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A hybrid approach based energy management for building resilience against power outage by shared parking station for EVs

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ABSTRACT

A major contribution of this work is to develop an efficient hybrid technique for building energy resilience against natural disasters, which cause power outages for commercial and residential buildings. The novelty of the proposed method is the combination of Chicken Search Optimization and the Spike Neural Network learning algorithm. The buildings are designed using shared electric vehicle parking station. Buildings are modeled with peer-to-peer functionality. Electric vehicle inside the parking station are available in a variety of forms, as the commercial building utilizes parking station at day time, also the residential building mostly utilizes at midnight. These variations help vehicles to be utilized for additional hours. A building is maintained through power management options to deal with these interruptions. The choices include peer-to-peer building operation, electric vehicle charging and discharging, partial charge capability, load reduction, and load adjustment. The proposed technique makes use of building components and does not require any additional components for building energy management. The main contribution of this paper is to diminish energy costs and increase energy resilience to natural disasters. Resiliency is described as the ability to restore harmful loads while experiencing minimum power loss after successive power outages. The performance of the proposed system is evaluated using the MATLAB platform and compared to existing systems.

1. Introduction

Electric vehicles (EVs) are practical technology that reduces fuel costs and environmental emissions. The price of gasoline fluctuates constantly, whereas the price of electricity is far more stable. In addition, electricity is less expensive than gasoline. As a result, EVs are convenient technology for reducing gasoline costs [1–3]. Additionally, electricity generated by EVs may be distributed through local rooftop solar systems or small-scale wind turbines, resultant at additional cost savings or even free energy [4–6]. Electric vehicles can also help to prevent environmental damage [7]. Traditional cars release carbon dioxide, which contributes to greenhouse gas emissions and has a detrimental influence on climate change [8]. Renewable energy resources and EVs can work together to attain better outcomes [9].

The benefit of EVs has motivated the researchers to reconsider its implications for electric grids and systems [10]; Rajesh et al., 2020; [11, 12]. Within the production segment, large-scale EV charging stations have electricity generated impacts by power plants. The huge vehicles electrification creates considerable effects in power grid operation [43]. The smart charge system for EVs ensures a 2.4% increase in solar power and a pair of 5% lessening in fossil power [13,14]. Plug-in EVs create effects in power system's economic UC[42].[42] The optimum charge with discharge pattern of EVs decreases the economic cost of UC issue. Carbonic acid gas emitted by conventional cars contributes to greenhouse gases, and then makes negative impact at the alteration of global climate. But, EVs don't emitting the pollution, also hybrid EVs emits less pollution likened with the standard cars [15–19]. RESs with EVs exactly cooperate to realize good results.

A study of IEEE 24-bus system specifies that the EVs in right buses reduce the risk cost as well as expansion of network [20,21]. The right charge-discharge regime of EVs eliminates traffic congestion. The EVs along the technology of vehicle-to-grid maximize the RES mixing, these technologies lessens the fluctuations of renewable energy including operational cost.

EVs are linked with distribution grids via aggregators and the

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Nomenclature

cl	Load curtailment level (%)
c_{PC}	Percentage of partial charge (%)
$e_{evR}^{T1,T2}$	Electric vehicle energy on residential building (kWh)
$e_{evC}^{T1,T2}$	Electric vehicle energy on commercial building (kWh)
$e_{evR}^{0,T2}$	Initial energy of electric vehicle on residential building (kWh)
$e_{evC}^{0,T2}$	Initial energy of electric vehicle on commercial building (kWh)
$e_{evR}^{\max}$	Electric vehicle capacity on residential building (kWh)
$e_{evC}^{\max}$	Electric vehicle capacity on commercial building(kWh)
$K_{VC}^{T1,T2}$	Positive variable to modify load level on commercial building
$K_{VC}^{\max}$	Load modification level at every hour on commercial building
$K_{VR}^{T1,T2}$	Positive variable to modify load level on residential building
$K_{VR}^{\max}$	Load modification level at every hour on residential building
$p_{CR}^{T1,T2}$	Curtailed load on residential building (kW)
$p_{evR}^{T1,T2}$	Power of electric vehicle on residential building (kW)
$p_{evC}^{T1,T2}$	Power of electric vehicle on commercial building (kW)
$p_{evRC}^{T1,T2}$	Charging power of electric vehicle on residential building (kW)
$p_{evCC}^{T1,T2}$	Charging power of electric vehicle on commercial building (kW)
$p_{evRD}^{T1,T2}$	Discharging power of electric vehicle on residential building (kW)
TE	Index of hours [1, …,24]
TF	Index of seasons [1, …,4]
$u_{evRD}^{T1,T2}$	Binary variable of discharging state for vehicle on residential building [0,1]
$u_{evCD}^{T1,T2}$	Binary variable of discharging state for vehicle on commercial building [0,1]
$p_{evCD}^{T1,T2}$	Discharging power of electric vehicle in commercial building (kW)
p_{evR}^{R}	Charging facility rated power on residential building (kW)
p_{evC}^{R}	Charging facility rated power on commercial building (kW)
$p_{FC}^{T1,T2}$	Fixed load demand on commercial building (kW)
$p_{FR}^{T1,T2}$	Fixed load demand on residential building (kW)
$p_{NC}^{T1,T2}$	Power among commercial building and grid (kW)
$p_{NR}^{T1,T2}$	Power among residential and grid (kW)
$p_{SC}^{T1,T2}$	Charging station power on commercial building (kW)
$p_{SR}^{T1,T2}$	Charging station power on residential building (kW)
T_1	Variable load demand on commercial building (kW)
$u_{evRC}^{T1,T2}$	Binary variable [0,1] of charging status for vehicle in residential buildingAbbreviation
CSOA	Chicken Search Optimization Algorithm
SNNLA	Spike Neural Network Learning Algorithm
EV	Electric Vehicle
UC	Unit Commitment
RESs	Renewable Energy Sources
EM	Energy Management
DR	Distribution Resources
PV	Photovoltaic
PEV	Plug-in Electric Vehicle
SOC	State Of Charge
SPS	Shared Parking Station
INM	Izhikevich Neuron Model
CAP	Cost Accuracy Percentage
SSA	Salp Swarm Algorithm
CSO	Cat Swarm Optimization
EVSE	Electric Vehicle Supply Equipment

aggregator is located during the network operator and the owner of vehicle. The paradigm is also recognized at smart distribution networks [22,23]. The voltage controlling [24], renewable energy resources, peak load cutting, enhancement of power quality, optimum grid function are the negative impacts of EVs in distributions grids. The EVs are incorporated in microgrids, in which optimum functioning of EVs can lessen the microgrid economic costs [25–27]. The microgrid is ideally reconfigured through EVs application [28]. The load frequency control on micro-grid is exited even though the operation of EVs [29]. The cost of electricity with environmental pollution can be diminished by optimum charge/discharge of EVs. The EM inside the buildings is substantially influenced by EVs. The EVs fast-charge system generates few effects of building load, these effects deal with the management of load requirements [30].

The negative aspects of EVs inside the buildings are voltage regulation, mitigation of renewable energy volatility, and peak load reduction. In the EM building, energy is also transmitted among the buildings, in order to create a competent EM system. This work proposes an efficient hybrid technique for increasing energy resilience in commercial and residential buildings during natural disasters that induce power outages. The proposed method is a hybrid of CSOA and SNNLA, and it was eventually known as CSOA-SNNLA technique. The main aim of this work is to diminish energy costs and increase energy resilience to natural disasters. Resiliency is defined as the ability to restore harmful loads while experiencing minimal power loss after successive power outages.

Rest of the paper is described as follows: Section 1 includes the introduction section, section 2 includes the literature review section of the recent research, section 3 includes system modeling, section 4 includes proposed methodology, section 5 includes the results section and section 6 includes the conclusion section.

2. Recent research work: a brief review

Several works were presented on literature depends on EM for building resilience beside power outage by SPS for EVs with DR program. Some of them are revised here [31], have presented data-driven load management of stand-alone residential buildings together with renewable resources, energy storage system, and electric vehicle. As one of the key problems of power generation in stand-alone residential structures, DSM plays a critical role in regulating electrical system reliability. This study focuses on two major developments: 1) data analysis through the clustering technique to enhance DSM efficiency and accuracy, 2) a state-of-art DSM modeling framework for standalone residential building. Regarding the initial novelty, the well-known linkage grouping technique was utilized to define variable rates over time and, in the second novelty, the MILP conveys the components of power system, load management as well as objective function contemplates the user priority and convenience to enhance the stand-alone power system reliability. The advantages of the presented method were the reliability of power system and energy supply qualities were considerably enhanced by using the above-mentioned DSM. In this work, the price of electricity during the day is often more dynamic than at night, making it more difficult to design a successful EV charging approach in parking lots to diminish the energy cost.

[32] have presented energy management based on hybrid optimization among electric vehicle and electricity distribution system. It investigates cooperative evaluation of EMS operation with numerous considerations like EV fleet arrival time two-way energy trading capabilities in EV driving plan, impact of PV uncertainty on EV operation EMS depends, establishing dissimilar prioritization factors that affect the energy sale to the grid as resources on total cost of system. The outcomes demonstrate that the method was effective in finding the nearby global optimal solution through less computation and decreases the complexity of proposed algorithm. The energy consumption of the system was 720.34 KJ. The theoretical analysis is very hard based on the use of the optimization algorithm. Also, the probability distribution could change in the entire iterations. This is the major drawback of this work.

[33] have presented an optimal design of commercial electric vehicle charging stations (EVCS). The main objective was to develop a neared statement for the PEV charging station capacity issue. The initial issue was related with calculating the best service capacity for cargo lots located in the work centers where PEV parking statistics were provided in advance. The second problem was the optimization of arrival rates for a specified station capacity. The mathematic models were extended for the case wherever multiple charger technologies serve customer demand. Markovian queues were utilized to model the charging station system. Related optimization issues solved with convex optimization techniques. The main advantages of analytical calculations as well as discrete event simulations were performed and the outcomes display that 60% of waiting times and 42% of queue length may be decreased with optimal capacity planning. Although it is quite reasonable for night charging in the residential area, it is not appropriate for the daytime parking charging issue presented under this study.

[34] have presented charging powers of EV fleet: Evolution and implications for Commercial Charging Sites. The paper has presented the state of maximal charge and power of onboard chargers was exhaustively analyzed with data from two commercial charging sites. During the year 2020–2040, average commercial energy consumption would rise by 134%, from 5.6 to 8.7 kWh/EV to 13.0–19.6 kWh/EV. Based on supported charging powers, that document discussed charging characteristics at commercial charging stations. In general, the study's findings are highly beneficial. The benefits include the capacity to increase the accuracy and dependability of future simulations relating to topics like load forecasting, flexibility assessment, and appropriate charging infrastructure size.

[1] have presented vehicle-to-home and renewable capacity resources coordination for EM resilience. The presented method creates energy hub involving hardware resources, software tools (DR program). Every capacity resources with grid power were returned to lessen the daily functional building cost, resiliency development, self-healing. The outcomes show that the capacity resources lessen the daily functional cost. The main drawbacks of their approach have affected the system accuracy due to the inadequate charging infrastructure of EVs.

[35] have suggested Resilience oriented vehicle-to-home function with the help of battery swapping method. The battery swapping mode performs EV to depart the building in every day hour when required through the owner. The introduced method creates the EV obtainable for owner in the least day time while the EV arrives to building using empty battery. The introduced method upgrades the acceptance rate of EVs regards long charge times. The super capacitor was applied to get rid of photovoltaic uncertainties at off-grid mode. The outcomes indicate that the battery swapping method was ready to upgrade the resilience, but lessens the energy cost. Uncertainty of EV connection point, penetration level, and the connection and disconnection period cause increased level of load demand. This is the main drawback of their work.

[36] have suggested increasing self-consumption of renewable energy through Building to Vehicle for multi users associated during a virtual micro-grid. A dynamic simulation tool was generated to review energy, the suggested V2B2 mode utilized with cluster of multi-users manufactured from non-residential buildings, EVs using bidirectional charge for raising self-consumption of energy created on-site via photovoltaic panels. The outcomes display that the suggested V2B2 mode maximizes the match amid on-site renewable production and entire system requirement by minimizing grid operation, but maximizing the system economic convenience. In this approach, it can also be expensive, tend to be heavy, are plagued with limited public charging infrastructure.

[37] have performed an intelligent grouping system was introduced by taking into account the coupling relationship in the mid of EV trip information, battery status was recognized depending rate of contribution of charging process [38]. have introduced real-time EMS depending adaptive regulation of multiple parameters, involve drive cycle, drive distance, and battery SOC [39]. have proposed a resilience-driven critical load restoration approach to improve restoration capacity of distribution system through emergency conditions. The main advantages of this work are; these are efficient, quiet, and torque-rich. However, the accuracy is limited due to the public charging infrastructure.

2.1. Background for the research work

Review of current research work displays energy management to build resilience against equipment failure is a very important contributing factor. Based on climate change, extreme weather events of high impact and low probability, like hurricanes, floods and ice storms, have become more common and drastic on current years. An insignificant damage caused by natural disasters is extensive disruption of the power system. Therefore, outage prevention and fast outage recovery are key factors. The ability of power systems to cope through natural disasters is generally considered to be the resilience of the power grid. Due to uncertain features of the disaster and power system complex measures to improve resilience must be considered. EVs contain battery electric vehicles, hybrid electric vehicles and plug-in electric vehicles to reduce emissions from the conversion system in the road network. It is a revolutionary opportunity to restore the resilience of power systems to disasters offered by electric vehicles based on high electric efficiency, mobility and bi-directional charging capability of electric vehicles. Therefore, a hybrid technique is required for a promising solution that overcomes these problems. Within the literature to unravel this topic not numerous works depends on methodologies were exhibited; these problems and difficulties have inspired this research work.

3. Modeling of EM to build resilience beside power outage by SPS in EVs

In this section, EM to build resilience beside power outage through SPS for EVs with DR is presented. To form the robust model, 2 commercial with residential buildings are deemed, therefore the SPS is designed for EVs in Fig. 1.

Most of the information flow is bidirectional. Two-way information flow provides decision support to power distribution panel, utility switch, smart power integrated node, EV cable, smart meter, and energy management system. The power distribution panel is a high-voltage power supply that distributes battery power to vehicle high-voltage components through the central control box, like utility switch, integrated power node intelligent, a high voltage DC/DC, etc. In general, there are two kinds of EV cables that are part of the EVSE: Battery cables – Unlike low-voltage cables, they are designed for higher electrical currents and voltages. Charging cables: utilized to connect the vehicle to an exterior electric source. The major advantage of getting a smart meter is that is no longer need to take manual gas and electric readings. With a smart meter, all the data is sent to buildings automatically, giving them accurate readings. These readings are fed to proposed energy management system to estimate energy savings, cost savings, and resiliency

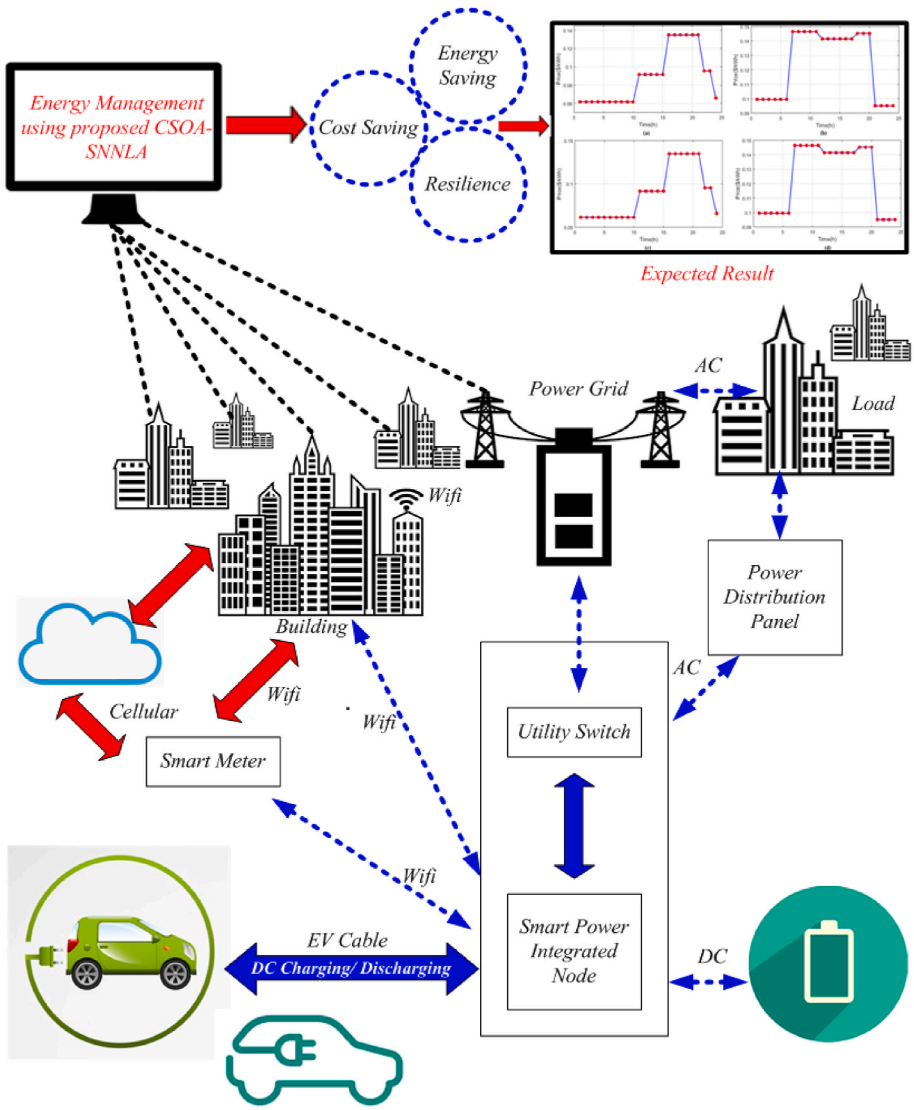

Fig. 1. EM for Building Resilience against Power outage for EVs.

using the proposed CSOA-SNNLA approach. The EVs intimate the parking station contains various patterns of accessibility on account of commercial building continually utilizes parking station at day times as well as residential building utilizes at midnight. These variations aid the model for using additional hours.

4. Proposed model of energy resilience

The energy resilience is enhanced using optimum use of EVs, DR program, SPS function. Fig. 2 portrays the stages of resilience.

Here, the response of the system is understood by vulnerability. The resistance refers to the ability to recover after suffering the disturbance on system. System robustness is described as the system ability to continue function under disturbances. This involves that information is necessary on how the system responds to dissimilar degrees of disturbance. Recovery concerns the restoration of normal operations after an unplanned event. Based on the electric vehicles the buildings are provided with SPS. Also, the buildings loads have been designed into fixed with variable loads. The variable loads are feasible, its power tuned to meet the resilience criteria.

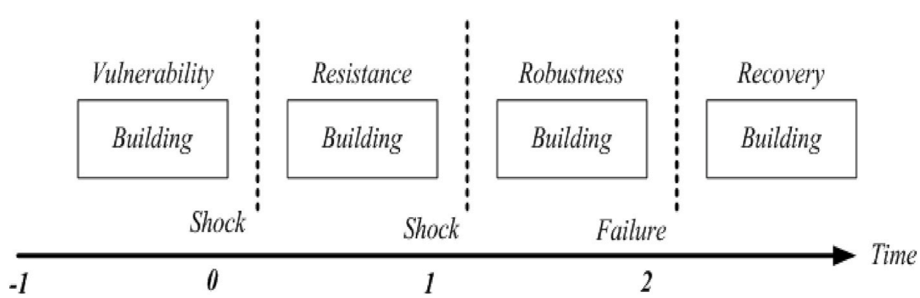

Fig. 2. Stages of resilience.

There are two kinds of buildings are founded: (i) residential (ii) commercial. Since the building contain different energy profiles and also on various times periods its EVs are parked in parking station. While the market is open the building of commercial utilize the parking station on day and if closed the market then quit the parking station, mostly the market will close during night times. Moreover, on night times the residential buildings mostly utilize the parking station. The energy resilience is enhanced since the EVs are obtainable at more hours as well as among disruptions and events the model can be exploited from their energy.

4.1. EVs for residential building

EVs often depart the building at day hours and at evening or night it comes back to the building it will happen in the residential buildings. During evening-night the EVs are obtainable in parking station, they are accomplished to contribute in EM scheme. The buildings through shared Parking Station of EVs are shown in Fig. 3.

The EV shared parking stations are outfitted in the buildings. Building loads are also modeled with fixed and variable loads. Variable loads are adaptive, with the ability to change its power and energy to meet resilience requirements. Along with residential and commercial buildings, two types of buildings are deemed. These models maximize the model's flexibility. Since the buildings contain various energy profiles and its EVs are parked beneath the parking station for varying time period. Commercial buildings park at the parking station during the day and leave when the market closes, especially at night. Residential complexes, on the other hand, commonly use the parking station overnight. Because EVs are available most of the time, such a nexus builds energy resilience because the model may profit from its energy in the event of interruptions and events. Residential building EVs set to leave the building at 9am then return at 4 p.m. Much process is evaluated via equations (1)–(13).

The mathematic modeling begin 1 a.m. which is given at equation (1) and also utilizing the lifted energy from the before hour the EV energy on this hour is measured and charge-discharge power of EV in current hour.

The energy 2–8 a.m. is measured is given as follows,

$$e_{evR}^{T1,T2} = e_{evR}^{T1=24,T2} + p_{ev}^{T1,T2} \forall T_1 \in [1], T_2 \in [1, ..., 4] \tag{1}$$

$$e_{evR}^{T1,T2} = e_{evR}^{T1=24,T2} + p_{ev}^{T1,T2} \forall T_1 \in [2, ..., 8], T_2 \in [1, ..., 4] \tag{2}$$

The vehicles quit the building on the time of 9–16 h then the power with energy of the vehicle is equivalent to zero which is denoted in equations (3) and (4)

$$e_{evR}^{T1,T2} = 0 \forall T_1 \in [9, ..., 16], T_2 \in [1, ..., 4] \tag{3}$$

$$p_{evR}^{T1,T2} = 0 \forall T_1 \in [9, ..., 16], T_2 \in [1, ..., 4] \tag{4}$$

Vehicles return to the building in 17 h and persist energy inside its battery through (5). The vehicles have been linked with electrical system of building 18–24 h they charge or discharge through (6).

$$e_{evR}^{T1,T2} = e_{evR}^{0,T2} + p_{evR}^{T1,T2} \forall T_1 \in [17], T_2 \in [1, ..., 4] \tag{5}$$

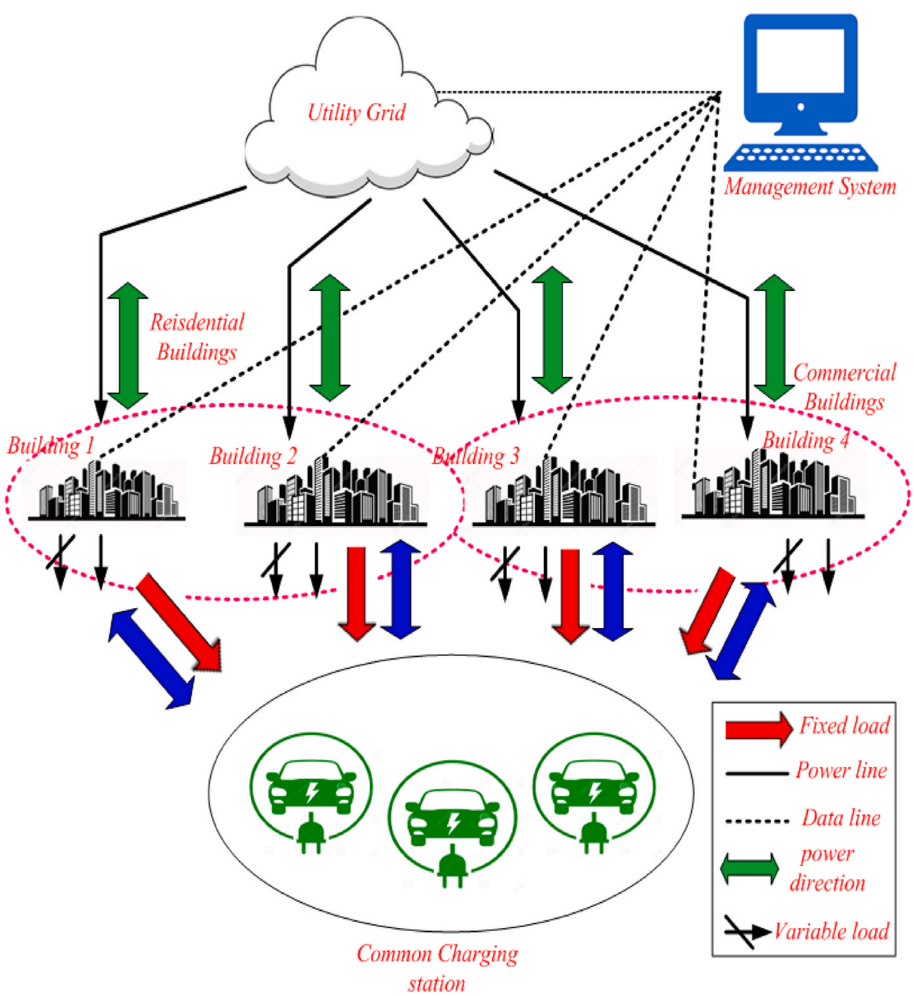

Fig. 3. Buildings with shared parking station for EVs.

$$e_{evR}^{T1,T2} = e_{evR}^{t1-1,T2} + p_{evR}^{T1,T2} \forall T_1 \in [18, ...24], T_2 \in [1, ..., 4] \tag{6}$$

Vehicles must be fully or partially charged when they leave the building at 8am. In this paper, the partial charging capacity of vehicles is taken into account, thus expanding the resilience of the system against events. Regarding, the vehicle is permitted to go away the building that is lack of full charge as mentioned in (7). The vehicle is permitted for charging partially, so the residual energy has employed to produce load requirement subject to the outage of grid. The vehicles discharge capacity is computed by (8). In (9), the utmost energy in the vehicles is a smaller amount than its capacity.

$$e_{evR}^{T1,T2} \geq e_{evR}^{\max} \times c_{PC} \forall T_1 \in [18], T_2 \in [1, ..., 4] \tag{7}$$

$$e_{evR}^{T1,T2} \geq e_{evR}^{\max} - e_{evR}^{T1,T2} \forall T_1 \in [8], T_2 \in [1, ..., 4] \tag{8}$$

$$e_{evR}^{T1,T2} \leq e_{evR}^{\max} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{9}$$

EV power is formed by 2 events: (i) charging, (ii) discharging, which is represented in (10). The discharge power denotes '-ve' mark. The electrical vehicle is in either charge or discharge state, it does not permitted to control on both the states in identical time.

$$p_{evR}^{T1,T2} = p_{evRC}^{T1,T2} - p_{evRD}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{10}$$

$$p_{evRC}^{T1,T2} = p_{evR}^{R} - u_{evRC}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{11}$$

$$p_{evRD}^{T1,T2} = p_{evR}^{R} - u_{evRD}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{12}$$

$$u_{evRD}^{T1,T2} = u_{evRC}^{R} \leq 1 \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{13}$$

4.2. EVs of commercial building

Here, EVs from the building of commercial will arrive at 9 a.m. then depart at 13 p.m. They came back at 18 then left at 23. Here, 1–8 a.m. Vehicles do not obtainable with its energy including power indicates zero expressed in (14), (15), [26].

$$e_{evC}^{T1,T2} \geq 0 \forall T_1 \in [1, ..., 8], T_2 \in [1, ..., 4] \tag{14}$$

$$p_{evC}^{T1,T2} = 0 \forall T_1 \in [1, ..., 8], T_2 \in [1, ..., 4] \tag{15}$$

From 9 a.m. to 13 p.m.; the vehicles have been linked with building (17). When allowed the partial charge, the vehicles leave at 13 (18). The vehicles discharge capacity is computed by (19).

$$e_{evC}^{T1,T2} = e_{evC}^{0,T2} + p_{evC}^{T1,T2} \forall T_1 \in [9], T_2 \in [1, ..., 4] \tag{16}$$

$$e_{evC}^{T1,T2} = e_{evC}^{T1,T2} + p_{evC}^{T1,T2} \forall T_1 \in [10, ..., 13], T_2 \in [1, ..., 4] \tag{17}$$

$$e_{evC}^{T1,T2} \geq e_{evC}^{\max} \times c_{pc} \forall T_1 \in [13], T_2 \in [1, ..., 4] \tag{18}$$

$$e_{evC1}^{T2} = e_{evC}^{\max} - e_{evC}^{T1,T2} \forall T_1 \in [13], T_2 \in [1, ..., 4] \tag{19}$$

The vehicles not arrived at parking station as a result the energy with power implies zero.

$$e_{evC}^{T1,T2} = 0 \forall T_1 \in [14, ..., 17], T_2 \in [1, ..., 4] \tag{20}$$

$$p_{evR}^{T1,T2} = 0 \forall T_1 \in [14, ..., 17], T_2 \in [1, ..., 4] \tag{21}$$

Vehicles return in 18 h (22), which are 19–23 inside the parking station (23). The vehicles have adequate amount of energy when leaving the station (24).

$$e_{evC}^{T1,T2} = e_{evC}^{0,T2} + p_{evC}^{T1,T2} \forall T_1 \in [18], T_2 \in [1, ..., 4] \tag{22}$$

$$e_{evC}^{T1,T2} = e_{evC}^{T1,T2} + p_{evC}^{T1,T2} \forall T_1 \in [19, ..., 23], T_2 \in [1, ..., 4] \tag{23}$$

$$e_{evC}^{T1,T2} \geq e_{evC}^{\max} \times c_{pc} \forall T_1 \in [23], T_2 \in [1, ..., 4] \tag{24}$$

$$e_{evC2}^{T2} = e_{evC}^{\max} - e_{evC}^{T1,T2} \forall T_1 \in [23], T_2 \in [1, ..., 4] \tag{25}$$

The capacity of EV is denoted in (26). The vehicle does not linked with building after 23, its energy, power are ignored (27), (28).

$$e_{evC2}^{T2} \leq e_{evC}^{\max} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{26}$$

$$e_{evC}^{T1,T2} = 0 \forall T_1 \in [23, 24], T_2 \in [1, ..., 4] \tag{27}$$

$$p_{evR}^{T1,T2} = 0 \forall T_1 \in [23, 24], T_2 \in [1, ..., 4] \tag{28}$$

The EV power is modeled by charge with discharge powers (29). The EV does not allowed to run both the charge-discharge modes simultaneously (30) to (32)

$$p_{evC}^{T2} = p_{evCC}^{T1,T2} - p_{evCD}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{29}$$

$$p_{evCC}^{T1,T2} = p_{evC}^{R} \times u_{evCC}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{30}$$

$$p_{evCD}^{T1,T2} = p_{evC}^{R} \times u_{evCD}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{31}$$

$$u_{evCD}^{T1,T2} + u_{evCC}^{T1,T2} \leq 1 \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{32}$$

4.3. Mathematical modeling of electric vehicle

$$EV_d(t) = \frac{1}{\sigma^* \sqrt{2\Pi}} e^{-(t-\mu^*)/2\sigma^{*2}}, 0 < t < 24 \tag{33}$$

where, σ^* as standard deviation, μ^* is the mean value. The EV arrival is estimated depends on the eqn. (34)

$$EV_a(t) = \frac{1}{\sigma^* \sqrt{2\Pi}} e^{-(t-\mu^*)/2\sigma^{*2}}, 0 < t < 24 \tag{34}$$

here μ^* and σ^* value are 17.01 and 3.2. The EV distance is estimated with below eqn.

$$EV_d(d) = \frac{1}{d\sigma^* \sqrt{2\Pi}} e^{-(\ln d-\mu^*)/2\sigma^{*2}}, d > 0 \tag{35}$$

here d refers travel distance and μ^* and σ^* value denotes 3.2 and 0.9.

4.4. Power flow model

The power amid the residential building besides grid is computed utilizing (36), the power during the building of commercial and grid is computed utilizing (37). The power balance on SPS is expressed in (38),

$$p_{NR}^{T1,T2} = p_{FR}^{T1,T2} + p_{VR}^{T,T2} + p_{SR}^{T1,T2} - p_{CR}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{36}$$

$$p_{NC}^{T1,T2} = p_{FC}^{T1,T2} + p_{VC}^{T,T2} + p_{SC}^{T1,T2} - p_{CC}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{37}$$

$$p_{SR}^{T1,T2} + p_{SC}^{T1,T2} = p_{evR}^{T,T2} + p_{ecC}^{T1,T2} \forall T_1 \in [1, ..., 24], T_2 \in [1, ..., 4] \tag{38}$$

The upstream grid blackout is delineated through (39), (40), here the traded power amid grid implies zero.

$$p_{NC}^{T1,T2} = 0 \forall T_1 \in [TF], T_2 \in [TE] \tag{39}$$

$$p_{NR}^{T1,T2} = 0 \forall T_1 \in [TF], T_2 \in [TE] \tag{40}$$

4.5. DR program

The load involves 3 terms: (i) fixed, (ii) variable, (iii) curtailable. The DR program optimizes the variable with curtailable loads. Fig. 4 shows the Electric Vehicle assisted Demand side EM system.

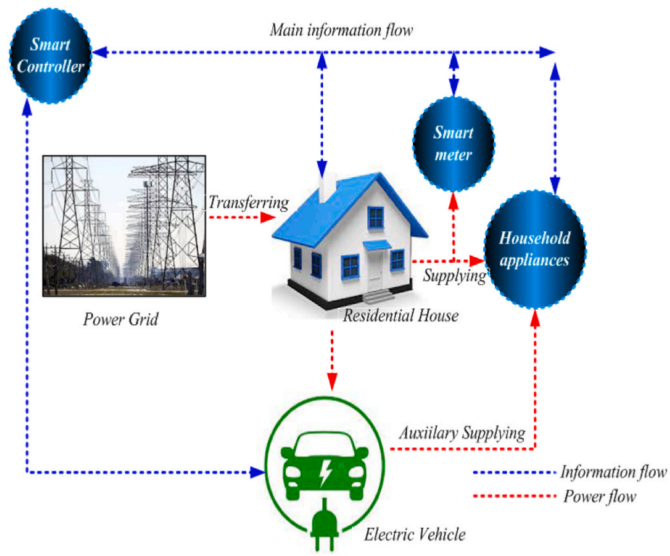

Fig. 4. Electric Vehicle assisted Demand side EM system.

The level of curtailment load is scaled as a percentage of base fixed loads.

$$p_{CR}^{T1,T2} \le p_{FR}^{T1,T2} \times cl \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{41}$$

$$p_{CC}^{T1,T2} \le p_{FC}^{T1,T2} \times cl \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{42}$$

The building of residential variable load is computed as fixed load percentage (43). The load adjustment level on every hour is controlled by (44), the entire energy of variable load is computed using (45)

$$V_{VR}^{T1,T2} = p_{FR}^{T1,T2} \times vl \times K_{VR}^{T1,T2} \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{43}$$

$$K_{VR}^{T1,T2} \le K_{VR}^{\max} \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{44}$$

$$\sum_{T1 \in [1,...24]} K_{VR}^{T1,T2} = 24 \forall T_2 \in [1,....,4] \tag{45}$$

$$p_{VC}^{T1,T2} = p_{FC}^{T1,T2} \times vl \times K_{VC}^{T1,T2} \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{46}$$

$$K_{VC}^{T1,T2} \le K_{VC}^{\max} \forall T_1 \in [1,...,24], T_2 \in [1,....,4] \tag{47}$$

$$\sum_{T1 \in [1,...24]} K_{VC}^{T1,T2} = 24 \forall T_2 \in [1,....,4] \tag{48}$$

5. Proposed methodology of chicken search optimization algorithm and spike neural network learning algorithm

This paper proposes an EM for building resilience against outage by SPS for EVs with DR program. The proposed system is consolidation of CSOA and SNNLA, and hence it is known as CSOA-SNNLA method. To create more robust model, the 2 commercial with residential buildings are deemed, also the SPS is designed for EVs. EVs inside the parking station are available in a variety of forms, as the commercial building utilizes at day time, also the residential building mostly utilizes at midnight. These variations help to utilize the vehicles for additional hours. Load is structured through the parts of modifiable, curtailable, critical, and fixed. The modifiable with curtailable adjusted through CSOA technique. The part of critical might help any time. The EVs are obtainable in SPS along its charge/discharge process is optimized by SNNLA method.

5.1. Chicken search optimization algorithm

Step 1: The chicken swarm is initialized, then fix parameters *N; NR; NH; Nc; Nm; G, M*
Step 2: To every chicken, compute their fitness value, then initialize the current with global optimum location, let t = 1
Step 3: If mod (t, G) D 1, sort every chickens increasing order as per its fitness values, NR chickens act from roosters, every rooster representing a group. The last NC chickens assigned as chicks, others will be chickens.
Step 4: Inform the rooster, hen, and chick locations utilizing (49), (50), and (51).

$$X_i^J(T+`1) = X_i^J(T) * \left(1 + RandN\left(0.\sigma^2\right)\right) \tag{49}$$

$$X_i^J(T+`1) = X_i^J(T) + s_1 * Rand * \left(X_{R1}^J(T) - X_i^J(T)\right) + s_2 * Rand \tag{50}$$

$$X_i^J(T+`1) = \omega * X_i^J(T) + fl * \left(X_M^J(T) - X_i^J(T)\right) \tag{51}$$

Step 5: Recomputed every chicken fitness value, and then updated the global optimum with current optimum position to every chicken.
Step 6: Check if the condition of repetition conclusion is fulfilled, if so, output the comprehensive optimum position then stopover the repetition; else, move Step 3

5.2. Spike Neural Network Learning Algorithm [38]

Step 1: Initiation

Initiate the decision variable is utilized to specify that synaptic weights in SNN. It is essential to deliver that upper and lower bound of synaptic weights.

Step 2: Membrane Structure

The proposed approach contains a 2-layer: skin, several membranes. The skin requires outer membrane structure has objects in its region. It has numerous elemental membranes on skin membrane.

Step 3: Reaction Rules

A CRO is an established rules mechanism for the evolution of objects at membrane. CRO consumes four essential reaction rules, exactly about wall, decomposition, synthesis, interaction, self-organization, and other processes. The proposed algorithm has 2 individual objects and 2 evolutions of objects in the membrane. The maximum number of colliding molecules on membrane 2. The object on cell takes characteristics of random walk or Brownian motion.

$$W^* = W + \gamma \oplus Levy\ (\lambda) \tag{52}$$

SSN learning algorithm utilized to $\gamma = 1$ *and* $\lambda = 1.2$. Eqns. (53) and (54) delivers those evolution rules of both objects.

$$W_1^* = \begin{cases} W_2 + (W_2 - W_o) * \ normalized * 0.12, rand < 0.1 \\ W_1 + (W_0 - W_2) * \ rand, Otherwise \end{cases} \tag{53}$$

$$W_2^* = \begin{cases} W_1 + (W_1 - W_o) * \ normalized * 0.12, rand < 0.1 \\ W_2 + (W_0 - W_1) * \ rand, Otherwise \end{cases} \tag{54}$$

Step 4: Fitness Function

Fitness function depends on synaptic weights of INM. This synaptic weight of the spike neural network is altered to execute reaction rules.

Step 5: Assessment Indicators

It is employed to judge the performance of related methodologies.

$$cpi = \frac{n}{N} \tag{55}$$

here n denotes number of rigorous classifications. The SNN algorithm is finished it is prepared to generate that control pulses based on gain parameters. Fig. 5 shows the flowchart of the proposed CSOA-SNNLA approach.

6. Result and discussion

In this section, an EM is proposed to build resiliency against power outages by SPS for EVs with DR. The proposed system is consolidation of CSOA and SNNLA; therefore it is named CSOA-SNNLA system. System includes residential and commercial buildings. At first, the system is simulated under normal operating conditions and system is simulated under different interruptions. Table 1 illustrates the parameter of demand response and electric vehicles.

6.1. 2–8 outage of each weather conditions

2-8 outage of weather condition during summer, winter, spring and fall is shown in Fig. 6. The 2–8 outage during summer is shown in Fig. 6 (a), the 2–8 outage during winter is shown in Fig. 6(b), the 2–8 outages during spring is shown in Fig. 6(c) and the 2–8 outage during fall is shown in Fig. 6(d). In each figure, two periods of electrical resistance are examined; they are off and on peak load conditions. During off-peak hours, the power outage continues for 2–8 h. This system cannot be

Table 1
Demand response program and parameters of electric vehicles.

Parameter	Level
Vehicles initial power (%)	10
Residential building vehicle capacity (kWh)	20
Commercial building vehicle capacity (kWh)	30
Charging facility power (kW)	30
Part load option (%)	80
Residential building maximum load (kW)	20
Commercial building maximum load (kW)	10
Variable load level (%)	20
Critical load (%)	10
Charge Reduction Penalty Cost/Electricity Cost (%)	400
Partial Charge Penalty Cost/Electricity Cost (%)	300
charge adjustment level at every hour	3
Maximal load shedding if EVs are accessible (%)	90
Maximal load shedding if EVs are not accessible (%)	100

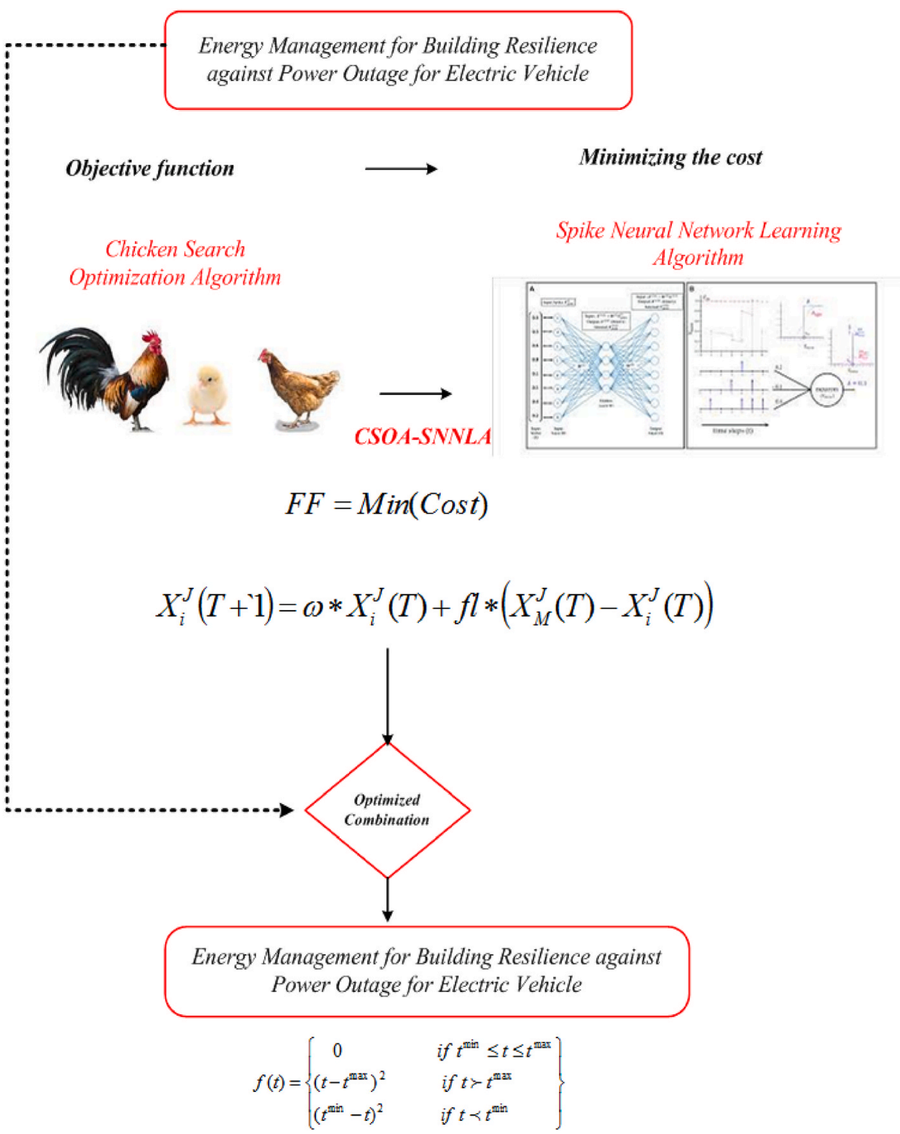

Fig. 5. Flowchart of CSOA-SNNLA

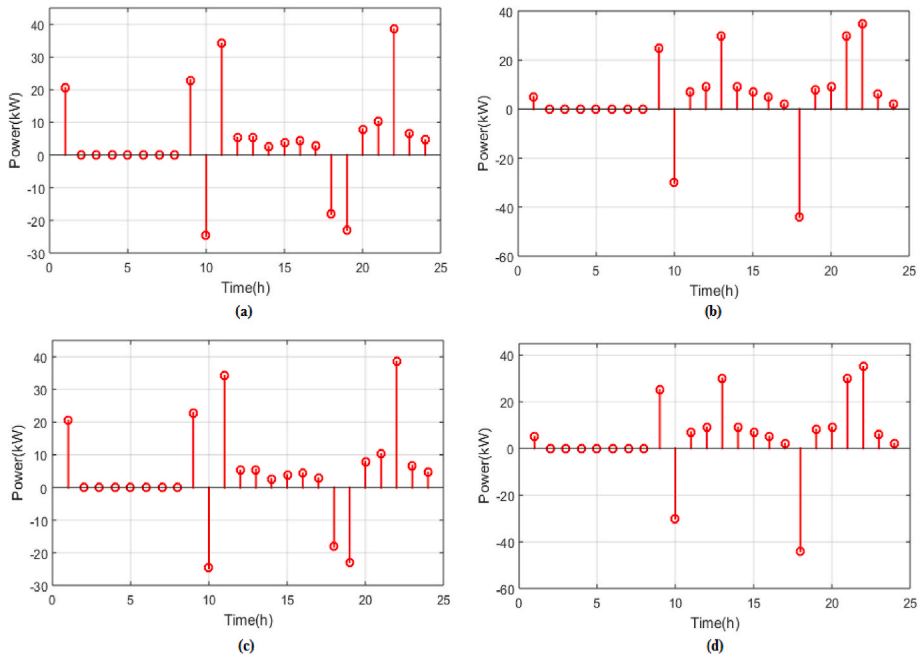

Fig. 6. 2–8 Outage of weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

activated if there is a power outage for more than 7 h that may be deal with specified model during shutdown stages. The building may continue their operation using the accessible energy resources, such as EVs are demand response programs.

6.2. 7–12 outage of each weather conditions

7-12 outage of each weather condition during summer, winter, spring and fall is presented in Fig. 7. The 7–12 outage during summer is shown in Fig. 7(a), the 7–12 outage during winter is shown in Fig. 7(b), the 7–12 outages during spring is shown in Fig. 7(c) and the 7–12 outage during fall is shown in Fig. 7(d). Two periods of electrical resistance are examined one at off-peak load and other at on-peak load condition. EVs can enable the building to continue their operation using available energy resources such as demand response programs.

6.3. Charging and discharging of each weather conditions

Fig. 8 suggests the charge-discharge process of EVs at buildings. Electric vehicles can operate with partial load when required. Though, in this case, the actions are not modeled and the project does not adopt the partial load option. As a consequence, the vehicles are completely charged when they leave. The vehicles are loaded and unloaded to diminish energy consumption are not to handle. It is clear that vehicles are charged while power is low exclusive as well as discharged while power is more exclusive as 18–19 h.

6.4. Load profile of each weather conditions

Load profile of weather condition during summer, winter, spring and fall is shown in Fig. 9. In subplot (a) load profile of weather condition during summer is presented. Here the commercial and residential load

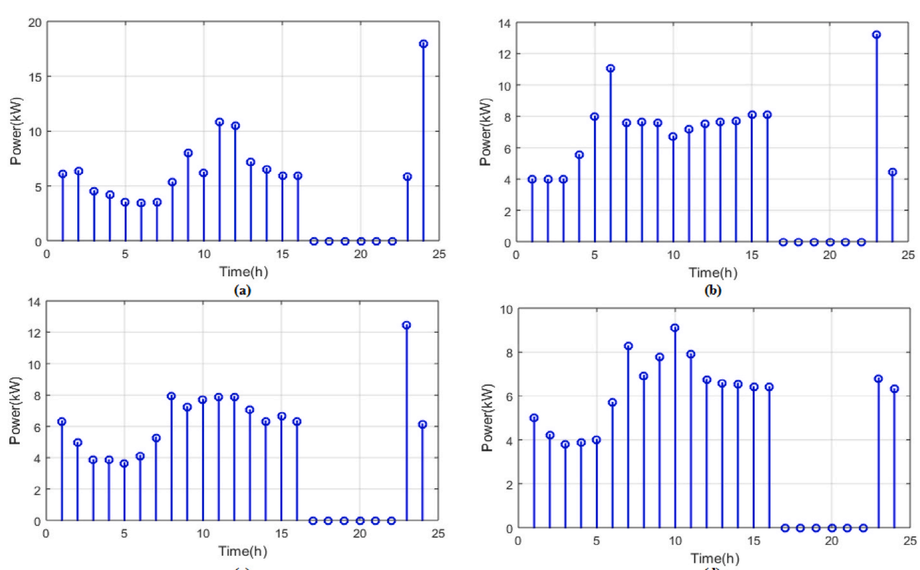

Fig. 7. 7–12 Outage of weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

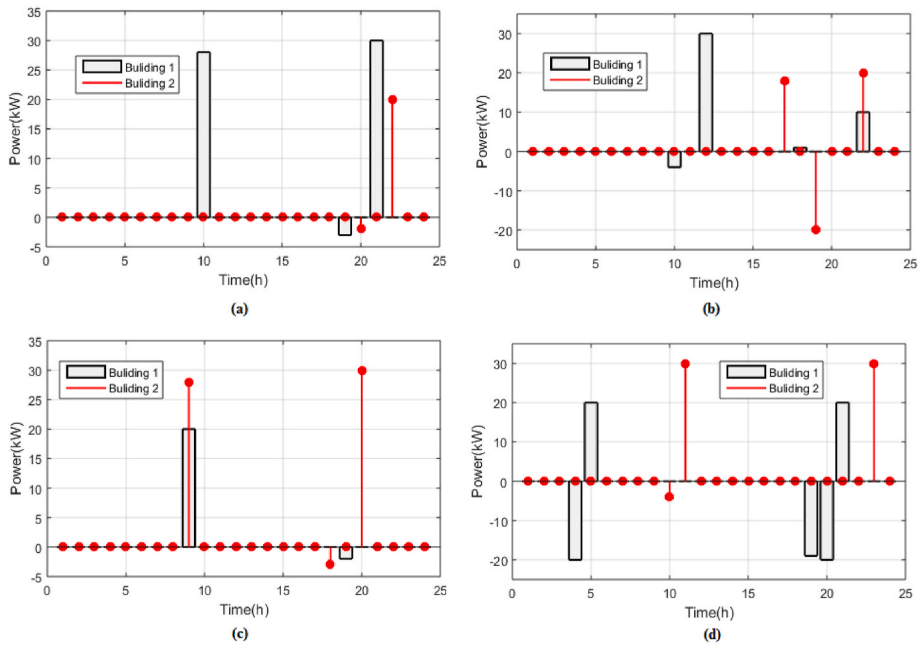

Fig. 8. Charging and discharging of building during weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

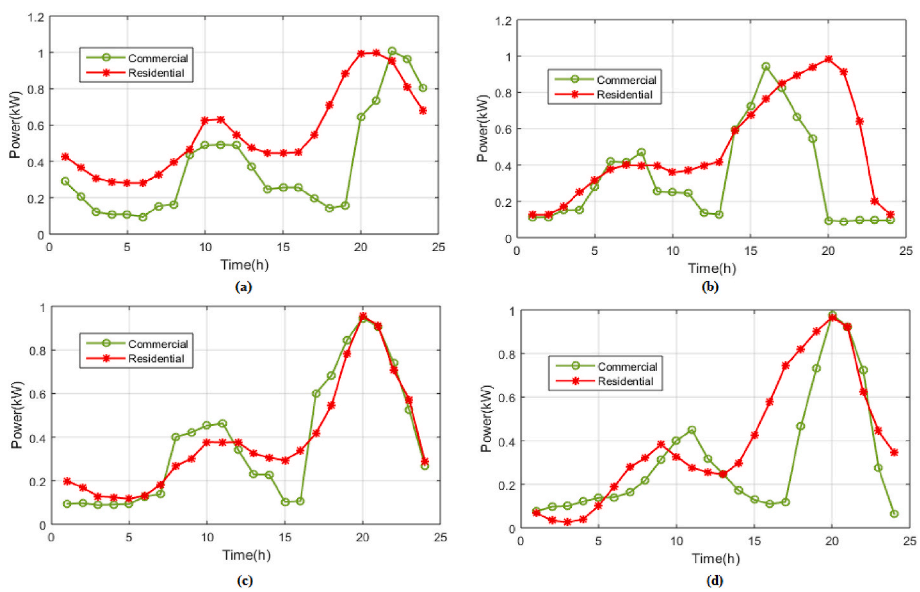

Fig. 9. Load profile of weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

profile is presented. Here the power flows from the commercial of 0.3 W at 0 h and it increased up to 0.45 W at 10 h time interval and it greatly increased up to 1 W at 22 h. The power flows from the residential of 0.4 at 0 h then it maximized up to 0.6 W at 10 h and it greatly maximized up to 1 W at 20 h. In subplot (b) load profile of weather condition during winter is presented. Here the commercial and residential load profile is presented. Here the power flows from the commercial of 0.15 W at 0 h and it increased up to 0.45 W at 8 h and it greatly maximized up to 0.99 W at 16 h. Power flows from residential 0.19 in the 0 h time period, then increased to 0.6 W in the 13 h time period, and increased to 1 W in the 20 h time period.

In subplot (c) load profile of weather condition during spring is presented. Here the commercial and residential load profile is presented. Here the power flows from the commercial of 0.15 W at the 0 h time period and increased to 0.45 W at the 8 h time period and increased to 0.99 W at the 16 h time period. Power flows from residential 0.19 in the 0 h time period, then increased to 0.6 W in the 13 h time period, and increased to 1 W in the 20 h time period. In subplot (d) the load profile of the climatic conditions during the fall is presented. Here is the commercial and residential load profile. Here the power flows from the commercial of 0.15 W at the 0 h time period and increased to 0.45 W at the 8 h time period and increased to 0.99 W at the 16 h time period. Power flows from residential 0.19 in the 0 h time period, then increased to 0.6 W in the 13 h time period, and increased to 1 W in the 20 h time period.

6.5. *Power commercial of each weather conditions*

The electrical grid to commercial building is shown in Fig. 10. In spring, the electricity is entirely positive and does not transmit power

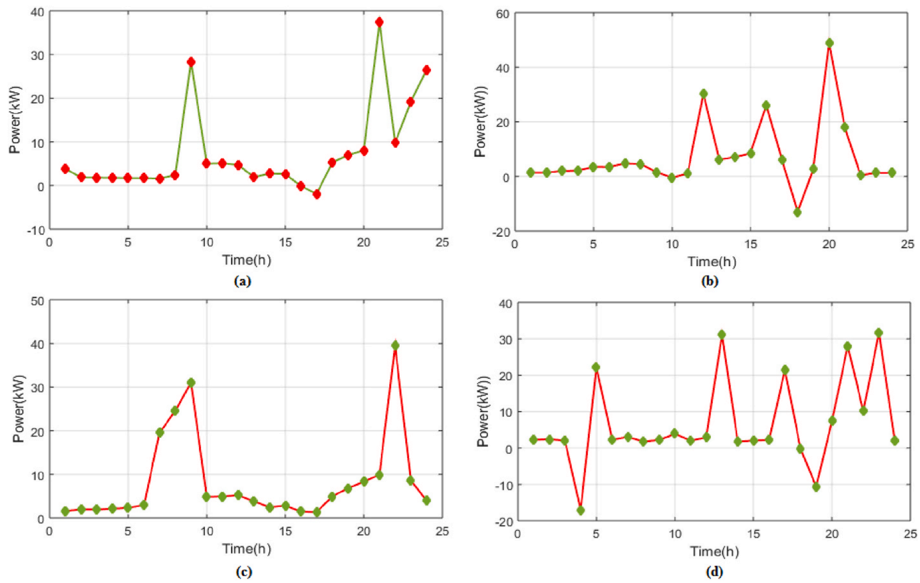

Fig. 10. Power commercial of each weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

with the grid. At summer, the building transmits power grid at 6:00 p.m. At that time electricity is expensive so it was necessary to make a profit. In autumn, charging power is not like other seasons. As a consequence, the building may pump their excess energy into the grid. In winter, there is also energy transfer among building and grid.

6.6. Power Residential of each weather conditions

The grid for the residential building at all stations is portrays in Fig. 11. The power required by building is substantial as well as energy management options cannot help the building transmit power to the grid at peak times. Power is received as upstream network at the entire times.

6.7. Price of each weather conditions

Fig. 12 portrays price of each summer, winter, spring and autumn weather condition. In subplot (a) the price during the summer is presented. In summer, the price of energy remains constant at $0.06/kWh in the period from 0 to 10 h and the price of energy increases to $0.09/kWh in the period from 11 h and the price of energy increased considerably to $0.13/kWh within 24 h. In subplot (b) the price during the winter is presented. In winter, electricity prices remain unchanged at $ 0.1/kWh in 0–6 h and sharply rise to $ 0.14/kWh over 7 h. In subplot (c) the price during the spring is presented. In spring, the price of energy remains constant at $0.06/kWh in the period from 0 to 10 h and the price of energy increased considerably to $0.14/kWh in the period of 15 h. In subplot (d) the price during the fall is presented. In autumn, the energy price remains constant at $0.1/kWh in the 0–5 h time period and the energy price increased sharply to $0.14/kWh in the 7 h time period.

6.8. Charge power vs plan cost

The nominal power of charging installation against project cost portrays in Fig. 13. Since the vehicle's battery capacity is low, it is

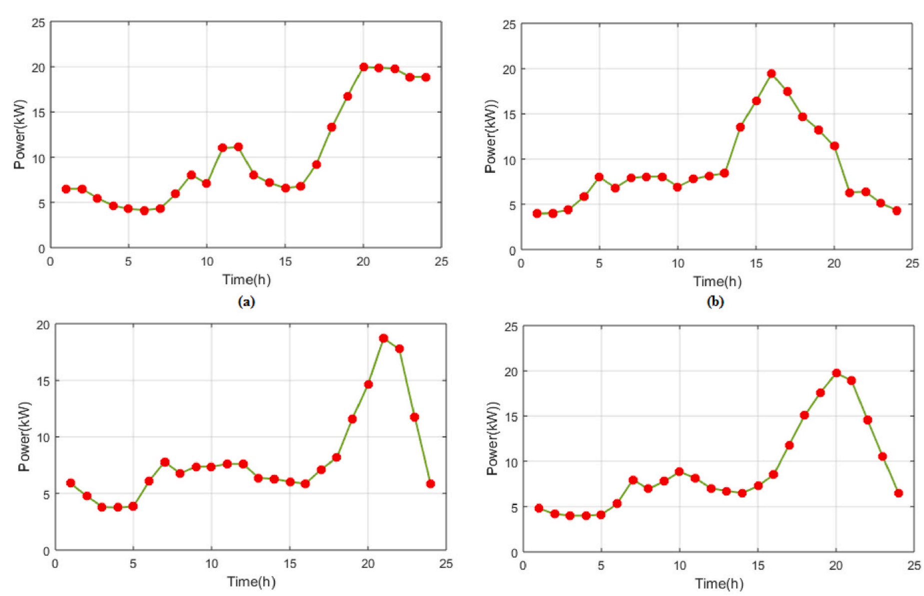

Fig. 11. Power Residential of each weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

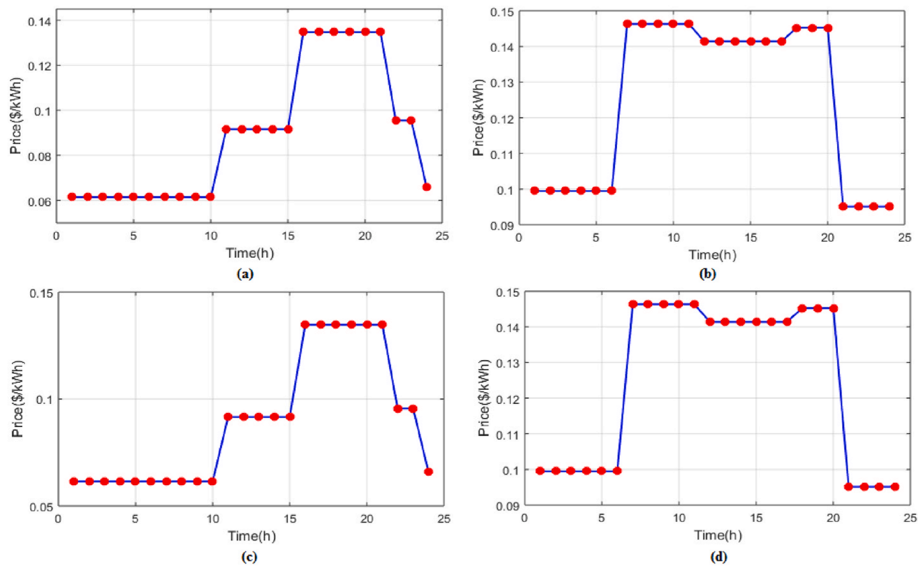

Fig. 12. Price of each weather conditions (a) Summer (b) Winter (c) Spring (d) Fall.

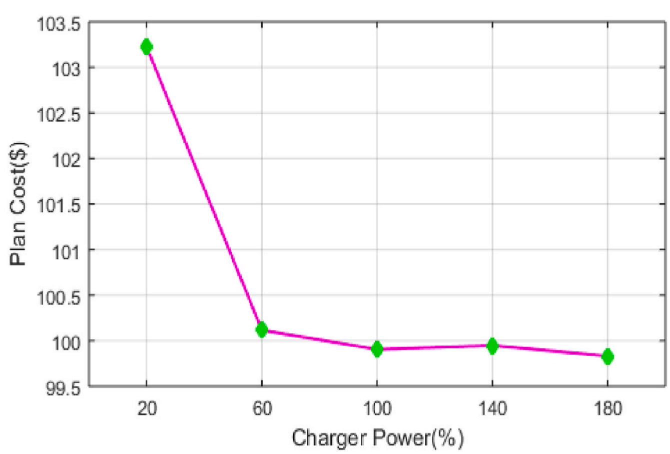

Fig. 13. Charger power vs. plan cost.

important to note that installing a greater charger will not have an important impact on cost of project.

Table 2 shows the various costs under normal state without event. Operated EM option to handle with power outage is tabulated in Table 3. Table 4 shows the output of EM option at 8 h under power outage. The output of EM choice under power outage at 13 h is tabulated in Table 5. The output of EM option at 24 h under power outage is tabulated in Table 6.

From Table 7 viewed that the accuracy percentage of dissimilar systems has a low CAP. The proposed system is high and more optimal to dissimilar methods. The CAP estimate of proposed system is 7.375%. A different conventional procedure, for instance, SSA, CSO and comparable load demand is related as well as total cost is solved. The viability of the proposed system has been established at comparative outcomes.

Table 2
Various costs without event under normal condition.

Item	Cost
Cost of energy for commercial building ($/year)	6285.100
Cost of energy for commercial building ($/year)	8364.000
Overall cost of energy ($/year)	1651.200
Cost of vehicles partial charge ($/year)	0
Load cost ($/year)	0

Table 8 tabulates the model fitted at entire accessible sample across the outcomes for 5 cut-off points: This model fitted at the general accessible data in 1st column, the fitting sample has 80% existing data in 2nd column, 75% existing data on 3rd column, 70% existing data on 4th column, 66% existing data on 5th column, 50% on 6thcolumn.

Table 9 tabulated the statistical index proposed and existing methods. The proposed value of, means is 0.854, median is 0.840 and standard deviation is 0.027. The CSO of means is 0.876, median is 0.864, and standard deviation is 0.022. The SSA of means is 0.917, median is 0.899, and standard deviation is 0.030. From this analysis, it concludes that the proposed method is better than the existing one. Table 10 depicts the comparison table for proposed with existing techniques. The efficiency of proposed methods becomes 95.700%. The existing methods, like CSO, and SSA efficiency becomes 79.300%, 86.500%. From the result the proposed method has higher efficiency compared to the other techniques.

7. Conclusion

This paper proposes an energy management to build resilience against power outage through SPS for EVs with DR program using CSOA-SNNLA technique. The performance of the proposed system is implemented in MATLAB platform and related with several existing systems. The plan does not use partial load and load shedding selections under normal non-event conditions. Energy management tools i.e. demand response scheme and EVs can be used to send energy to the electrical phase. Due to the low load requirement, commercial building may transmit power to electrical phase, but receives electricity only from the residential building phase. Variable loads adjust to diminish energy costs. The power outage is modeled at dissimilar times of day. The vehicles diminish the cost of this energy program by approximately 25%. The model can accept power outages of 2–8 h under off-peak load conditions and 17–22 h under peak load conditions. Finally, this paper proposes some resilience improvement measures for energy management of building in future research. The proposed approach CSOA-SNNLA approach is traditionally cooperative without any central control and works based on simple and local behaviour. A collective behaviour capable of solving complex tasks emerges only through its interactions. These features lead to major advantages of adaptability, robustness and scalability of swarms. In real life, this optimization approach has been revealed to enable groups to arrive optimized decisions, prioritizations, and forecasts in much less time than traditional

Table 3
Operated EM options to deal through power.

Partial vehicles charge						Load curtailment			
Hour of Back out	Cost ($/Year)	Summer	Winter	Spring	Fall	Summer	Winter	Spring	Fall
1–6	15,661	–	–	–	–	–	–	–	–
7	15,849	–	–	–	–	–	–	–	–
8	16,894	✓	✓	✓	✓	✓	✓	✓	✓
9	16,670	–	–	–	–	✓	✓	✓	✓
10	15,661	–	–	–	–	–		–	–
11	15,736	–	–	–	–	–	–	–	–
12	15,767	–	–	–	–	–	–	–	–
13	16,694	✓	✓	✓	✓	✓	✓	✓	✓
14	17,015	–	✓	–	–	✓	✓	✓	✓
15	17,029	–	✓	–	–	✓	✓	✓	✓
16	17,444	–	✓	–	–	✓	✓	✓	✓
17	17,691	–	–	–	–	–	–	–	–
18	15,991	–	–	–	–	–	–	–	–
19–20	15,661	–	–	–	–	–	–	–	–
21	16,010	–	–	–	–	–	–	–	–
22	15,871	–	–	–	–	–	–	–	–
23	15,826	✓	✓	✓	✓	✓	✓	✓	✓
24	15,739	–	–	–	–	✓	✓	✓	✓

Table 4
Output of EM option in power outage at 8 h.

Load Curtailment at 8 h (kW)				Charger level for vehicles (%)			Variable load level at 8 h (%)		
	Proposed	SSA	CSO	Proposed	SSA	CSO	Proposed	SSA	CSO
Summer	1.567	0.924	0.678	100	80	75	0	0	0
Winter	4.882	4.020	4.010	100	80	75	0	0	0
Spring	1.374	1.154	1.146	100	80	75	0	0	0
Fall	1.515	3.064	3.015	100	80	75	0	0	0

Table 5
Output of EM in power outage at 13 h.

Load Curtailment at 8 h (kW)				Charger level for vehicles (%)			Variable load level at 8 h (%)		
	Proposed	SSA	CSO	Proposed	SSA	CSO	Proposed	SSA	CSO
Summer	4.882	1.240	1.678	80	100	70	0	0	0
Winter	5.882	5.020	5.010	80	100	70	0	0	0
Spring	3.374	2.154	2.460	80	100	70	0	0	0
Fall	2.415	4.074	3.015	80	100	70	0	0	0

Table 6
Output of EM option in power outage at 24 h.

Load Curtailment at 8 h (kW)				Charger level for vehicles (%)			Variable load level at 8 h (%)		
	Proposed	SSA	CSO	Proposed	SSA	CSO	Proposed	SSA	CSO
Summer	6.882	4.240	2.678	60	100	55	0	0	0
Winter	2.882	1.020	4.010	60	100	55	0	0	0
Spring	7.374	5.154	3.460	60	100	55	0	0	0

Table 7
Performance comparison of dissimilar systems.

Solution	Best	Worst	CAP %
CSO	0.641	3.669	4.722
SSA	0.565	3.761	5.647
Proposed	0.423	3.550	7.375

methods. In other words, thinking together about optimization makes groups smarter and faster. According to recent study, the electric vehicle (EV) market is predictable to be worth at least Rs 475 billion by 2025. The penetration of electric two-wheelers is predicted to reach up to 15% by 2025 from the current 1%.

Data availability statement

Data sharing does not apply to this article as no novel data has been produced under this study.

Ethical approval

This article does not have any studies with human participants executed by any of the authors.

Code availability

Not applicable.

Table 8
Optimal size for fitting and validation samples.

Data splitting: optimal cut-off point −100 iterations											
Solution strategy fitting size	100%	80%		75%		70%		66%		50%	
	All sample	Median	-CVar	Median	-CVar	Median	-CVar	Median	-CVar	Median	-CVar
CSO	5.640	5.700	32	5.300	38	5.600	48	5.600	56	6.300	87
SSA	0.220	0.200	69	0.715	25	0.200	115	0.200	101	0.300	134
Proposed	0.420	0.481	27	0.733	23	0.520	39	0.517	36	0.530	39

Table 9
Statistical analysis.

Solution Technique	Mean	Median	Standard Deviation (SD)
SSA	0.917	0.899	0.030
CSO	0.876	0.864	0.022
Proposed CSOA-SNNLA	0.854	0.840	0.027

Table 10
Comparison table for proposed with existing techniques.

Techniques	Efficiency
Proposed CSOA-SNNLA	95.700%
CSO [40]	79.300%
SSA [41]	86.500%

Consent to participate

Not applicable.

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.

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