer entities among the energy production and consumption units (Hannan et al., 2017).

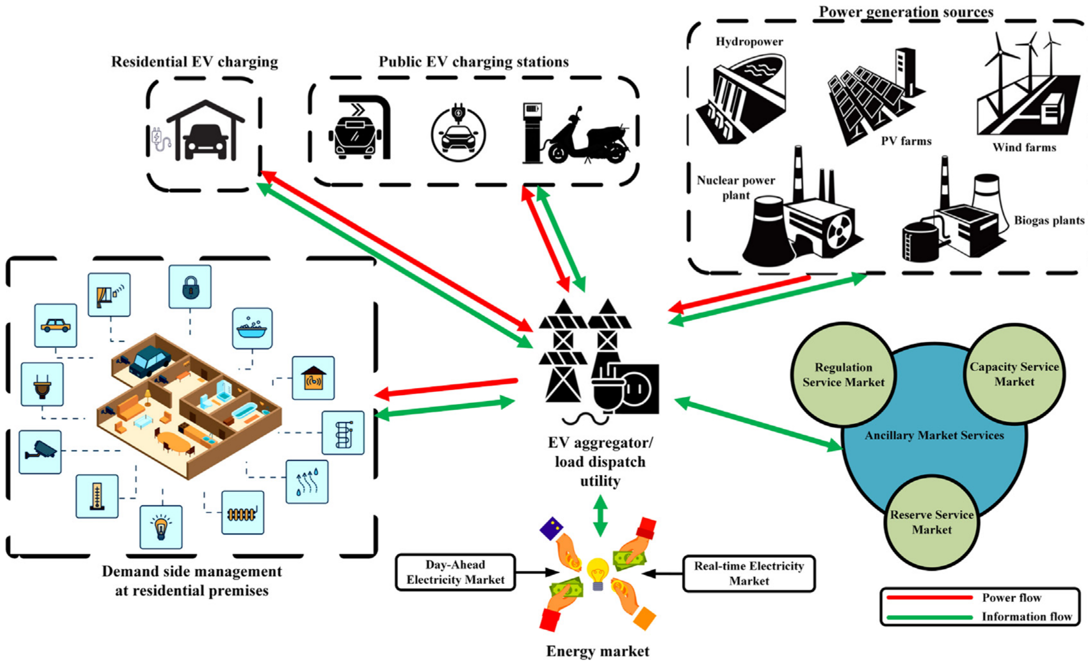

Fig. 1. EV operation in overall smart grid scenario with participation in electricity markets.

Demand-side management (DSM) has seen a growing interest in the number of programs implemented by utility operators to reduce energy consumption at the end-user side of the metering infrastructure. Participating in DSM-related programs can significantly benefit electric power markets by facilitating their operation more efficiently and profitably. This can be achieved using peak demand reduction strategies and tackling spot-pricing volatility management techniques (Tronchin et al., 2018). DSM forms an integral constituent of an SG infrastructure, and its architectural integration can be achieved by using communication systems, sensor-based control devices, automated metering devices, smart devices, and processing hardware specialized in optimization activities. The latest information and communication technology (ICT) devices can provide greater efficiency in grid operation and facilitate the communication of recurrent tariff changes, which would greatly benefit DSM programs (Panda et al., 2022b). This permits a dynamic pricing mechanism to be easily integrated with the RES generation pricing mechanism based on the real-time generation from distributed energy sources. This helps in maintaining a balance between the real-time energy demand and supply. Other solutions involved in DSM architecture like smart meters and advanced ICT devices, together with the primary components, can present a viable opportunity for achieving reduced energy consumption costs, maximum exploitation of RES, and provide favorable solutions to customers for their active participation in the electricity markets.

Necessary support in DSM programs can be provided by the integration of EVs, which can operate in a wide variety of ways either as a load, supplier to the electric utility or as independent battery ESS systems. With the latest SG technologies, the distribution system operators (DSOs) can coordinate EV charging periods and pricing tariffs, log metering infrastructure data and, thus, successfully implement DSM programs. When the consumers act as active participants in the DSM programs, they can utilize three feasible approaches to modify their energy usage patterns:

- Reduction of energy consumption profile by load reduction techniques (Panda et al., 2021a);
- Shifting of energy consumption to other periods (Panda et al., 2021b);
- Using alternative energy sources reduces the dependability of the main utility supply.

  All these strategies can be implemented by incorporating EVs as load in conjunction with energy sources in a similar manner to that used in DSM techniques, and they have been illustrated in Fig. 1:
- EVs can reduce dependence on supply from the grid by acting as ESS and supplying energy in case of shortfalls.
- They can modify their charging/discharging pattern to level the grid load consumption patterns.
- They can act as buffers for RES to provide the grid with a stable source of power flow.
- They can provide regulation services to the DSO by offering real-time support in case of necessity (Ehsani et al., 2012).
- Different tariffs when using power from EVs can be imposed on consumers to motivate them to shift their energy dependence from the utility grid.
- The coordinated fleet operation can maximize the business values in the energy market and optimize the central control and charging process of EVs (Ehsani et al., 2012).

2. Outline of the paper

The highlights of this review paper over other similar papers in the existing literature is a detailed discussion of the entire EV-DSM implementation, starting from the conceptualization to modeling, real-world demonstrations, and applied optimization techniques available in the research domain. This article also gives a well-rounded discussion to address the issues, challenges, and solutions in adopting EV-DSM. A section focusing on future research prospects and scope of research is presented to aid the researchers in selecting their line/field of focus and to give novelty to the available as well as surveyed literature. To sum up, as a whole, a methodological and reviewed analysis of the working and implementation of EV-DSM in a smart grid environment is presented in this article with a detailed description of the following points:

- To explain briefly the DSM techniques and applications commonly applied in SG scenarios and highlight their potential

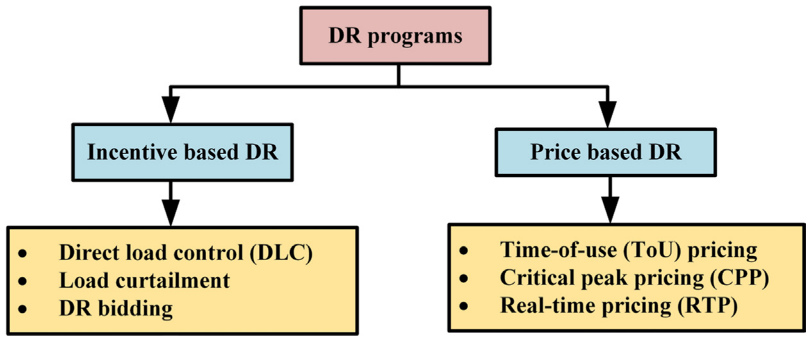

Fig. 2. DR programs in DSM operations.

in EV integration scenarios and their benefits in the SG infrastructure.

- To survey the available optimization techniques and models of EV-DSM in recent literature to facilitate the researchers in expanding their work and arrive at effective and better optimization techniques.
- After an introspective discussion on the surveyed literature, establish the future research directions and scope and recommend valuable and viable suggestions for researchers to continue in the EV DSM optimization and modeling domain.

The remaining sections of this article are structured as follows: Section 3 explains the DSM methodology and its sub-disciplines for implementation in the current smart grid infrastructure with electric vehicle integration implementations. Section 4 describes the parameters necessary for EV modeling and optimization. In Section 5, EVs' charging/discharging behavior is studied in the SG scenario and discussed briefly. Section 6 addresses the challenges faced by EV DSM implementations in smart distribution systems. Section 7 presents some of the pilot demonstrations of EV-based DSM around the globe. Section 8 summarizes some charging models based on charging methodology and the financial programs associated with EV DSM. Section 9 explains the strategies incorporated for EV DSM optimization, with various optimization applications across the available research domain being discussed concerning the constraints and decision variables. The major findings from this literature survey based on thoughtful discussion and the possible future scope and research directions are illustrated in Sections 10 and 11, respectively, with the conclusions being summarized in Section 12.

3. Demand side management

Demand Side Management is "the planning, implementation, and monitoring of distribution network utility activities designed to influence customer use of electricity in ways that will produce desired changes in the load shape" (Pang et al., 2012). Four major strategies are involved in DSM (Haney et al., 2010): Energy Efficiency (EE), Time of Use (ToU), Spinning Reserve, and Demand Response (DR). DSM implementations can be integrated into several forms. They can be classified mainly into two main classes based on the behavioral changes of the agents of the DR program. They can either be incentive-based or price-based programs. The main feature of price-based DR is that the consumers react to electric tariff signals, whereas, in incentive-based programs, the consumers are incentivized independent of electricity tariffs (Vardakas et al., 2014). Fig. 2 illustrates various DR programs that are employed under DSM operations.

3.1. Incentive-based DR

Based on the form of incentive programs, the incentive-based DR programs are mainly categorized into three groups (Vardakas et al., 2014):

- *Direct load control (DLC)* Usually have an aggregating entity as a third-party manager, with direct control over the operation and running schedule of selective consumers' appliances. The flexibility of operation on the consumer side is rewarded through incentives based on the market energy demand.
- *Curtailable load (CL):* The utility company raises requests for demand adjustment, but the consumer controls the usage pattern of their appliances. The participatory consumers are rewarded with incentives or fees for complying with the requests; otherwise, penalty fees can be levied on them.
- *Demand-side Bidding (DSB):* This program involves consumer-centric bidding on load shaving in a dedicated electricity market. If the market entities accept their bidding price, they must adjust their loads accordingly.

3.2. Price-based DR

On the period of the usage of loads and the demand for supplied power at the utility level, price-based DR influences the consumer usage pattern by varying tariffs over a period of time (Vardakas et al., 2014). The tariff decided will be variable in comparison to a flat rate tariff strategy where the tariff is equivalent at every time period. Such price-based DR is categorized into three major groups:

- *Time-of-use tariff (ToU)* This market-oriented model categorizes the entire day time frame into various time durations with varying electricity tariffs. Generally, these time periods and the applied tariff are fixed over a longer duration.
- *Critical peak pricing (CPP):* This pricing scheme is generally used as a complementary technique to either a flat pricing strategy or ToU tariff during a limited number of peak usage periods annually.
- *Real-time pricing (RTP):* This pricing strategy involves an hourly variable price signal, with changes reflected through spot pricing. Consumers get notified on a day-ahead or hour-ahead basis in the electricity market.

4. 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

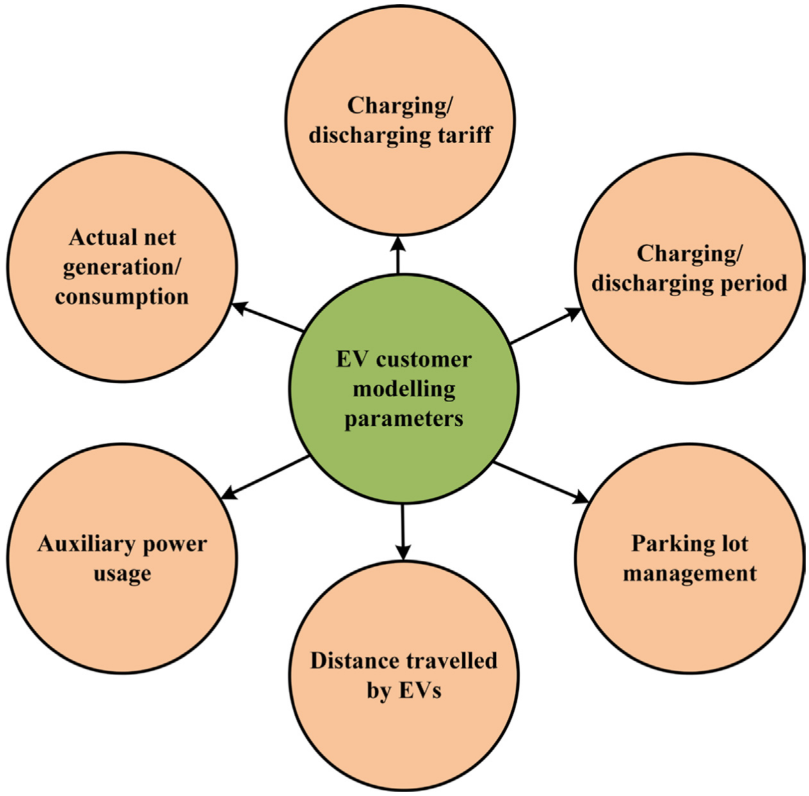

Fig. 3. The data to be collected to model EV in optimization problems.

are the primary issues and concerns. On the contrary, when large-scale 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
- Actual net generation and consumption (based on number of EVs, state of charge (SoC) of battery energy storage system (BESS) of EV, and owner's consent of participation)

5. Charge/discharge behavior of EVs

EVs can act as controllable and curtailable loads during the charge cycle and as ESS or as power generation sources during the discharge cycles. Since EVs remain parked at their stationary locations most of the time, the EV-BESS can be utilized to the maximum extent during such periods and act as decentralized ESS systems in the SG topology either as a generating entity or as a load source as and when required.

When consideration of EV is to be done as a shiftable or controllable load source, careful planning and management have to be done for the anticipation and organization of the timing of the second cycle of charging. Basic timers can be employed to ensure that the customers can get their EVs plugged in as soon as they reach their residential premises (Franke and Krems, 2013; Pagani et al., 2019). Another solution is to postpone the charging period to another time slot by planning to charge on the basis of the electricity tariff to deter many EV owners from being responsible for scheduling their charging schedule instead of hours of non-peak usage. Incentivized tariffs for participating EV owners can also present a feasible enabling factor to encourage users to adjust their charging and discharging schedules to maximize incentives offered by the utility.

In the V2G mode of operation, battery deterioration and degradation is a major cause of concern in maintaining the efficiency and reliability of the system (Wang et al., 2016), despite the major advantages that the EV integration holds in the smart grid scenario from the utility as well as from the customer point of view. Battery technology used in EVs needs to be advanced further to address the degradation issue of batteries. Second-life batteries could be a suitable candidate for EV-BESS integration, as demonstrated in Hossain et al. (2019), Debnath et al. (2014) and Reid and Julve (2016), even after the degradation of the state of health (SoH) of the primary battery sources available in EV setups. Large-scale EV implementations in G2V and V2G mode can also effectively mitigate SG systems' issues through their coordinated and controlled operation (Al-Ogaili et al., 2019).

For proper EV implementation in SG systems, the entire topology of the network (Mwasilu et al., 2014) may require modification, with EVs being controllable loads. EV-based DSM can allow for the postponement of their charging patterns to avert peak usage periods and be connected to the grid for V2G implementation during peak periods with provision for contingency services by applying proper discharging strategies. DSM-EV can be realized using these methodologies of V2G and G2V concepts as discussed in Onishi et al. (2020). This cycle of charge/discharge can be coordinated at the utility levels with consumer willingness to participate. It can be very intuitive to develop various consumer-centric

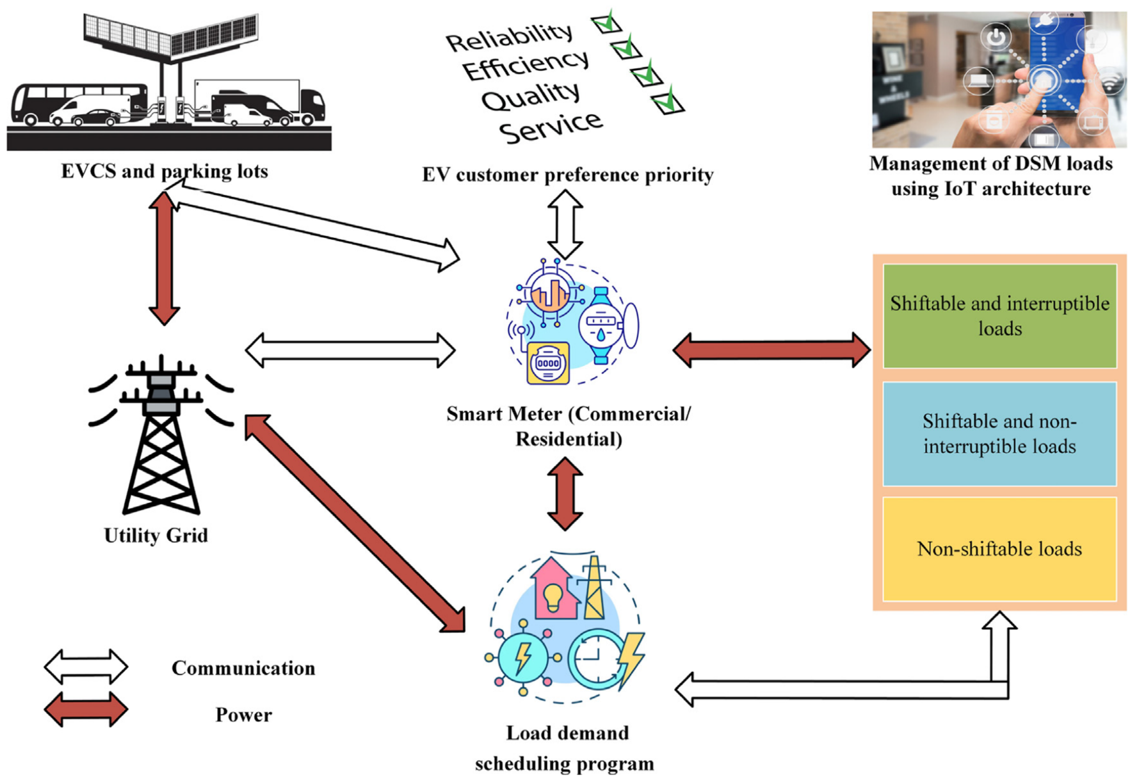

Fig. 4. The general EV operation in coordination with DSM programs and smart devices.

DSM programs and provide other ancillary services through EV integration with the SG infrastructure.

Considering the possibilities and benefits offered by EVs and their inclusion in the SG system, DSM and DR programs can be applied in various aspects of SG energy management strategies. This can be done through proper infrastructure and coordinated operation, as shown in Fig. 4. A similar control and operational structure are illustrated in Fig. 5, which describes the interaction among the various participatory components of the EV-DSM system. The next step is the selection of appropriate DSM programs for proper EV-DSM implementation (Patnam and Pindoriya, 2021), which is done on the basis of the available data collected from various usage patterns and sources. Various factors need to be considered for consideration of proper variables to be introspected into while formulating DSM optimization strategies. The prime objectives of the DSM-EV programs can be realized only if various uncertainties, constraints, and available resource values are considered.

5.1. Ancillary service potential of EV-DSM and V2G

The availability of EVs maximizes the potential of V2G with consideration of consumer acceptance, drive cycles, participation willingness, and system readiness concerning the technical, market, and regulatory mechanisms (Sarabi et al., 2016). It is found that the adoption of V2G along with DSM concepts has reduced the requirement of electricity supply from coal and natural gas sources by about 2.8% and 8.8%, respectively. In addition to these benefits on the generation side, the consumers, through the adoption of DSM, can contribute to the reduction of the power generation cost and maximize the power utility company's revenues by approximately 3.65% by the reduction in the peak power requirement and generation. For a demonstration of the feasibility of V2G projects in real-time implementations, a few pilot projects implementing EV-DSM obtained from Insights (2022) have been tabulated in Table 1 to represent the successful program implementations around the globe.

6. Challenges to EV-DSM implementation in smart distribution systems

The integration of EV into the SG architecture brings along several advantages and operational flexibility. However, the technology that is presently being implemented has not matured considerably. Many serious issues have cropped up due to the sudden surge in EV integration. Many technical, socio-economical, and environmental challenges must be overcome to optimize the EV-DSM technology, which is almost the same as encountered in terms of V2G and G2V operations (Yilmaz and Krein, 2012), as illustrated in Fig. 6.

6.1. High investment cost

A major roadblock in the EV-DSM implementation is the initial and running investment cost incurred by both the consumers and the power system. The first step towards the implementation of EV-DSM is the proper implementation of primary V2G and G2V architecture. The power system needs to be altered in certain technical aspects concerning the hardware and software infrastructure to accommodate the higher penetration of EVs and the rescheduling of several smart devices on the end-user side. Each EV participating in DSM application in the SG will require a bidirectional EV charging system comprising complex power converters, controllers, and high current and high tension cabling in conjunction with maintenance of safety standards. V2G can potentially increase power losses when implemented, which is another serious issue that needs to be minimized as it can lead to financial losses. The regular charging/discharging cycle of EVs will require advanced converter designs to accommodate conversion and switching losses at multiple stages in the distribution systems (Dehaghani and Williamson, 2012).

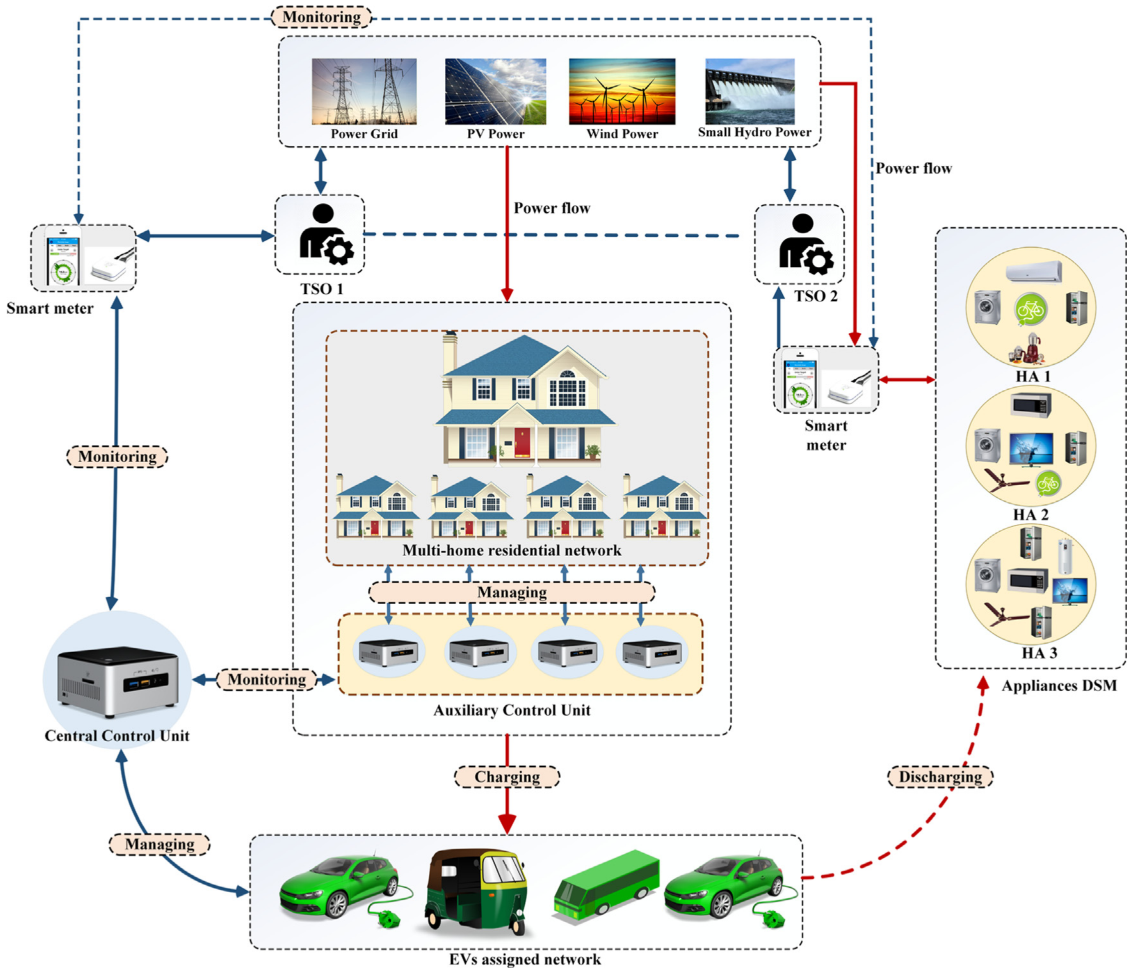

Fig. 5. The operational structure and operation of EV-DSM.

6.2. Consumer acceptance

With the shift of consumers from fossil fuel-based ICE vehicles to hybrid EVs, the consumer hesitancy in adopting hybrid EVs is not a steep introduction to EV technology. But in the future large-scale adoption of EVs, the high initial cost of ownership, range anxiety, and adjustment to EV-focused drive cycle and charge/discharge cycle can be a major deterrent in preventing consumers from readily adopting EVs, replacing the traditional ICE-based vehicles. To address range anxiety issues among consumers, they must be aware of scheduled and planned charging. This will prevent most EV owners from resorting to emergency charging to cover range issues on unplanned trips (Fasugba and Krein, 2011). Further improvements can be made in the electric vehicle charging station (EVCS) to accommodate higher penetration of charging facilities to encourage users not to charge unnecessarily and charge when necessary. Automated management of EV charging can also be implemented to intelligently manage the EV BESS SoC and ensure proper cutoff with respect to daily driving habits to avoid excess charging and overburdening of the grid (Bashash and Fathy, 2013).

6.3. Battery degradation and battery health

The continuous charge/discharge cycle in EVs can cause changes in the battery's composition. This can cause an increase in the internal resistance of the battery cells and decrease the usable battery capacity (Dogger et al., 2010). The battery also suffers from aging issues due to constant burnout from regular use of the rate of charging/discharging, high voltage usage, depth of discharge (DoD), and battery temperature.

7. Pilot demonstrations of EV-DSM

Some of the projects currently implemented across the globe in the SG scenario have been tabulated in Table 1. The tabulation has showcased the participation of EVs in their respective geographical locations and the parameters like number of EVs employed, number of EVCS present, the DSM principles applied with respect to EVs, and the grid or ancillary services provided by the EVs to the SG system (Insights, 2022). This gives us an overview of how far the applications of EV-DSM have come forward in the demonstration and pilot projects.

8. Charging models of EVs based on DSM application

The entire topology of the V2G and G2V systems can be structured to fulfill each requirement pertaining to a specific objective of the optimization problem. The DSM programs can be developed on the basis of the charging topology of the EV-DSM system, or it can be structured to benefit the utility or the consumer from a financial standpoint. The focus of the architecture helps the entire supply setup to be able to function on the basis of a single objective or multiple objectives inclined towards similar results.

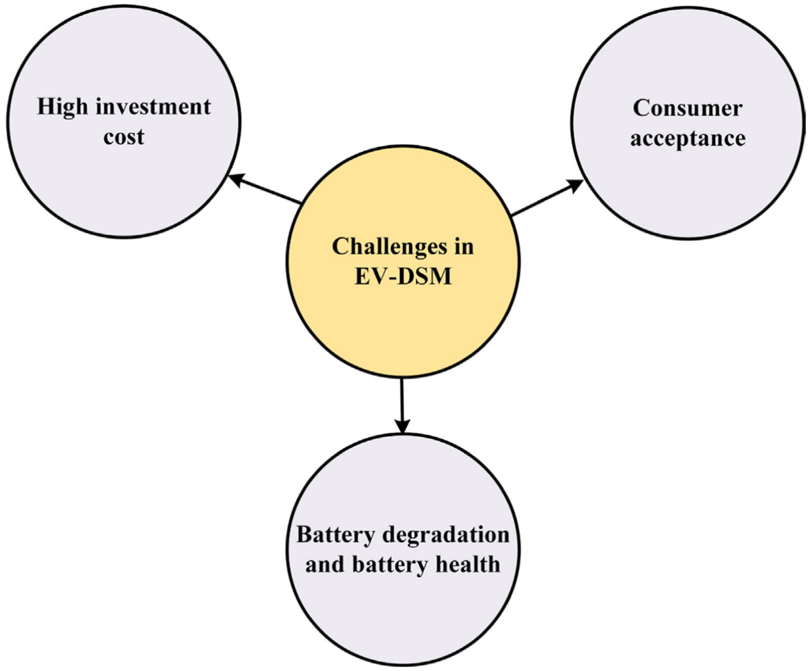

Fig. 6. Challenges in EV-DSM operations.

8.1. Financial EV-DSM modeling

These EV-DSM programs are generally focused on maximizing profits generated by the consumer and the utility and minimizing losses incurred by the system as a whole. Many financial models are implemented in existing research with a prime focus on financial objectives. They can employ traditional energy efficiency, energy management, or cost minimization techniques. In de Hoog et al. (2015), a smart charging market-centric mechanism is presented for optimal allocation of the total available charging capacity to ensure network stability. After consideration of the various network-specific constraints, the DSM model can offer higher charging capacities to EV owners on the basis of higher tariffs. This presents a more efficient and strategy-proof implementation of DSM to avoid unfair usage by other participating entities in the EV-DSM model. Mallette and Venkataramanan (2010) employs plug-in hybrid electric vehicles (PHEVs) to allow for residential consumer flexibility and to offset all the uncertainties from PHEV charging. It will enable dynamic ToU rates to be implemented in Madison Gas & Electric service region. Similarly, from the tariff perspective, Ren et al. (2019) considers the EV users' pricing model with other pricing factors like the aggregator profit model and the consumer satisfaction model. This presents a thorough analysis of the changes reflected in the electricity tariff rates, policies, aggregator's demand side response, and profit-making ability to arrive at a feasible pricing strategy. Some research also focuses on the market scheduling and contract-based day ahead scheduling of EVs in the market scenario. The day-ahead participation using large-scale integration of EVs through PEVs is demonstrated in Raghavan (2016), incorporating demand response to maximize the net profit and surplus power generation of independent system operators (ISOs). The whole model is formulated with respect to the power generation capacity, grid, and power balance constraints. The real-time controlled charging and the leverage gained by such charging methodology can significantly benefit the EV owners and the ISO by avoiding the avalanche effect. The resultant grouping of EVs results in a financially profitable DSM implementation, as demonstrated in Kühnbach et al. (2021). The real-time market model in Danxi et al. (2017) also takes into account the real-time electricity tariff of the consumer, and through flexible DSM approaches, they can cut through valley filling and improve peak shaving and frequency regulation, thereby improving the ancillary service capability of EVs. Blockchain-based trading has recently garnered interest in the electricity market scenario due to its security and authenticated trading process. In Knirsch et al. (2018), a blockchain protocol is used with the EV users giving out signals based on their demand and similarly with the charging stations sending blockchain bids like auction bids. This blockchain-based approach significantly improves DSM techniques' reliability and transparency. The main disadvantage of using BESS is the deteriorated performance of the batteries after their usable SoH period. A solution on this front would be the adoption of retired BESS of the residential premises and the automotive batteries as second-life batteries. In Tong et al. (2015), a single-family household residential DSM setup is demonstrated using PV and BESS (primarily made of retired vehicle traction batteries as second-life battery sources) to act as an energy buffer for relaying excess photovoltaic (PV) generation during off-peak period and discharging them during peak periods. Here, the day-ahead market pricing signals were obtained to initiate bids and thus provide the additional feasibility of retired EV batteries in their second life form. Aliasgahri et al. (2019) uses an uncertainty-based modeling technique focusing on joint analysis of EV drive cycle and day-ahead market pricing. The Time of Use and incentive-based DR is applied and ultimately maximize the profit of DSM and EV aggregators.

8.2. Charge scheduling based EV-DSM modeling

Charge scheduling-focused EV-DSM programs are set up keeping in view EVs' charging and discharging behavior in general and how the coordination among the charging scheduling can greatly benefit DSM applications. They can be on a utility level until the consumer-end implementation, considering the consumer's willingness to participate in these programs. On an infrastructure level, Arellano et al. (2013) aims to analyze the impacts of DSM integration with varying penetration levels of EVs into the distribution grid with simulation tools being used with different

Table 1
EV DSM pilot demonstrations implemented across the globe (Insights, 2022).

Name of the V2G project	Country	Started in the year	Number of available EVs/charging stations	DSM principles applied			Other available services		
				Load shifting	Load leveling	Spinning reserve	Frequency regulation	Backup power	Arbitrage
M-Tech Labo	Japan	2010	5	✓	✓				
Smart MAUI	Hawaii	2012	80	✓					
Zem2All	Spain	2012	6	✓			✓	✓	
US Air Force	USA	2012	13	✓		✓	✓	✓	
Cenex EFES	UK	2013	1	✓			✓		
US DoD, Smith Trucks	USA	2013	5	✓				✓	
Amsterdam Vehicle2Grid	Netherlands	2014	2	✓					
Torrance V2G School Bus	USA	2014	2	✓			✓		
Clinton Global Initiative School Bus Demo	USA	2014	6	✓			✓	✓	
ITHECA	UK	2015	1	✓					
PV-powered bi-directional EVCS	Netherlands	2015	1	✓					
Distribution system V2G for enhanced grid stability	USA	2015	2	✓	✓				
The Mobility House	Germany	2015	1	✓					
Smart PV Charging	Netherlands	2015	22	✓	✓				
SEEV4City	UK	2016	6	✓			✓		✓
KIA-Hyundai Technical Center	USA	2016	6	✓					
Grid Motion	France	2017	15	✓			✓		✓
INVENT	USA	2017	50	✓	✓		✓		
BlueBird School Bus V2G	USA	2017	8	✓			✓	✓	
SaMDES	UK	2017	2	✓				✓	
V2Street	UK	2018	2	✓	✓				✓
E-REGIO	Sweden	2018	2	✓	✓		✓		✓
SOLARCAMP	France	2018	1	✓	✓		✓		✓
FlexGrid	Netherlands	2018	1	✓					✓
EV-elocity	UK	2018	35	✓					✓
uYilo	South Africa	2018	1	✓	✓		✓		
Powerloop	UK	2018	135	✓	✓			✓	✓
Deelzedon Project	Netherlands	2019	80	✓	✓		✓		
BloRin	Italy	2019	1	✓			✓		
Peak Drive	Canada	2019	21	✓	✓				
Piha V2H trial	New Zealand	2019	2	✓					
Smart micro grid EMS	China	2019	5	✓			✓	✓	
UNDP Windhoek V2G	Namibia	2019	2	✓					
V2G EVSE Living Lab	UK	2019	2	✓				✓	
Realizing EV to Grid Services	Australia	2020	51			✓	✓		
Electric Nation V2G	UK	2020	100	✓	✓	✓			
Milton Keynes Council	UK	2020	4	✓					
V2G at Lelystad	Netherlands	2020	14	✓	✓		✓	✓	
V2G Zelzate	Belgium	2020	22	✓		✓	✓		
VIGIL	UK	2020	4	✓	✓	✓			
V2G@home	Netherlands	2021	1	✓				✓	
Bidirektionales Lademanagement	Germany	2021	50	✓			✓		✓

load profiles to suggest modifications in the charging topology to ensure more efficient and reliable energy management. On the automation front in the control aspect of the SG infrastructure, to give better efficiency and performance through DR programs, an automated demand response (ADR) approach is being implemented in some test case scenarios. ADR implements a DR strategy to relay control signals at the end user level to the main control unit at the utility level without enacting any human intervention. Improved ICT has allowed for seamless integration of ADR strategies in place of conventional DR programs. In Xiang et al. (2018), the ADR strategy is implemented with the integration of plug-in electric vehicles (PEVs) and BESSs through blockchain profiling. The ADR strategy can properly implement optimizing coordinated EV charge/discharge operation and derive a proper price formation mechanism. For the mechanical and conventional approach of DSM in already established residential architecture, Rautiainen et al. (2016) demonstrates a physical implementation of DSM using smart meter technology where the main fuse at each residence acts as a switch and trigger mechanism for the DSM program to be executed when the current exceeds the main fuse rating of the EV charger and thus presents a controlled charging case. Many approaches can be taken as a control measure on the strategy-based implementation of the charging models. A two-stage modeling strategy is implemented in Ran et al. (2021), comprising charging facility siting in the first stage and EV relocation in the second case with further optimization using sample average approximation and robust optimization. A two-level control strategy is implemented in Khemakhem et al. (2019), where the first level employs DR to schedule home appliances coupled with PEV usage. The second level comprises PEV energy management, allowing for bidirectional power flow and ultimately facilitating G2V and V2G to enhance the load profile. The advantages of lower annual demand charges of a DC fast charger are utilized in implementations as demonstrated in McPhail (2014). Here, appropriately sized BESS units are used to implement DR and thus lessen the annual demand charges and mitigate the impacts on the network. Shao et al. (2012) uses customer comfort index to assess the impact of DR on the convenience at the residential distribution circuit. Here, several EV load profiles and charging profiles are analyzed to minimize the impact of EV charging in the distribution system. Financial models can be used in conjunction with charging models to allow for a more holistic control and planning approach in EV-DSM. Sharma and Jain (2020) employs an RTP DR strategy using price signals to propose an energy charge scheduling of EVs through an EV aggregator to formulate a charging cost minimization strategy with EV aggregator profit maximization. An ICT-based heterogeneous Ethernet-based mesh network for implementation of DSM-EV is proposed in Bhattarai et al. (2015) for charging coordination using synchronized data and control signal exchange. Yuan et al. (2020) proposes a traffic-grid coupling network on charge estimation and prediction model to formulate a DR strategy using and aggregating EV charging loads. An advanced WINSmartEV EVCS software is designed in Chynoweth et al. (2014) to allow for intelligent charge scheduling and flexibility in DSM programs using EVCS infrastructure.

9. Optimization of EV DSM

The power system integration of EVs into the existing smart grid and traditional grid architecture involves the fulfillment of multiple objectives which may conflict with each other, but they need to be resolved to free the entire system uncertainty and non-linearity (Gould et al., 2013). EV-DSM integration is also limited by several parametric constraints which may arise during the fulfillment of single or multiple objectives. In an EV integrated system of architecture, EVs' random and dynamic usage and charging cycles increase the system complexity. Similarly, the load management at the user end needs to be realized efficiently to manage the power flow between the EVs and the utility. Optimization techniques are applied to implement the EV-DSM system in an overall V2G environment to resolve these issues. Optimizing the entire architecture and control process allows for greater flexibility in intelligently utilizing EV mobility in various grid services and achieving many V2G services and objectives.

9.1. Objectives of EV-DSM optimization

The implementation of EV-DSM can involve various services and operational mechanisms, where V2G and G2V technology would allow for various DSM principles like load shifting, peak reduction, valley filling, spinning reserve, and incentivized tariffs implemented to obtain the desired services. Other services can also be considered to improve the grid's operational flexibility and support the grid-like voltage and frequency regulation. DSM implementation is the technique to fulfill single or multiple objectives in a single optimization problem. They can minimize the cost of operation, the power losses, and the system's profits.

(1) *Operation cost*

In a unit commitment (UC) problem, the minimization of the operation cost of an overall power system is a primary objective when viewed from the standpoint of the utility company. The utility operating in a grid involves the general costs related to the UC problems in the dispatch of power generation units. This operational cost includes fuel costs, start-up costs of distributed generation (DG) or power plant, and the V2G integration costs (Saber and Venayagamoorthy, 2010; Ghanbarzadeh et al., 2011).

The fuel cost of a DG unit or a power plant can be expressed as a second-order function from the unit-generated power as (Wu et al., 2010):

$$FC_i\left(P_i(t)\right) = a_i + b_i P_i(t) + c_i P_i^2(t) \tag{1}$$

where P_i is the output power of the system, a_i, b_i, and c_i are the positive fuel cost coefficients.

The start-up cost translates to the cost incurred to restart a plant to its generation capacity. The boiler's temperature influences the plant's start-up cost for a conventional gas turbine-based generation plant. For example, after a prolonged shutdown, a cold start boiler will require more fuel to bring up the boiler to its operating temperature during start-up. Meanwhile, a boiler unit with short interval periods of the shutdown will require lower amounts of fuel to operate the boiler unit at start-up.

$$SC_i(t) = \begin{cases} h\_cost : MD_i \le X_i^{off}(t) \le H_i^{off} \\ c\_cost : X_i^{off}(t) > H_i^{off} \end{cases} \tag{2}$$

$$H_i^{off} = MD_i + c\_s\_hour_i \tag{3}$$

where SC_i is the total cost of start-up of the unit, *h_cost* is the start-up cost at high operating temperature, *c_cost* is the start-up cost at low operating temperature, MD_i is the minimum duration of unit downtime, X_i^{off} is the unit downtime duration, H_i^{off} is the transition duration from hot-cold start-up, and $c\_s\_hour_i$ is the period of cold start.

Based on these initial costs incurred at the generation plant end, the EV-DSM incentives and tariffs are added to get the final objective function to minimize the overall power system operating costs.

$$\min TC = Fuelcost + Start - upcost + EVDSM\ cost \tag{4}$$

(2) *Profit maximization*

Several optimization techniques can be employed for EV-DSM implementations to maximize the incentives and benefits offered to the EV owners and power system operators (Sortomme and El-Sharkawi, 2010). V2G services, in general, can provide several advantages in the power system operation. Therefore, maximum EV penetration can maximize the profits at the consumer and aggregator levels. The EV owners can be appropriately incentivized on the basis of their energy injection into the grid from EV-BESS and the period of service available while plugged in.

In Soares et al. (2013b), the focus is given to the maximization of profits for EV users operating in V2G mode, where the objective function has been specified as follows:

$$\max EVuserincome = \sum_{t=1}^{T}\left[\sum_{V=1}^{N}\left(P_{discharging(V,t)} \times C_{discharging(V,t)}\right) - \left(P_{charging(V,t)} \times C_{charging(V,t)}\right) \times \Delta t\right] \tag{5}$$

where t is the time of operation, T is the number of time periods, V is the vehicle serial number, N is the total cumulative number of EVs participating, $P_{discharging(V,t)}$ is the discharging power of 'Vth' at the time t, $C_{discharging(V,t)}$ is the discharge tariff offered to the EV owner at time t, $P_{charging(V,t)}$ is the charging power of 'Vth' at time t, $C_{charging(V,t)}$ is the charging tariff from the grid offered to the EV owner at time t, and Δt is the difference in time periods.

(3) *Auxiliary support for renewable power generation*

The cluster of EVs can perform as a backup by consideration of them in a pool as a large bank of BESS to provide the required amount of power in cases of shortfall of renewable source generated power. They can act as BESS to absorb excess power generated from renewable energy sources (Ahn et al., 2011). With the maximum injection of renewable energy into the utility grid system, there is an opportunity for a cleaner and greener power network to be established while reducing power generation costs. In Ghofrani et al. (2012), maximum injection of renewable generation is accommodated into the grid system using the optimization objective function, thereby minimizing the generation costs from conventional power generation sources. The objective function used in Ghofrani et al. (2012) is as follows:

$$\min F = \sum_{t=1}^{T} xP_{conv}^2(t) + yP_{conv}(t) + z \tag{6}$$

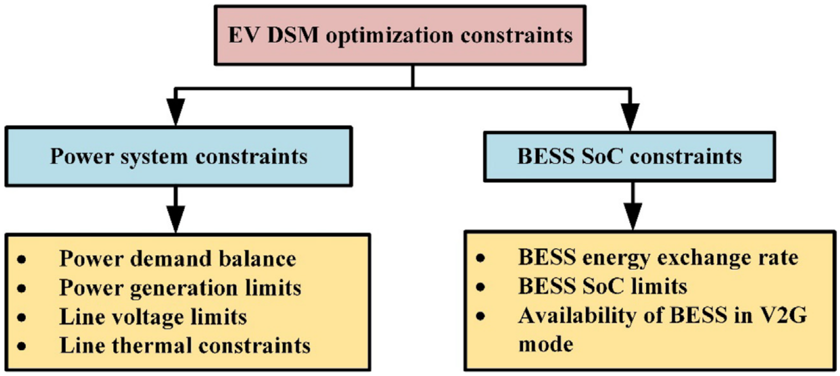

Fig. 7. EV DSM optimization constraints.

where x, y, and z refer to cost coefficients and $P_{conv}(t)$ is the power generation from conventional generation sources.

(4) *Demand load curve*

The EVs operating in V2G mode can utilize excess stored energy from the BESS systems and inject active power to support the grid services. The primary objective of active power injection is to flatten the load demand curve for a more uniform load profile utilizing peak load shaving and load shaping techniques. The profiling of the demand load curve can also mitigate power losses. In Wang and Wang (2013) and Hai-Ying et al. (2011), the objective functions focus on peak load shaving and load shaping services by minimizing the error between the real obtained load curve and the required target load curve. The objective function is defined as follows:

$$\min Error = \sum_{t=1}^{T} (P_{Load,t} - P_{target,t}) \tag{7}$$

where T is the number of time periods, $P_{Load,t}$ is the load demand at time t, and $P_{target,t}$ is the required target load demand at time t.

(5) *Loss minimization*

In Celli et al. (2012), A V2G control mechanism is proposed to provide load shaping in conjunction with loss minimization. The objective function as defined in the strategy is as follows:

$$\min Loss = \sum_{t=1}^{T} \left[I_{Load}(t) - \sum_{V=1}^{N} I_{EV,V}(t) \right]^2 \tag{8}$$

where T is the number of time periods, N is the number of participating EVs, I_{Load} is the current demanded by the load curve, and $I_{EV,V}$ is the current demanded by vth number of EVs.

9.2. EV-DSM optimization constraints

The optimization problems pertaining to DSM scenarios, especially EV-DSM, involve several constraints. The V2G integration of EVs pertaining to UC problems requires two main constraints to be satisfied. These constraints can be either power system-specific or EV-centric, as illustrated in Fig. 7.

(1) *Power system constraints*

I. Power demand balance:
The demand–supply of power between the grid must be satisfied, including the supply from grid-connected EVs and the demand catered by the utility to charge the EVs using power from the grid. This also requires that the system losses be also compensated to avoid shortfalls (Saber and Venayagamoorthy, 2010). The objective function used in Saber and Venayagamoorthy (2010) is as follows:

$$P_{grid} + P_{V2G} = D_{Load} + SystemLosses \tag{9}$$

where P_{grid} is the power supplied by the grid from conventional generation sources, P_{V2G} is the power that the EVs inject into the grid, and D_{Load} is the total load demand.

II. Power generation limits:
The amount of power generation is prefixed depending on the limits of the generating capacity. The generation capacity is dependent upon the environment and operational constraints. The load demand and the losses incurred by the system must remain within these limiting constraints (Gould et al., 2013; Fazelpour et al., 2014).

$$P_{Generation,\min} \le D_{Load} + Losses \le P_{Generation,\max} \tag{10}$$

where $P_{Generation,min}$ is the minimum power generated by the grid, $P_{Generation,max}$ is the maximum generation capacity of the grid, and D_{Load} is the load supply–demand at a specific time.

III. Line voltage limits:
The power system needs to maintain the grid bus voltage within the permissible and operational limits for the proper functioning of the distribution system (Gould et al., 2013; Soares et al., 2013b; Rostami et al., 2015).

$$V_{Bus,\min} \le V_{Bus} \le V_{Bus,\max} \tag{11}$$

where V_{Bus} is the grid bus voltage, $V_{Bus,min}$ is the permissible minimum grid voltage level, and $V_{Bus,max}$ is the maximum grid voltage level.

IV. Line thermal constraints:
The conductors in distribution systems have a specific maximum current carrying capacity that they can tolerate for safe operation. Excessive load on the conductors and cables can lead to overheating and damage to the distribution lines (Ghanbarzadeh et al., 2011; Ghofrani et al., 2014).

$$P_{cable} \le P_{cable,\max\_heat} \tag{12}$$

where P_{cable} is the current carrying capacity of the cable, P_{cable,max_heat} is the maximum current carrying capacity of the cable before it starts to overheat.

(2) *EV-centric constraints*

I. BESS energy exchange rate constraint:
To ensure the safety of the battery and for prolonged battery life, the power exchange rate of the battery must be below the safety limits of power exchange (Bashash and Fathy, 2013; Celli et al., 2012; Rostami et al., 2015; Ghofrani et al., 2014; Corchero et al., 2014; Bai and Qiao, 2015).

$$P_{Battery,\min} \le P_{Battery} \le P_{Battery,\max} \tag{13}$$

where $P_{Battery}$ is the BESS power exchange rate, $P_{Battery,min}$ is the minimum permissible BESS power exchange rate, and $P_{Battery,max}$ is the maximum permissible BESS power exchange rate.

II. BESS SoC constraints:
Battery degradation is a significant concern when the EVs operate in V2G or G2V mode, as the EV batteries are susceptible in their chemical compositions and need to be maintained accordingly so as not to exceed the safe operating capacity of the battery. The EV battery should not be fully discharged, and a predetermined range capacity should always be made available to the user to not hinder the user's comfort level during general driving usage (Saber and Venayagamoorthy, 2010; Wang and Wang, 2013; Ghofrani et al., 2014; Corchero et al., 2014; Akhavan-Rezai et al., 2015).

$$SoC_{EV,\min} \le SoC_{EV} \le SoC_{EV,\max} \tag{14}$$

where SoC_{EV} is the SoC of the BESS, $SoC_{EV,min}$ is the minimum permissible SoC, and $SoC_{EV,max}$ is the maximum permissible SoC.

III. Availability of EV-BESS in V2G mode:
The EV is required to be in grid-connected mode to be able to provide V2G facilities. The EVs in drive mode or not connected to the grid services will be exempted from consideration as participating EVs (Saber and Venayagamoorthy, 2009a,b).

9.3. Optimization methods

The existing research surveyed below in this review article indicates that various methods and optimization algorithms in single or multi-objective formulation and single or hybrid approaches have been formulated and implemented in EV DSM programs to solve optimization problems in the SG environment. The artificial neural network (ANN), dynamic programming (DP), fuzzy computation, game theory algorithm, linear programming (LP), particle swarm optimization (PSO), hybrid PSO, ant colony optimization (ACO), genetic algorithm (GA), differential evolution (DE), stochastic optimization are the most widely used optimization algorithms current employed in the domain of EV DSM optimization problems. As of the current research directions, hybrid optimization algorithms are being presented as viable and promising optimization methods owing to their efficient computation and decreasing computational burden. Table 2 tabulates the DR problem formulation on the basis of the objective functions, constraints, and decision-making variables of various surveyed algorithms used in EV DSM programs. This section gives us an insight into the methodologies employed and an overview of the present research in the EV DSM optimization domain.

10. Discussion and findings

During the systematic review of the papers as a part of the literature survey, several research gaps were identified in the present research scenario and implementations in various projects across the research domain. Some of the key findings as identified during the survey include:

- Most of the research papers have addressed the DSM formulation in the EV scenario by incorporating bidirectional power flow, but the uncertainty in demand and supply forecasting leads to inefficient power flow control.
- The limited participation of EVs in the distribution level restrains the individual customers from directly participating in the ancillary services market and the energy market (Mukherjee and Gupta, 2014; Jin et al., 2013). Clustered EVs must be able to collectively participate in forming and maintaining such groups in the proper sizing and architecture, which would be scalable in future implementations.
- The clustering of uncoordinated EVs, which generally operate in a decentralized setup among different utility operators, seems like a challenging task. A proper service-oriented architecture must be implemented to group the operation and participation of different EV aggregating companies to make the EV DSM integration into the commercial markets more profitable and easier to implement on a technical front.
- The drive cycle of the EV owners on an individual basis has not been considered on an end-user level. The optimization of charging and discharging can be improved to a great extent with personalized scheduling of EV charge/discharge operations on the basis of the user's comfort and usage cycle.
- The ICT technologies are implemented mainly at the transmission system operator (TSO) and DSO levels. They need to be integrated directly into the end-user location with a two-way communication channel to ensure more engaging and detailed EV charge scheduling operations. The EVs can provide personalized data collected during diagnostic and data collection schedules to supply the EV aggregator with proper charge schedule data. This will allow the EV aggregator to optimally dispatch loads on the basis of detailed SoC, SoH, BESS capacity, and drive cycle condition data.
- The customer's security and privacy are prioritized in the public domain. Consumers need to be made aware that their privacy is to be ensured when they avail themselves of the services at public locations, such as sharing the consumer's charging location history and charging and discharging profile. The public charge scheduling setup presents the issue of EVs sending private information or erroneous data to affect the grid operation and load dispatch schedule. Even though research is present in EV communication strategy concerning privacy issues, their effect on EV DSM scheduling in coordination with secure communication protocols and procedures to mitigate them has not been explored in detail.
- Meta-heuristic optimization techniques have been studied in a few research formulations. Their efficiency in forecasting the load and charge schedule of EVs in DSM operation can be exploited to a greater extent with the discovery of newer and more efficient meta-heuristic techniques. This would ensure better computation with less complexity in arriving at a proper solution.
- Consumer comfort must be prioritized in DSM operations regarding their drive cycle usage and charge/discharge patterns.
- The maximum penetration of EVs in the grid system can facilitate better usage of RES generation, and the high capacity of EV BESS can provide ample reserve for power relaying which is necessary in cases of intermittent generation sources. The DSM operation in the case of EVs ensures maximum utilization of the BESS capacity in conjunction with RES generation.
- The centralized control architecture of EVs is necessary for setting up standards of DSM operation and charge scheduling.
- Higher EV penetration into the distribution grid and the associated DSM operation can cause problems during peak usage periods, where other factors such as voltage drops and thermal overloading of transformer equipment and cables might occur.
- Robust control, device monitoring, and remote upgrade capabilities in EV DSM architecture are to be given importance as they may facilitate further up-gradation and provide better and more reliable operation and communication.

Table 2
The optimization papers surveyed across EV DSM optimization problems.

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Zong et al. (2020)	ANN	• RTP	• Minimization of the total cost to consumers	• Battery SoC • Battery charge/discharge power	• RTP pricing values • PEV charging/ discharging rate
Ferdowsi et al. (2014)		• Peak shaving	• Minimization of transformer loading	• Transformer limits • Line current carrying capacity	• Transformer parameters • Number of EVs • EV charging power
Bakhshinejad et al. (2021)		• Peak shaving • IBR	• Minimization of energy cost • Minimization of network losses • Minimization of voltage magnitude deviation	• EV battery SoC • EV charging power • Grid power balance limits	• Participating active loads • Power injected into the grid
Lin et al. (2020)		• Peak shaving	• Maximization of revenue	• Load charge/discharge limits • EV SoC • Maximum charge/discharge power • Charging time constraints	• Charging tariff • Day-ahead forecasted prices • EV drive cycle
Zeynali et al. (2021b)		• ToU	• Minimization of the total cost • Maximization of revenue	• BESS DoD • RES generation limits • DG unit operating costs	• Available tradeable power • RES generation-dependent parameters
Korkas et al. (2022)	DP	• Load shifting	• Minimization of energy costs without sacrificing user preferences and satisfaction	• EV charge/ discharge power • EV battery SoC	• RES generation parameters • Utility tariff rates
Zhang et al. (2015)	Fuzzy Logic (FL)	• Load shifting • Peak shaving	• Minimization of total operation cost	• Power balance constraints • Spinning reserve constraints • Generator limits • Wind power penetration rate	• Fuel cost • Startup cost
Faddel and Mohammed (2018)		• ToU • CPP • Valley filling	• Minimization of peak load demand	• EV SoC • Bus voltage limits	• EV charge/discharge time • Market pricing signals
Vujasinović and Savić (2021)		• ToU • Valley filling • Load shifting	• Maximization of profit of consumers through maximum EV integration	• EV SoC • Charging preference limits of consumers	• Electricity tariff • EV availability
Narimani et al. (2017)		• Load shifting	• Minimization of generation costs, emissions, and energy losses	• Active power output limits • Generator limits • Total flexible load limits	• Flexible load operation time
Raoofat et al. (2018)		• Valley filling	• Minimization of high ramp rates in G2V mode	• EV SoC • Ramp rate limits • Wind power output limits	• EV charging current
Liu et al. (2016)	Game Theory	• Load shifting	• Minimization of cost for residential users	• The discharge rate of PEV	• Hourly electricity tariff • PEV energy consumption
Xu and Chung (2014)		• Peak shaving	• Minimization of energy cost	• Transmission limits • EV charge/discharge limits	• Total load demand • Cost function • Welfare function
Rassaei et al. (2015)		• Load shifting • Peak shaving	• Minimization of peak demand using distributed EV integration	• Charging outlet limits • Energy trading limits	• EV charging time • Number of participating EVs under the same aggregator
Tushar et al. (2017)		• Peak shaving • ToU	• Minimization of electricity costs • Minimization of deviation between predicted and actual load demand	• EV storage limits • ESS storage limits • EV SoC limits	• EV availability • Load demand

(*continued on next page*)

Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Liu et al. (2017)		• ToU • Peak shaving	• Minimization of the peak-to-average ratio (PAR) of the total energy demand	• Energy balance limits • PEV discharge limits • Charging/discharging time limits	• Cost function • Load demand
Kong and Liu (2015)		• ToU	• Maximization of profits in the market environment	• EV charging limits	• Number of participating EVs • Bidding tariff
Zheng et al. (2020a)		• Peak shaving • ToU • Valley filling	• Minimization of charging the cost of EV	• Grid power limits • EV SoC limits	• Satisfaction income of EVs • Battery loss of EV • Charging cost
Shokri and Kebriaei (2018)		• Peak shaving • Valley filling	• Minimization of energy cost • Minimization of battery degradation	• Client usage parameters	• Cost function • Residential load demand • PHEV driving behavior
Abapour and Zare (2019)		• ToU • RTP	• Minimization of electricity tariff for the customers	• Hourly power demand limits • Total energy consumption limits	• Availability of EVs in the parking lot • SoC of EVs • Battery power rate • Load demand
Azimian et al. (2018)		• RTP • ToU	• Maximization of system stability • Maximization of profits	• Average power generation limits • Daily energy usage limits	• EV availability • Load demand
Shinde and Swarup (2018)		• RTP	• Maximization of profits of utility companies	• Charging rate limits	• Price function of utility
Yoon et al. (2015)		• RTP	• Maximization of retailer profits • Minimization of generation cost	• Charging rate limits	• Charging period of EVs • Battery charging efficiency
Safdarian et al. (2014)	LP	• Peak shaving • Valley filling	• Minimization of energy expenses of individual customer	• Charging rate limits • Battery SoC for driving cycle	• Appliance operating time • Appliance power demand
Gang and Lin (2018)		• Load shifting • RTP • ToU	• Minimization of peak load in the distribution network • Minimization of consumer tariff	• Power limit of EV	• Availability of appliances • Power generation
Astaneh et al. (2015)		• Peak shaving • Valley filling • ToU	• Minimization of difference between peak and off-peak tariff • Minimization of EV charging cost	• Base tariff limits • Price deviation limits • EV SoC limits • EV charging power limits • Feeder baseload limits	• Electricity tariff • Operation time slot
Yao et al. (2016)		• Valley filling	• Maximization of EVs availability in charging • Minimization of monetary expenses	• Charging load limits • EV SoC limits	• Charging decision value/vector
Wang and Paranjape (2014)		• Peak shaving • ToU	• Minimization of home electricity expenses	• EV availability period	• EV demand • Electricity tariff
Li et al. (2021a)		• RTP • ToU	• Minimization of operation cost of EVCS and energy management system (EMS)	• Power supply constraints • ESS constraints • Heating system constraints • EV power balance limits	• Load demand • EV and ESS reserve tariff • Heating compensation prices
Mou et al. (2014)		• Peak shaving	• Minimization of variation of the load curve	• EV SoC	• EV charging load

(*continued on next page*)

- Most EVs can be connected to the internet through the global system for mobiles (GSM), Wi-Fi, ZigBee, and other communication networks, which the aggregators can exploit and coordinate operation among the constituent EVs as the dispatchable load to the distribution grid (Falvo et al., 2014).
- In the DSM environment, EVs suffer from a lack of methodologies to maximize revenues and grid utilization. The primary reason can be attributed to the lack of policies for participating entities in wholesale electricity markets and low priority to commercialize DSM due to environmental,

Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Battistelli (2013)		• Peak shaving • Load shifting	• Maximization of revenues	• EV charging level limits • Grid power limits	• Hourly tariff • DG power generation capacity • Hourly critical load demand
Cheng et al. (2020)		• RTP • ToU	• Minimization of PAR and system costs	• PV power trade limit • EV SoC limits	• PV generation capacity • EV charging load • EV availability
Chen et al. (2017)		• RTP	• Minimization of costs, peak charging load • Maximization of PV integration	• EV charging demand limit	• EV availability • EV charging load
Luo et al. (2017)		• RTP	• Minimization of cost of the system	• EV charging limits • EV SoC limits	• Grid power consumption • Appliance schedule • Hourly tariff
Guo et al. (2021a)		• Peak shaving	• Minimization of operational costs and emissions	• Thermal unit limits • Power flow and grid constraints • PEV constraints • Power balance limits	• EV SoC • Thermal generation requirement
Pal and Kumar (2017)		• ToU	• Minimization of the total cost for the consumer	• Power balance limits • EV SoC limits • Power transaction limits	• EV charging/ discharging time • The usable capacity of EV ESS
Luo et al. (2019)		• ToU	• Minimization of the total cost for the consumer	• EV charging limits • EV operation time limits • EV battery capacity limits	• Real-time tariff
Chandra and Chanana (2018)		• RTP	• Minimization of the total energy cost of a smart home	• Power balance limits • Power trading limits • EV SoC limits • PV generation limits	• PV generated power • EV availability
Chen and Chang (2016)		• Peak shaving • Load shifting	• Minimization of individual consumer costs at lower participation levels	• EV SoC limits • ESS storage limits • DER generation limits	• Price indicators • Customer fairness index
Upadhaya et al. (2019)		• ToU	• Maximization of EVCS operating profits	• EV SoC limits • ESS charge/discharge power limits • Efficiency limits	• Short-term forecasted loads • Load reduction signal
Zhang and Li (2015)		• ToU • Peak shaving	• Minimization of energy cost	• EV charging limits	• Cost function • Total charging demand
Pal et al. (2017)		• RTP • Load shifting	• Minimization of generation costs for the customer and utility	• Shiftable load power limits • EV SoC limits	• EV availability
Şengör et al. (2020)		• Peak shaving	• Minimization of PAR of the system	• Grid power injection limits • EV SoC limits	• EV charging efficiency
Agrawal et al. (2018)		• ToU	• Minimization of overall system cost	• ESS power limits • EV charge/discharge power limits	• Cost function
Hou et al. (2021)	PSO	• ToU	• Maximization of revenues • Minimization of load fluctuation	• EV aggregator power limits • Grid power limits • EV charge/discharge power limits	• Charging tariffs from the grid • Service revenues of EV aggregator
Soares et al. (2013a)		• Load shifting • Peak shaving	• Minimization of operating costs for the network operator	• Grid power balance limits • Bus voltage limits • Line thermal limits • EV charge/discharge limits	• EV SoC • Network power injection • DG power injection

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economic, and social barriers (Warren, 2014; Harish and Kumar, 2014).

• In one of the test case scenarios undertaken in the power system in Indonesia, it is observed that the impacts of V2G

Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Wang et al. (2019)		• Peak shaving	• Minimization of fuel and startup costs	• Power balance constraints • Generation limits • Up/downtime constraints • Spinning reserve limits • EV charge/discharge power limits	• Fuel economics cost • Startup/shutdown time
Xu et al. (2020)		• RTP	• Minimization of the load curve • Maximization of customer profit	• Power capacity and balance constraints • EV charge/discharge limits • EV charging time limits	• EV availability • The power exchanged from the grid
Gomes and Saraiva (2017)	Evolutionary PSO	• ToU	• Minimization of system cost	• Active and reactive power generation limits • Grid voltage limits	• Power flow from the grid • EV availability
Rotering et al. (2021)	ACO	• Peak shaving	• Minimization of overall system cost	• DG generation limits • Grid power balance limits	• Cost function
Rasheed et al. (2020)	GA	• Peak shaving	• Minimization of cost variance • Maximization of user satisfaction	• EV SoC limits • EV charge/discharge power limits	• EV availability • Load demand from the grid
Liu et al. (2015)		• Valley filling • Peak shaving	• Minimization of PAR	• EV SoC limits	• EV availability
Lee and Park (2013)		• Peak shaving	• Minimization of PAR	• EV SoC limits	• Power demand • EV availability
Li et al. (2021b)		• ToU	• Maximization of profit • Minimization of PAR • Minimization of variance	• EV SoC limits • EV charge/discharge power limits	• EV availability • EV charging power
Li et al. (2019)	Improved partheno-genetic algorithm (IPGA)	• Load shifting	• Minimization of annual construction maintenance cost	• Grid power limits • System reliability constraints • DG and ESS penetration limits • EVCS charging power limits	• EV availability at EVCS • DG power generation capacity
Ramachandran and Ramanathan (2015)	Hyper-heuristic optimization	• Load shifting	• Minimization of total cost and emission	• EV SoC limits • Electricity tariff limits	• Emissions from CPP • DG active in the grid
Galván-López et al. (2015)	DE	• Peak shaving	• Maximization of energy consumption using EV ESS • Minimization of PAR	• EV SoC limits	• EV availability
Hao et al. (2021)	Virus colony search (VCS) optimization	• Peak shaving	• Minimization of smart parking costs	• Upstream grid power limits • EV SoC limits • Power equilibrium limits	• Cost function
Pal et al. (2020)	Hybrid GA and PSO	• Load shifting • ToU	• Minimization of total tariff for customers in 24 h	• Energy balance limits	• EV availability
Ji et al. (2016)	Model predictive control (MPC)	• Peak shaving • RTP	• Minimization of total operational cost for energy management	• Heat pump capacity limits • Heat pump thermal capacity limits • SoC of EV limit	• Heat pump generated power • EV availability • Fuel price • Natural gas price
Khatami et al. (2018)		• RTP	• Minimization of ramping requirements from power plant	• Power balance constraints • Service quality constraints of EVs	• EV charging load request vector
Di Giorgio et al. (2014)		• RTP	• Minimization of cost of energy consumption considering EV owner preferences	• EV SoC limits	• EV SoC level • Price signal • Volume signal

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Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Van Kriekinge et al. (2021)		• Peak shaving	• Minimization of electricity bills and peak load	• EV SoC limits • EV charge/discharge power limits • Grid power balance limits	• Energy tariff • Capacity tariff
Mehrabi et al. (2020)	Nonlinear programming (NLP)	• RTP	• Maximization of total profit considering social welfare	• EVCS EV loading limits • EV SoC limits • EV BESS temperature limits	• EVCS operation time
Bashash and Fathy (2011)	Robust programming	• Peak shaving • Load shifting	• Maximization of EV V2G power integration	• Grid power balance limits • EV power trajectory limits	• EV availability
Zeynali et al. (2021a)	Robust mixed-integer linear programming (RMILP)	• Load shifting	• Minimization of total operational costs and emissions	• CAES operational limits • BESS charge/discharge limits • EV SoC limits • RES generation limits	• EV availability • Grid power injection
Hosseini et al. (2020)	Robust mixed-integer quadratic programming (RMIQP)	• Peak shaving • Load shifting	• Minimization of PAR and energy cost for the users	• RES generation limits • Appliance loading limits • EV SoC limits • Power demand–supply balance limits	• Appliance operation time • Grid power exchange tariff
Farsangi et al. (2018)	Stochastic programming	• RTP • Peak shaving	• Minimization of operational cost	• DG power limits • Fuel cell power limits • EV SoC limits • Grid power Balance limits	• Cost of power at DG units
Zheng et al. (2020b)		• ToU	• Maximization of expected profits of EV aggregator	• Bidding amount capacity limits • EV charger capacity limits	• EV charge/discharge power • Grid electricity tariff
Shafie-khah et al. (2015)		• ToU • CPP • RTP • Incentive-based pricing	• Maximization of a parking lot profit	• EV SoC limits • Parking lot stored energy limits	• EV arrival and departure SoC
Cao et al. (2016)		• ToU • DLC	• Minimization of maximum transformer loading during the charging operation	• EV SoC limits • EV charge/discharge limits • Grid power balance limits	• Load demand curve • EV availability • Transformer loading capacity
Shafie-Khah et al. (2015)		• ToU • Incentive-based pricing	• Maximization of a parking lot profit	• EV SOC limits • EV battery efficiency	• EV battery capacity • Cost of degradation • Availability of EVs • EV charge/discharge tariff
Shafie-Khah et al. (2016a)		• ToU	• Maximization of EV aggregation profit	• EV SoC limits	• Market electricity tariff • Spinning reserve capacity • EV availability
Afzali et al. (2020)		• ToU	• Maximization of expected profit • Minimization of risks and costs associated with DR	• Available DR limits • EV charging/ discharging power limits • EV SoC limits	• Intraday price • RES generation capacity
Wang et al. (2021)	Conditional value at risk (CVaR) function optimization	• RTP	• Minimization of EV charge/discharge cost	• EV charge/discharge rate limits • EV SoC limits • EV charging time limits	• EV charge/discharge power
Guo et al. (2021b)	CVaR-based stochastic programming	• Load shifting	• Minimization of operation cost, emissions, and renewable power curtailment	• Active and reactive power limits • Power flow and balance limits • EV SoC limits	• Shiftable appliance schedule • EV availability

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Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Jeon et al. (2020)	Multi-period security constraint optimal power flow (MPSOPF)	• ToU	• Minimization of generation costs, contingency costs, load-following costs, and load shedding costs.	• EV SoC limits • Distributed energy resource (DER) generation limits • Load shedding and load following reserve limits	• Electricity ToU tariff • Electricity load curve
Sadati et al. (2018)	Techno-economic optimization	• ToU • CPP • RTP	• Maximization of income of distribution operator • Minimization of operational costs	• RES generation limits • Bus and line voltage limits • Available DR limits • EV SoC, efficiency, and power exchange limits	• EV energy trading tariff • Bidirectional power flow tariff • Battery depreciation cost
Wu et al. (2016)	Stochastic dynamic programming (SDP)	• ToU	• Minimization of customer's energy charges considering residential power demand and EV charging	• EV SoC limits • EV charger power limits • Grid power injection limits	• Time index • Residential load demand
López et al. (2018)	Deep learning (DL)	• ToU • Peak shaving	• Minimization of overall vehicle energy cost	• EV SoC limits • EV charger efficiency limits	• Cost function • Real-time electricity tariff • EV availability
Jahangir et al. (2020)		• ToU	• Minimization of energy costs in the real-time market	• Voltage and current limits • EV SoC limits	• Real-time electricity tariff • EV load demand
Reka et al. (2021)	Robust adversarial reinforcement learning (RARL)	• ToU	• Minimization of customer's electricity bill considering privacy concerns	• RES generation limits • EV SoC limits	• Dynamic electricity tariff • Appliance schedule
Sheikhi et al. (2016)	Reinforcement learning (RL)	• Peak shaving	• Minimization of monetary and non-monetary costs in DSM	• EV battery SoC limits	• Energy prices • Load demand curve • Total cost function
Jiang et al. (2018)		• ToU	• Minimization of the load demand curve of the system	• EV SoC limits • EV charge/discharge power limits	• Charging reward function
Chiş et al. (2016)		• ToU	• Minimization of charging cost over the day-ahead time frame	• EV BESS charge/discharge time limits • EV charge/discharge rate limits	• EV availability • Real-time electricity tariff
Yuan et al. (2018)	Hierarchical reinforcement learning (HRL)	• Peak shaving	• Minimization of hydrogen consumption	• EV SoC limits • Fuel cell operation limits	• Fuel consumption • Fuel cell operation status
Arif et al. (2016)	RL-based pursuit algorithm (PA)	• RTP • ToU	• Minimization of total energy cost	• EV SoC limits • EV charge/discharge time limits	• Reward function
Wang et al. (2015)	Correlation optimization algorithm (COA)	• ToU	• Minimization of electricity cost of the consumers considering PV generation and ToU pricing	• PV generation limits • EV operation time limit	• Grid supply of power • Electricity price
Vandael et al. (2012)	Market-based multi-agent system optimization	• Peak shaving	• Minimization of total operation costs	• Aggregated energy constraints • Power limit of EV fleet • EV battery capacity limits	• Cost function • Demand function

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and EV-DSM depend up to a great extent on the usage patterns of EV consumers. The policy-making and incentives offered by the regulatory and government agencies influence the consumers on a large scale to adopt the V2G methods and thus be more willing to participate in DSM programs (Huda et al., 2020).

- Commercialization of DSM in the EV public and residential use cases is not put at the forefront of the current use scenario. Only the technical implementations of EV-DSM are in great demand, which has little to minuscule focus on improving the financial state of operation. Commercialization of these DSM programs can bring better and more active

Table 2 (*continued*).

Ref	Optimization algorithm	DR programs used	Objective function	Constraints	Decision variables
Li et al. (2016)	Alternating direction method of multipliers (ADMM)-based decentralized optimization algorithm	• Peak shaving	• Minimization of the load curve	• EV SoC limits • EV charging efficiency limits • EV charge rate limits • Network constraints	• EV charging load
Tan et al. (2014)		• Valley filling • Load shifting • Peak shaving	• Minimization of total generation cost	• EV charging/discharging efficiency limits • EV ESS capacity limits • EV SoC limits	• Load demand curve • EV availability
Zhou et al. (2016)	Multi-EV reference and single-EV real-time response (MRS2R) online algorithm	• Peak shaving • Valley filling	• Minimization of payment by EV customers	• EV SoC limits • EV BESS capacity limits	• EV availability
Gan and Zheng (2020)	Interior point optimization	• Valley filling	• Minimization of peak valley difference and improvement of stability	• EVCS charging/discharging time limits • Grid power limits	• Active power load • Grid bus voltage magnitude
Rahbari-Asr and Chow (2014)	Constrained nonlinear optimization problem with Karush–Kuhn–Tucker (KKT) conditions	• Peak shaving	• Minimization of charging cost for EV owners	• Charging power limits • Grid power limits	• Cost function
Tong et al. (2017)	Decision-table-based control optimization	• Peak shaving	• Maximization of economic benefits • Minimization of grid power consumption	• EV BESS SoC limits • Balancing current limits	• PV generation during daytime • SoH of BESS
Thomas et al. (2016)	Monte Carlo simulation using mixed-integer linear programming (MILP)	• ToU	• Minimization of building energy consumption	• EV charging time limitations • EV SoC limits • Energy balance limits	• Load demand curve
Chen et al. (2014)	Convex optimization	• Valley filling	• Minimization of EV charging costs	• EV charging rate constraints • EV SoC limits	• EV availability
Wang and Paranjape (2017)		• RTP • Valley filling	• Minimization of electricity costs	• Consumer comfort limits • EV charging time constraints	• EV availability
Wu et al. (2017)		• Peak shaving	• Minimization of total electric energy costs	• Power balance limits • EV SoC limits • Home ESS SoC limits	• Number of available EVs
Wang and Paranjape (2015)		• RTP	• Minimization of electricity cost for the consumer	• EV charge/discharge power limits • Load threshold • EV SoC limits	• Number of available EVs • Real-time energy tariff
Kessels et al. (2007)	Quadratic programming	• Peak shaving	• Maximization of vehicle's fuel economy	• Power flow limits • EV SoC limits	• Cost function
Zhao et al. (2019)	Non-intrusive load extracting (NILE) algorithm	• Load shifting • Peak shaving	• Minimization of the daily cluster charging costs of EVs	• Power balance limits • Ramping rate limits • EV user comfort constraints	• EV charging power • Availability of EVs
Sharma and Jain (2021)	Monte Carlo based Risk-averse charge scheduling optimization	• ToU • RTP	• Maximization of profits	• EV SoC limits • EV charging period limits	• Electricity tariff • EV drive cycle

participation of EV users to participate in DSM programs willingly (Patil and Kalkhambkar, 2020).

11. Future scope and research directions

This literature survey carefully examines the current research and the advances in the domain of EV-based DSM. Several areas of improvement and novel research are suggested to the readers to enhance the already existing technological advancements in the EV-DSM domain and its implementation. After an introspective discussion based on the identified research gaps, some valuable suggestions regarding future research directions and prospective areas of research are suggested:

- Virtual power plant integration on a system-wide scale can be beneficial for maximum utilization of smart loads and appliances to participate in DSM, with EVs being the smart energy hubs concerning energy dispatch and storage (Mohanty et al., 2022; Panda et al., 2022a).
- Hybrid incentive-based and tariff-based financial models can be formulated to optimize load control features such as the DSM response speed, duration of the program, advance alert and notification systems, geo-location sensitive based analysis, and real-time load monitoring rate (Yesilbudak and Colak, 2018; Behrangrad, 2015; Shariatzadeh et al., 2015).
- The meta-heuristic-based optimization can be hybridized, or newer, more efficient heuristic algorithms can be used for better computation in the scheduling of DSM operation. PSO, GA, wavelet transform modified ANN, adaptive FL, support vector machine computation, autoregressive moving average value integration with models can be implemented to get higher load forecast accuracy considering regulation of loads, dispatch, scheduling, and unit commitment problems of smart grids (Khan et al., 2016; Raza and Khosravi, 2015).
- K-map algorithms, fuzzy constrained algorithms, self-reorganizing maps, multilevel hierarchy-based clustering techniques, artificial bee colony (ABC) optimization, and ACO can be implemented to extract crucial information from aggregated load consumption profiles and in the classification of various load types in smart distribution systems (Yang and Shen, 2013).
- EV DSM models need to be more comprehensive in their operation for better practical implementation, i.e., varying charging rates, standards implemented at EVCS premises, standardized BESS swapping station methodologies, and active participation of EVs in the overall market trading and ancillary service support scenario. More research needs to be focused on obtaining an optimized trade-off between the performance of the system and the computational complexity.
- With price-sensitive scheduling, the effective and easy management of charging demand during peak/off-peak usage periods is an excellent prospect for DSM aggregators. With large-scale EV integration into smart grids, it is a very feasible research direction to be focused upon with an emphasis on EV charging strategies on the basis of price response and price elasticity dynamics (Biviji et al., 2014).
- There is a serious lack of datasets which is necessary for training machine learning and deep learning models. Only two well-known EV charge scheduling datasets are in the available research domain for researchers. Other data sets that have been developed are available to commercial companies. More machine learning models must be developed to represent varying architectures and geographical locations.
- Smart devices attached to the charging infrastructure on the end-user locations can make the aggregator more dynamic in its flexibility by offering optimized charging schedules to the user based on their comfort and convenience. The embedded system architecture can be further enhanced by offering modular control to different aspects of the control strategies so that the latest technologies can be added in further upgraded EV automotive models and hardware revisions.
- Climate-based EV-DSM scheduling can be researched further as it would affect RES generation to a large extent, and the forecasting-based scheduling can help the RES to be dispatched more efficiently on the basis of meteorological data (Nazaripouya et al., 2019).
- Global awareness and policy-making decisions could influence consumer behavior in adopting EVs as their preferred transportation measure. Thus in future implementations, policy-making and government-assisted policies to facilitate more and more consumers coming onboard in EV-DSM programs can be a niche area to focus on Ravi and Aziz (2022).
- The environmental impacts of EVs constitute a significant concern on the manufacturing and disposal front. The high carbon footprint is a major environmental deterrent to green automobile adoption. Further research on these aspects can be focused on bringing about a more eco-friendly production/disposal process of the sensitive components of EVs. The waste-to-energy potential of the above can be leveraged to a great extent to convert the byproducts of manufacturing/disposal to usable energy (Ravi and Aziz, 2022).
- Simultaneous bidirectional power flow, i.e., individualized EV charge/discharge operation scheduling, can allow for greater flexibility in managing the load consumption profiles of the overall system. Further work can be focused on this specific area for selective scheduling operations as this would allow for a more diverse control of EVs using the DSM and scheduling operations (Sassi et al., 2021).
- The influence of PHEVs over the charging/discharging patterns is a novel issue. These drivetrains have smaller BESS, and thus the involvement of these smaller BESS systems does not leverage the load-leveling due to the short dispatch and buffer schedule owing to their inherent battery capacity. Provision of intermittent power supply from these sources apart from the usual DSM operations is an area to focus on in further research (Masuta et al., 2014).
- Communication protocols between smart control devices could help implement IoT-based control strategies to coordinate the dynamics of DSM in the form of telematics and drive cycle patterns of the EV users. IoT-based control provides a promising direction for further communication and technological advancements (Nikam and Kalkhambkar, 2021).
- The focus of this article was mainly on the individual and aggregated operation of EVs as individual BESS units in complete freedom of mobility. There is no standardization based on the models of EVs adopted by the customers in the market. One aspect of standardization that can be given focus in the EV-BESS DSM domain is the standardization of operation and battery technologies at the battery swapping station. This has rarely been discussed in the recent literature reviews, although it looks promising in future consideration once battery technology and practices are standardized (Revankar and Kalkhambkar, 2021).

12. Conclusion

In this review paper, existing research on the DSM operation of EVs, which has witnessed significant interest in the energy management domain in the last few years, has been reviewed extensively. The general structure, operation, and charging models of DSM and EV-DSM integration into the present smart grid scenario have been discussed and represented. The optimization aspect of EV DSM scheduling has been tabulated and represented with a focus on the objective function, constraints, and decision variables. With the expected increase in V2G technology adoption, it is estimated that the DSM operations can play a viable opportunity for the customers and utility aggregators to be active participants in the scheduling, dispatch, and market-oriented energy trading. The research directions this review article provides can help the researchers identify the potential gaps that have been discussed previously, and they can be given due importance in finding solutions to the existing area of issues and challenges.

CRediT authorship contribution statement

Sarthak Mohanty: Writing – review & editing. **Subhasis Panda:** Conceptualization, Writing – review & editing, Writing – original draft. **Shubhranshu Mohan Parida:** Writing – review & editing, Supervision. **Pravat Kumar Rout:** Investigation, Formal analysis, Supervision. **Binod Kumar Sahu:** Writing – review & editing, Supervision. **Mohit Bajaj:** Conceptualization, Investigation, Supervision. **Hossam M. Zawbaa:** Writing – review & editing. **Nallapaneni Manoj Kumar:** Writing – review & editing. **Salah Kamel:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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