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Development of Short-Term Load Forecasting Model for DSM by Regulating Charging and Discharging of EVs and ESS with RES Based on the Prediction of this Model

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Abstract

Global organisations are concentrating on lowering greenhouse emissions as a result of the enormous environmental pollution caused by the usage of conventional energy sources. The expensive price of an electric vehicle and the absence its charging stations, however, prevent their mass adoption. This study suggests a data-driven demand side management strategy can be used to manage the electricity demand for an electric vehicle charging station of electric vehicles connected to a microgrid powered by photovoltaics. The suggested approach lessens dependency on traditional energy sources and addresses the lack of electric vehicle charging facilities by utilising solar-powered charging stations to meet energy demands during peak times. Real-time data from photovoltaic power plants, industrial and residential demands, and electric vehicle charging stations was gathered so that it could mimic the system. The electric vehicles are charged during the off-peak times in order to regulate the energy that is supplied to the microgrid and also determine the energy storage system's level of charge, a hybrid genetic algorithm sperm swarm optimisation approach was designed. The outcomes show that the electric vehicle charging station effectively offset peak demand during those hours.

Keywords: Load Forecasting, Electric Vehicle Charging Station, Demand Side Management, Hybrid Optimization, Renewable Energy Integration.

1. Introduction

There is an urgent need to reduce greenhouse gas emissions as the world faces more serious environmental problems [1]. Electrification of transportation and the usage of renewable energy sources (RES) are two of the most promising strategies being investigated to address these issues and the world's energy needs [2]. Therefore, the usage of RES and electric vehicles (EVs) is becoming more prevalent in the power generation and transportation sectors. Although conventional energy sources account for the majority of the electricity produced today, RES are being incorporated into conventional grid to meet the growing demand for electricity [3]. As more minor units linked to the distribution grids, the centralised power system has given way to one with a more decentralised structure as a result of this evolution [4]. With the ability to accommodate additional capacities directly at the user end or the main grid itself, the distributed energy resources (DERs) could support the energy generation at the central level. Renewable energy production systems, however, are highly unpredictable and climate-dependent [5]. Hence, the load demand might surpass the maximum capacity if the grid balance is not efficiently maintained during peak hours, causing instabilities in the networks or even leading to a blackout [6]. For the majority of the time, generation capacity is underutilised, and peak demand periods are often brief. The majority of the time, short-term peak loads are managed using diesel engine plants or pump storage hydroelectricity. In order to manage the peak load, they can now be used as temporary energy storage devices because to advancements in EVs and battery technology. This is due to the fact that an EV's idle period is much larger than that of EV's charging time [7]. Hence, the other energy storage systems (ESS) along the electric vehicles are crucial for preserving the system's power balance. Peak demand management (PDM) with a renewable energy storage system reduces the environmental pollution and the use of fossil fuels.

Electric grid support services are often provided on a scale of hundreds of kilowatts to manage peak load on the grid, whereas a single EV can only supply a finite amount of electricity. The idea of an aggregator has been established in order to obtain large-scale power ratings [8], [9]. An EV aggregator can operate as a bridge power grids and the electric vehicles, acting as a third-party entity like an EV charging station. When enough EVs are combined, they can function as a reliable and significant part of DERs by utilizing a foundational energy storage system and can act as a substantial source of energy [10].

A better environment with much reduced greenhouse emissions and less noise pollution can be achieved by using electric automobiles. The higher price of electric vehicles and the absence of an electric vehicle charging infrastructure, however, continue to be significant barriers to mainstream EV adoption [11]. EV owners are waiting for suitable charging infrastructure, while investors are waiting for widespread EV adoption to benefit from EV charging stations.

Investigating other revenue streams is important to improve the viability of EV charging infrastructure. Grid peak-load control may be accomplished via an integrated EV charging station that makes use of RES and contains an ESS,

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generating income for investors [12]. By giving charging stations another source of income, this strategy would lessen the issue of an inadequate EV charging infrastructure.

When combined with EVs and an ESS, an EV charging station serves as a dynamic battery that can be utilised for demand-side management (DSM) during peak hours [13]. Fast reaction times, no start-up or shut-down fees, and a solution to the uncertain nature of RES are all advantages of the EV aggregator. A possible structure for incorporating EV charging stations into DSM operations is illustrated in Fig. 1.

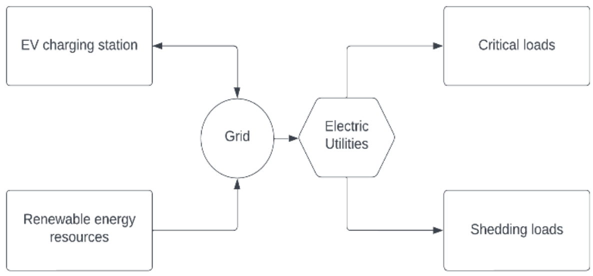

Fig. 1. Proposed model architecture for EV charging station system integration into microgrid.

In DSM programmes that include EVs, environmental issues are taken into account in addition to financial goals. Vehicle-to-grid (V2G), which enables EVs to provide grid support services while charging or parked, is an illustration of such a system. Moreover, V2G can lessen the demand for new power plants, improve the grid's integration of renewable energy sources, and cut overall carbon emissions [14]. Researchers looked into the possibility of peak shaving and frequency regulation in a grid that integrates renewable energy utilising V2G technology [15]. The findings demonstrated that by offering ancillary services, V2G has the potential to lower peak load and guarantee grid stability. Also, it was discovered that V2G increased the use of RES and decreased greenhouse gas emissions. The study also found a requirement for an ideal scheduling system that takes EV users' preferred charging practises into account and prevents battery deterioration [16]. DSM programmes that include EVs have the potential to reduce carbon emissions and improve grid stability, while also providing financial advantages to utility operators and customers.

These analyses emphasise the potential advantages of including EVs and ESSs in DSM plans to raise the general effectiveness and profitability of electric power networks. According to Tong et al., repurposing retired car traction batteries can increase the energy system's overall sustainability while giving EV owners an additional source of income. According to [17], [18] the integration of automatic demand response (ADR) and demand response (DR) approaches could increase the responsiveness and dependability of energy system, that could lead to cost savings and higher customer satisfaction. The optimisation strategy put forth by [19] can serve as a foundation for making wise choices that minimise energy expenditures while taking end-user wants and values into account. These studies show that adding EVs and ESSs to DSM plans could increase the sustainability, dependability, and profitability of electric power systems [20], [21].

A DSM optimisation method was created by the authors of [22] that uses load shifting based Time of Use (ToU) at the household level and takes into consideration different home appliances, EV charging stations, and rooftop PV systems. With rooftop PV systems supplying energy and lowering the grid's carbon intensity, this method significantly reduced daily electricity expenditures while simultaneously significantly reducing home carbon emissions. As electric vehicles and renewable energy sources continue to gain popularity, proper scheduling of household loads can dramatically improve grid resilience and energy efficiency. The synchronization of pooled EV operations underneath a demand response is optimised by the two-stage planning optimisation approach that the authors of [23] developed. The primary stage involves choosing the charging station’s location, while as the secondary stage is concerned with moving the vehicles. This model accounts for charging ability uncertainty as well as supply-side and demand-side uncertainties, which were estimated using a sample average approximation. Other demand response elements, such as the production of solar and wind power, are not taken into account by the model [24]–[26].

Using Matlab, the authors of [27] created a solar-powered electric vehicle charging station that is managed by a particular type of car connector. They conducted an analysis of the circuit's operation and determined the model's parametric design parameters. To show the power factor correction with various steady-state loads, hardware was developed. Unfortunately, the impact of EV charging station on DSM was not examined in this study. A data-based outcome analysis technique for the EV charging behaviour at the charging infrastructure was proposed in [28] for increasing the usage of public electric vehicle charging station and the quality of service. The study, however, did not take into account the limitations of additional factors linked to the EV charging station. Using EV charging stations as a component of the microgrid and EVs as a part of the transportation network, the authors of [29] presented an electric vehicle charging infrastructure as a cyber physical system (CPS). Suggested algorithms balanced regional load patterns, EV charging habits, and charging cost optimisation. Batteries' limitations, RES, residential and business loads, however, were not taken into account in the study. The authors of [30] provided a system of mathematical equations for modelling the charging loads of electric vehicles using probabilistic load model. They tested the applicability and precision of the proposed approach using an actual battery-swapping charging station.

The authors of [31] presented a pricing strategy to dynamically modify peak loads. They created a constraint optimisation issue and used a heuristic method to optimise it in order to reduce the overlap between household loads and plug-in electric vehicles (PEV) during their peak load times. To successfully execute Demand-Side Management programmes, a number of elements must be taken into account, including state of charge (SoC) estimations, power and load forecasts, the identification of suitable users, and the creation of automatic system for managing the DERs [32]. Data-driven control and model predictive control methods are now employed to design dynamic nonlinear systems in power systems [33], [34]. Moreover, data-based methods are also employed in the power networks for a variety of tasks, including economical dispatch [35], efficient charging, handling the uncertainties associated with RES [36], and predicting SoC for ESS and electric vehicles [37]. The aggregator needs to be aware of the charge levels of the energy storage systems and electric vehicles taking part, as well as the reserved energy levels of every system involved in managing the load, in order to operate a grid-connected, integrated photovoltaic EV charging station. Methods based on mathematical modelling are frequently employed for SoC estimate [38].

Due to batteries' complicated nonlinear nature, SoC estimation models frequently lack precision. These models often only work under predetermined conditions, like a specific battery type and a defined temperature, and new models must be created when other aspects are taken into account. Researchers have used hybrid optimisation techniques, which simulate the complexity of a system using pertinent data, to overcome these constraints. These techniques might give a more precise picture of the SoC levels in battery storage.

As the future goes towards precise control of end-user loads, load, and price projections in demand response in smart grids need to be more precise. In order to forecast load and pricing in DR, conventional time-series models like AR, ARIMA, and exponential smoothing have long been employed [39]. However, because these models assume linearity, it has been found that they are less accurate at predicting load. Due to its ability to approximation exceedingly complex relationships, hybrid optimisation approaches have been utilised to get around these restrictions. Hybrid metaheuristic techniques are also anticipated to offer even more precise load and pricing estimates in DSM as demand becomes more complicated [32].

In order to forecast load, the study used a hybrid metaheuristic method called Hybrid Genetic Algorithm Sperm Swarm Optimization (HGA-SSO). In order to take advantage of each technique's advantages, this algorithm combines Sperm Swarm Optimization (SSO) with Genetic Algorithms (GA). GA is a population-based optimisation technique that mimics the process of natural selection, while SSO is a swarm intelligence programme inspired by the behaviour of sperm cells. These methods are combined to increase the performance of load forecasting and the accuracy of the results.

HGA-SSO optimises the parameters of prediction models, such as artificial neural networks or ARIMA models, to increase the precision of load forecasting. The algorithm works by repeatedly updating a set of possible solutions, each corresponding to a specific set of parameters for the prediction model. To get the best answer, it uses SSO to scour the search space and GA to take advantage of the existing best solutions.

HGA-SSO minimises the discrepancy between the expected load and the actual load in load forecasting, which is commonly quantified using performance metrics like MAPE or RMSE. To accommodate particular load forecasting needs, such as short-term or long-term forecasting, the algorithm has been fine-tuned. According to earlier research, HGA-SSO performs better in load forecasting than conventional algorithms like GA or SSO alone. HGA-effectiveness, SSO's however, is dependent both on the nature of the issue at hand and how the algorithm is actually put into practise. For a particular load forecasting situation, it is crucial to carefully choose the suitable prediction model and fine-tune the HGA-SSO algorithm's parameters.

The creation of an efficient load scheduling and electrical transportation network management system for peak loads control in RES enabled power networks is the key contribution of this research. The first step of control comprises managing the electric vehicles and solar systems combined into the EV charging station infrastructure, while the second stage of control focuses on building an intelligent controller for managing the peak load for a microgrid which incorporates RES and EV charging station. The many components of the planned transportation network were modelled using a data-driven methodology to handle the complexity of the components. It is important to note that when mathematical component modelling is employed, some variables can be difficult to execute in real-time.

2. Architecture of the Proposed Model and Methodology Used

Demand-side management, which tries to balance the load profile throughout the day and monitor and control peak energy demands, is an essential component of energy management. DSM's main goals are to reduce the capital costs of power plants and improve the economic aspects of power utility. Using energy storage systems, which store energy during off-peak times and release the stored energy into the grid at peak times to satisfy the increased load demand, is one of the most efficient methods for peak clipping. Using an ESS for DSM is thought to be a potential approach in this regard. The research paper's suggested methodology, which takes a novel approach to DSM, uses an electrical transportation system to regulate peak demand.

2.1. Modelling of the proposed system

This research focuses on using a PV-connected EV charging station to control peak grid demand and increase the station's profitability. An energy storage system, an EV charging station, household loads, important commercial loads, renewable energy sources, and EVs utilised for charging and discharging are all included in the system. Fig. 2 illustrates a two-stage structure for coordinating power between the grid and the EV charging station. In the first stage, a direct mode integration of the ESS and EV is used based on a dynamic source model. In the second stage, the power allocation of every subunit like the solar photovoltaic and energy storage system is established. Accurate modelling of these unknown parameters is essential in the process of distributing electricity across the units because the load and solar photovoltaics are the have uncertainties in the microgrid.

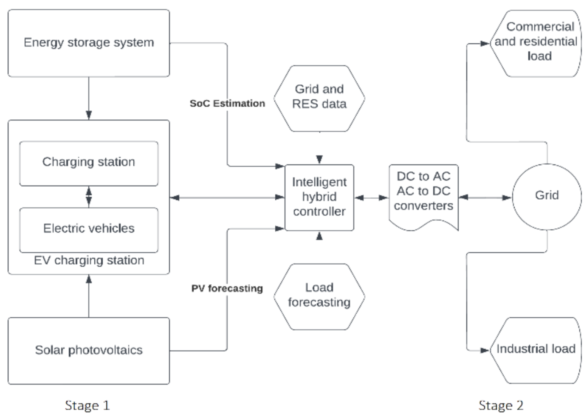

Fig. 2. Flow of power between the grid and EV charging. station.

2.1.1. Modelling of microgrid

The primary objective of this research is to create a model for demand side management load forecasting that makes use of electric vehicles. The main goal of the model is to lower overall expenses while optimising the total profits of the EV charging infrastructure throughout the dispatch period. The minimization of the sum of different expenses, including those associated with the EV charging station's grid supply, EV charging, and energy storage systems, can be quantitatively stated in Eq. 1.

$$\min C_p = \sum_{K=k_0}^{k_n}\left(\left(C_{Grid_s}(k) + C_{Grid_c}(k) + C_{EV_{cc}}(k) + C_{EV_{DG}}(k) + C_{ESS_{DG}}(k)\right)\right) \tag{1}$$

Eq. 2 defines the grid tariff as $C_{Grid_s}(k)$, which is applied during off-peak load.

$$C_{Grid_s}(k) = \beta_{gs}(k)\left|P_{gs}(k)\right|\Delta k \tag{2}$$

Eq. 3 defines $C_{Grid_c}(k)$ as the cost of the energy provided by the EV charging station during off-peak load.

$$C_{Grid_c}(k) = \beta_{CS_s}(k)|P_{CS}(k)|\Delta k \tag{3}$$

The power supplied $P_{CS}(k)$ and consumed $P_{gs}(k)$ by the EV charging station from the main grid, as well as the related energy purchase price $\beta_{CS_s}(k)$, sale price β_{CS_s} of the grid, are all represented in Eq. (3). The time period is represented by the symbol Δk.

Eq. 4 defines the term $C_{EV_{cc}}(k)$, which denotes the energy cost associated with charging an EV.

$$C_{EV_{cc}}(k) = \beta_{EV_{cc}}(k)|P_{EVC}(k)|\Delta k \tag{4}$$

In Eq. 4, P_{EVC} stands for the energy used by the EV while it is charging, and $\beta_{EV_{cc}}(k)$ stands for the grid's energy sale price at that time.

The terms "cost of energy storage system deterioration" and "cost of EV battery degradation" are provided in Eqs. 5 and 6, respectively.

$$C_{ESS_{DG}}(k) = \beta_{ES_{DG}}(k)|P_{ES}(k)|\Delta k \tag{5}$$

$$C_{EV_{DG}}(k) = \beta_{EV_{DG}}(k)|P_{EVd}(k)|\Delta k \tag{6}$$

The total power utilised by the ESS $P_{ES}(k)$ and EV $P_{EVd}(k)$ are shown in Eqs. 5 and 6, as well as the average charging costs for the energy storage system $\beta_{ES_{DG}}$ and electric vehicle $\beta_{EV_{DG}}$, respectively.

2.1.2. State of Charge of the Energy Storage System

An ESS's state of charge is a gauge of its capacity for energy. The ESS model is represented by Eq. 7 in terms of SoC.

$$SoC_{EVCS}(k+1) = \begin{cases} SoC_{EVCS}(k) + \left(P_{EVCS}(k)\frac{\Delta k \eta_{CSHS}}{E_{EVCS}}\right), \; P_{EVCS}(k) \geq 0 \\ SoC_{EVCS}(k) + \left(P_{EVCS}(k)\frac{\Delta k}{E_{EVCS}\eta_{CSDC}}\right), \; otherwise \end{cases} \tag{7}$$

Eq. 7 calculates the EV charging station's state of charge at time k, SoC_{EVCS}, taking into consideration the EV charging station's dispatched power $P_{EVCS}(k)$, charging efficiency (CSCH), and discharging efficiency (CSDC). E_{EVCS} is a representation of the EV charging infrastructural energy requirements.

The constraints of the model given in Eq. 7 are represented by Eqs. 8, 9, and 10.

$$SoC_{EVCS}^{min} \leq SoC_{EVCS}(k) \leq SoC_{EVCS}^{max} \tag{8}$$

$$P_{EVCS}^{min} \leq P_{EVCS}(k) \leq P_{EVCS}^{max} \tag{9}$$

$$P_{Grid}^{minCS} \leq P_{Grid}(k) \leq P_{Grid}^{maxgd} \tag{10}$$

SoC_{EVCS}^{max} and SoC_{EVCS}^{min}respectively, stand for the maximum and minimum charge levels of the EV charging stations. P_{EVCS}^{max} and P_{EVCS}^{min} respectively, stand for the maximum and minimum charging power requirements. P_{Grid} represents the maximum capacity of the grid. Also, P_{Grid}^{maxgd} and P_{Grid}^{minCS} respectively stand for the maximum and minimum power flowing from the grid to the EV charging station both in terms of EV charging station and vice versa. Eqs. 8, 9, and 10 describe these restrictions.

2.1.3. Modeling of EV charging station

The electric vehicle charging station is handled as one unit instead of considering it as a combination of various units like electric vehicles, energy storage system and solar photovoltaics in order to simplify the power coordination problem. The demand model of an electric vehicle charging station is created by taking into consideration the charging requirements and technological constraints of each electric vehicle. The concept presupposes that EV owners will exchange pertinent data like SoC, departure time, and arrival time. The charge level data of each energy source is gathered by the EV charging station for each time slot. Eqs. 11 and 12 show the limitations on how the EV charging station can operate during a given time period.

$$P_{EVCS}^{max}(k) = \sum_{n\epsilon N_k} P_{EV,n}^{max} + P_{ESS,n}^{max} \tag{11}$$

$$P_{EVCS}^{min}(k) = \sum_{n\epsilon N_k} P_{EV,n}^{min} + P_{ESS,n}^{min} \tag{12}$$

The terms $P_{EV,n}^{max}$ and $P_{ESS,n}^{max}$ in Eq. 11, respectively, denote the maximum power supply for the n^{th} electric vehicle and energy storage system. Similarly, $P_{EV,n}^{min}$ and $P_{ESS,n}^{min}$ represents the minimum amount of power that the n^{th} EV and ESS can supply, respectively.

Eq. 13 shows the maximum amount of energy that the ESSs connected to the EV charging station may produce, whereas Eq. 14 shows the energy produced by EVs for the full time period.

$$E_{ESS}(k) = \sum_{N=1}^{N=n} E_{ESS,n}(k) \tag{13}$$

$$E_{EV}(k) = \sum_{N=1}^{N=n}\left(SoC_{EV,n}(k+1) - SoC_{EV,n}(k)\right)E_{EV,n}(k) \tag{14}$$

EESS stands for energy given in its entirety to the n^{th} energy storage system at time k. A variable called $n(k)$ may stand for a particular index or parameter pertaining to the n^{th} energy storage system. The term "EEV" stands for "energy emitted by the n^{th} electric vehicle at time k." The term "SoC_{EV}" stands for the n^{th} electric vehicle's state of charge at time k.

2.2. Intelligent hybrid controller for power management

Using an intelligent controller is crucial for managing fluctuating demands and the discharging or charging of various power resources in DSM. An intelligent optimization-based controller is the best option for controlling the power flowing between the microgrid and electric vehicle charging station. The schematics of the control logic for managing peak loads is illustrated in Fig. 3. It determines if the total power demand on the grid P_{load} exceeds or is equivalent to the peak demand limit P_{min} and whether the present T falls inside grid's permitted time range ($T_{Pmin} - T_{Pmax}$). The EV charging station system is also restricted from taking part in peak load management unless its energy level exceeds a predefined threshold level. The controller determines if the charge level SoC of the EV batteries SoC_{EV} or the ESS SoC_{ESS} is larger than or equivalent to the designated threshold value after the current time surpasses the maximum time limit T_{Pmax} SoC_{EVCS}^{min}. If either condition is true, the controller will only permit the ESS to be charged if the peak load limit P_{load} is not reached P_{min}. By using this approach, the ESS will be charged at off-peak times, easing the loads on the system during peak times.

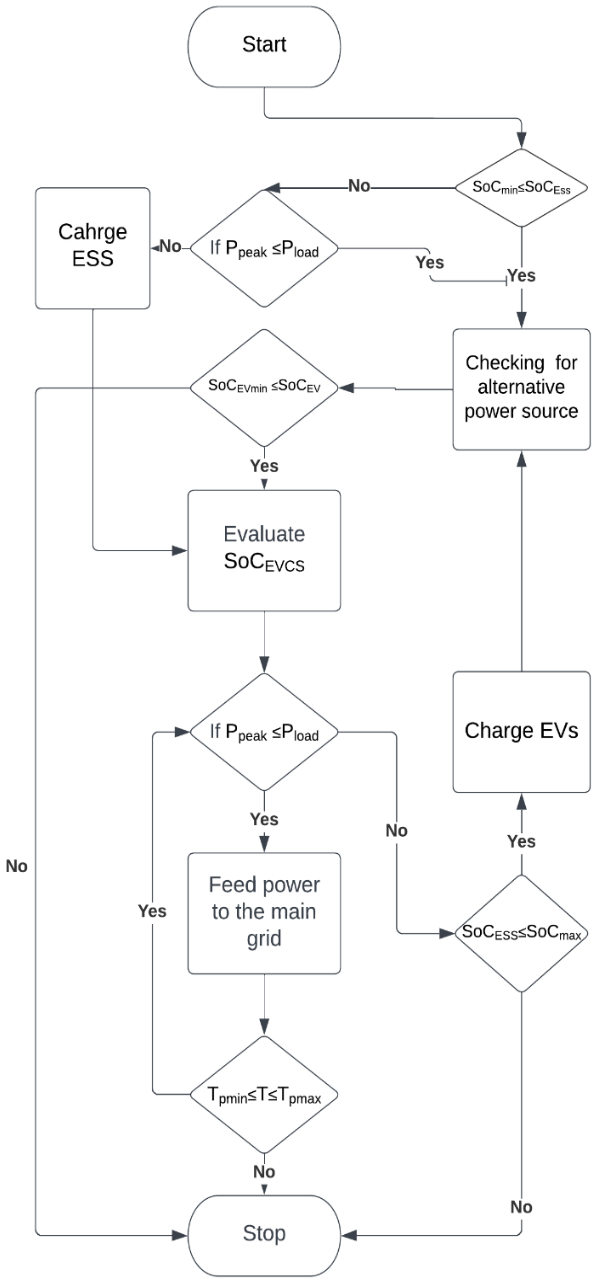

Fig. 3. Flowchart for management of peak loads.

3. Proposed Hybrid Genetic Algorithm-Sperm Swarm Optimization (HGA-SSO)

Hybrid metaheuristics are a valuable approach to resolving optimization problem as they find a middle ground between exploitation and exploration. Furthermore, they address the shortcomings of traditional algorithms by leveraging the strengths of multiple algorithms and mitigating their respective limitations.

In order to overcome difficulties in wireless sensor networks, sperm swarm optimization was suggested in a recent study. The natural fertilisation process, in which only one sperm cell is eventually successful after swarms of sperm cells travel towards the ova to fertilise it, serves as the model for this algorithm. The sperm cell swarm is randomly distributed in the cervix at the beginning of the optimisation process, moving at two speeds along the two-coordinate axis. The swarm's collective motion resembles "flocking" behaviour. In the female reproductive system, the pH value and temperature play an important role in the determination the motility and direction of the sperm cells' migration. These ideas are used by SSO to create a possible solution that explores a multidimensional searching to identify the best overall solution while also capturing the best local and overall solutions for subsequent iterations of optimisation.

The swarm of sperms functions as possible solutions that travel through a multidimensional search space to explore the overall optimal solution so that they can apply this biological process to an optimisation context. The algorithm also keeps track of the best results from the optimisation process, such as the ideal sperm, or the global parent sperm cell, which fertilises the ovum, and the local optimal solution, or the most effective sperm cell solution.

Over the past ten years, the genetic algorithm has become a well-liked optimisation technique for several applications, including ticket reservations, wireless sensor network, and power electronics [40]. An algorithm called GA was built on theory of natural selection proposed by Charles Darwin, in which the strongest individuals survive and procreate while the weaker individuals disappear. The GA method initiates with a chromosome population which is created at random and then undergo crossover and mutation procedures while being optimised.

Crossover operators allow for the precise exchange of genes from the chosen chromosomes, which serve as the parents and give rise to new offspring (solutions) [41]. This study uses a uniform crossover operator, which gives fewer diverse solutions but offers impartial exploration and may be utilised successfully on vast subsets. To avoid being stuck in local optima, mutation operators, in contrast, guarantee variation among individuals, in different generations of populations. Mutation operators produce a diverse result by changing a few genes on a single chromosome, causing it to inherit traits different from those of its parents [41].

3.1. Initialization

The sperm swarm optimisation algorithm goes through a number of iterations after the initiation phase in order to get the best outcome. The sperm cell swarm navigates the search space during each iteration using its prior placements as well as knowledge of the overall optimum solution. A velocity vector that tracks each sperm cell's motion is adjusted utilising Eq. 15 below:

$$V_{ij}^{(t+1)} = \omega V_{ij}^{t} + c_1 r_1 \left(P_{best_{ij}}^{t} - x_{ij}(t)\right) + c_2 r_2 \left(x_{sgBest_j} - x_{ij}(t)\right) \quad (15)$$

Where c_1 and c_2 are the coefficients of acceleration, ω is the inertia weight, r_1 and r_2 are randomized variables between 1 and 0, V_{ij}^{t} is the speed part of the i^{th} sperm cell in the j^{th} dimension at iteration i, and x_{sgBest_j} is the sperm cells' best location in the j^{th} dimension. The location of every sperm cell is revised after the velocity vector that use the Eq. 16:

$$x_{ij}(t+1) = x_{ij}(t) + V_{ij}^{(t+1)} \quad (16)$$

Where the i^{th} sperm cell's location in the j^{th} dimension at iteration t is represented by $x_{ij}(t)$.

The fitness of each sperm cell is then assessed and contrasted with the best fitness values for the individual and the world. A sperm cell's personal best is updated if another sperm cell has a higher fitness value than it does. Similar to this, the global best is updated if a sperm cell has a higher fitness value than the benchmark.

A stopping criterion, such as a maximum number of iterations or a desirable level of convergence, must be reached before the iteration process can cease. The algorithm then returns the best answer discovered during the iterations as the answer that best solves the optimisation problem.

3.2. Selection

Using the Roulette Wheel technique, two sperm cells are chosen out the initial population during the sperm swarm optimisation process, where each chromosome stands in for a potential solution. In order to choose particular chromosome sets for the crossover and mutation, this method randomly revolves the wheel. With the help of the Eq. 17, one may determine the likelihood of choosing particular candidates.

$$Prob_i = exp\left(\frac{-beta.Fiti}{WorstFit}\right) \quad (17)$$

$$Prob_i = exp\left(\frac{Prob_i}{\sum_{i=1}^{nPop} Fit}\right) \quad (18)$$

Where beta denotes selection pressure, $WorstFit$ is the poorest fitness attained, $nPop$ denotes population size, and $Fiti$ denotes chromosome fitness.

3.3. Crossover and mutation

After the sperm cells are chosen, the crossover procedure is started, that results in the development of a new population known as the crossover population. Then the process of mutation starts, when the sperm cells from the original population go through mutation to create a new mutant population.

3.4. Merging, sorting, and truncation

The mutation and crossover population are created, and then they are mixed and arranged in ascending order of fitness values. To make sure that just the finest population are kept, the resulting population is then trimmed to the population count, $nPop$, that was originally set.

3.5. Velocity and position updation

Eq. 19 is used to calculate the initial sperm velocity, or V_0, where V_1 is the maximum sperm velocity, Damp is the damping coefficient, and pH1 is the pH of the female reproductive system.

$$V_0 = Damp.V_i.log_{10}(pH_1) \quad (19)$$

The starting sperm velocity, V_0, is determined by the damping factor $Damp$, which ranges from 0 to 1, a pH value pH_1 and the current sperm velocity V_0 that is created at random and ranges from 7 to 14.

Eq. 20 represents the present best solution, which is established by the logarithms of two random pH and temperature values, $Temp_1$ and $Temp_2$, respectively. The difference between the sperm's personal best location, x_{sgBest_i} and the current location of sperm x_i during t^{th} iteration and is multiplied by these numbers (t). Eq. 21 represents the global best solution, which is established by the logarithms of two random temperature values ($Temp_1$ and pH_3). The difference between the sperm's present location at iteration t, x_i, and its optimal location globally, x_{sgBest}, is compounded by these numbers (t).

$$CurrentBestSol(t) = log_{10}(pH_2).log_{10}(Temp_1).(x_{sgBest_i} - x_i(t)) \quad (20)$$

$$GlobalBestSol(t) = log_{10}(pH_3).log_{10}(Temp_2).(x_{sgBest} - x_i(t)) \quad (21)$$

Using Eq. 22, which includes Damp (the damping factor), pH_1, pH_2, and pH_3 as random value of the pH between 7 and 14, $Temp_1$ and $Temp_2$ as random value of the temperature between 34°C and 39°C, and V_i (the velocity of each sperm), The sperm's present location at iteration t is indicated by the symbol x_i, whereas the global best location, denoted by the symbol x_{sgBest}, is indicated by the symbol x_{sgBest_i}. According to Eq. 22, where $x_i(t)$ denotes the sperm's current position at time t and $V_i(t)$ denotes its velocity at time t, the sperm's current position (current solution) is updated at each iteration. As a result, each sperm's location is continuously updated to produce the overall ideal result.

$$x_i(t) = x_i(t) + V_i(t) \quad (22)$$

When calculating the fitness, velocity and position constraints are set in order to keep the technique from straying too far from the overall ideal answer. Eq.s 23 and 24 are used to calculate the upper and lower velocity limitations.

$$V_{max} = 0.1(Var_{max} - Var_{max}) \quad (23)$$

$$V_{min} = -V_{max} \quad (24)$$

Var_{max} and Var_{min} are the maximum and lowest position limitations of the search domains in this case, whereas V_{min} and V_{max} are the minimum and maximum velocity limits.

The two populations are combined, sorted, and shortened to create a new population for the following iteration after updating the sperm cell's velocity and location. This population's fitness is assessed and contrasted with the prior global best practise. Fig. 4 illustrates the flow chart of hybrid genetic algorithm sperm swarm optimization process to provide a comprehensive picture of the complete procedure.

Steps involved in the proposed hybrid optimization algorithm:

i. Initialization of the population: Generate a random beginning population of potential solutions.
ii. Fitness evaluation: Using an objective function, assess the fitness of each potential solution within the population.
iii. Parent selection: Choose a portion of parents based on how well-suited they are for mating.
iv. Crossover: Construct new candidate solutions by performing crossover between the chosen parents.
v. Mutation: To add additional genetic material, perform mutation on a few of the new candidate solutions.

vi. Fitness assessment: Assess the new candidate solutions' fitness.
vii. Selection: To create the new population for the following iteration, choose the top candidate solutions.
viii. Termination: Verify that the criteria for termination have been met (e.g., maximum number of iterations reached or convergence of the solution). In that case, return to step III.
ix. Output: The optimal solution identified throughout the optimisation phase should be output.

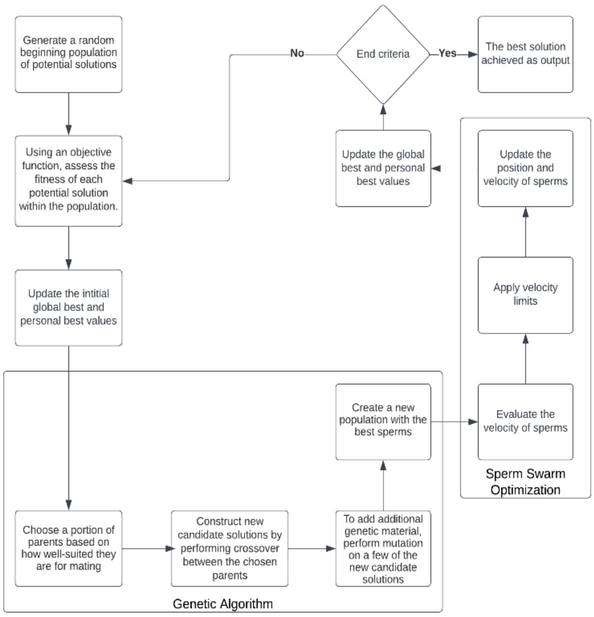

Fig. 4. Flowchart of hybrid genetic algorithm sperm swarm optimization process

The specifics of the crossover and mutation procedures might differ depending on how the algorithm is implemented, and the hybrid nature of the method is a result of the combination of swarm intelligence (sperm swarm optimisation) and evolutionary computation (genetic algorithm) techniques.

We have employed a cutting-edge strategy dubbed Hybrid Genetic Algorithm Sperm Swarm Optimisation, which outperforms conventional approaches in the field of load forecasting for Demand Side Management. Utilising the strength of both evolutionary algorithms and swarm intelligence, HGA-SSO is a novel optimisation technique. It combines the advantages of both genetic algorithms and sperm swarm optimisation. HGA-SSO uses the capacity to look for optimal solutions in a highly dynamic and complicated load forecasting environment, in contrast to existing methods that frequently rely on deterministic or heuristic approaches. HGA-SSO successfully adjusts to the constantly changing nature of load patterns driven by Electric Vehicles, Energy Storage Systems, and Renewable Energy Sources by using a hybridised approach. Since it optimises the control of EVs and ESS in real-time by making accurate predictions based on the existing and anticipated conditions, HGA-SSO genuinely beats traditional methodologies in this area of adaptability. The end result is a load forecasting model that is more precise and effective, which ultimately leads to improved DSM strategies and considerable cuts in energy expenditures and environmental effects. Our study shows that HGA-SSO offers higher performance and adaptability compared to traditional approaches, making it a possible solution to the problems associated with contemporary energy management systems.

4. Results

The intelligent optimization model proposed in this study was implemented using Matlab, and the load data used for load forecasting was obtained from reference [99]. The intelligent controller played a significant role in managing variable loads and the charging/discharging of different energy sources in demand-side management. An intelligent optimization-based controller was utilized to regulate the energy flow between the microgrid and the EV charging station. Fig. 5 shows the load forecasted by the intelligent controller over a 24-hour period, indicating that the load peaks during daytime hours, primarily due to air conditioning loads. The power profile of the electric vehicle charging station during various hours of the day is presented in Fig. 6, with power levels ranging from -55 KW to 95 KW. A positive value of power means that power is supplied to the microgrid while as a negative power value specifies that power is drawn from the microgrid, i.e., discharging and charging of the EV charging system, respectively. As seen in Fig. 5, the EV charging station is discharged during peak day hours and gets charged during off-peak night hours.

Fig. 7 depicts the photovoltaic power available and injected into the microgrid over different hours of the day, indicating that photovoltaic power is only available during daylight hours. In this model, the photovoltaic power and EV charging system together form the microgrid. The load profile of the conventional grid without the EV charging station and photovoltaic integration is shown in Fig. 8, and this load profile must match the forecasted demand curve as predicted by the intelligent controller. The load profile of the conventional grid after integrating the hybrid EV charging station and photovoltaic system is shown in Fig. 9. The integration of these hybrid renewable energy resources helped to clip peak load demands from the main grid as they provided power during peak day hours, thereby reducing power losses and improving voltage profiles. Approximate quantitative data associated with Figs. 5, 6, 7 and 8 is presented in Table 1, and Fig. 10 illustrates the merged load profiles of all associated quantities.

Table 1. Approximate power and load data of different sources during different hours of the day.

Time (h)	Total forecasted load (KW)	Total EVCS Power (KW)	Total PV (KW)	Total Hybrid EVCS and PV Power (KW)	Total Grid Power after EVCS and PV (KW)
00:00	25	-55	0	-55	80
01:00	24	-41	0	-41	65
02:00	25	-42	0	-42	67
03:00	24	-43	0	-43	67
04:00	26	-44	0	-44	70
05:00	30	-43	0	-43	73
06:00	39	-37	1	-36	75
07:00	45	-33	3	-30	75
08:00	73	30	4	34	39
09:00	98	47	6	53	45
10:00	109	60	6	66	43
11:00	122	74	7	81	41
12:00	138	84	8	92	46
13:00	171	95	9	104	67
14:00	150	87	7	94	56
15:00	127	73	6	79	48

16:00	115	60	5	65	50
17:00	97	49	4	53	44
18:00	72	36	1	37	35
19:00	63	24	0	24	39
20:00	51	-30	0	-30	81
21:00	39	-35	0	-35	74
22:00	38	-40	0	-40	78
23:00	33	-43	0	-43	76
Total	1734	233	67	300	1434

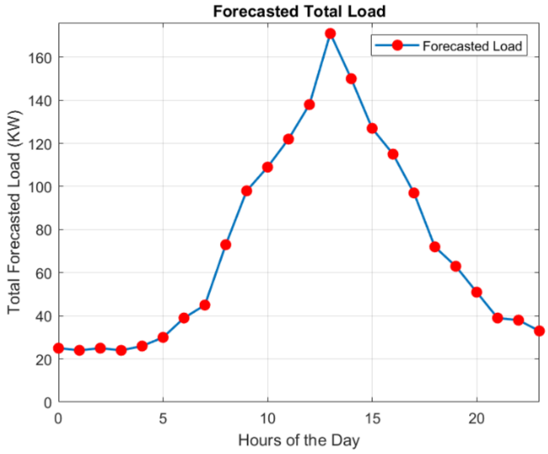

Fig. 5. Load profile of forecasted demand during different hours of the day.

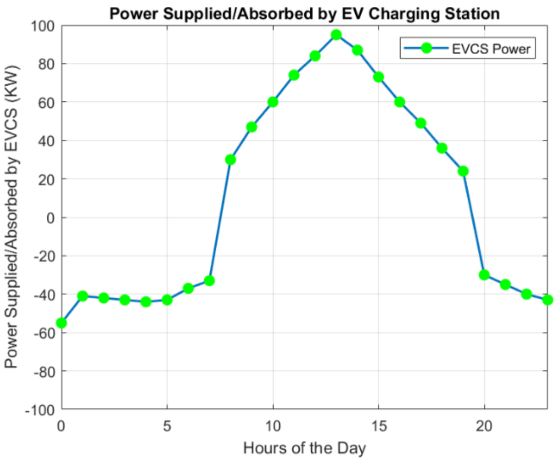

Fig. 6. EV charging station's power profile of during different hours of the day.

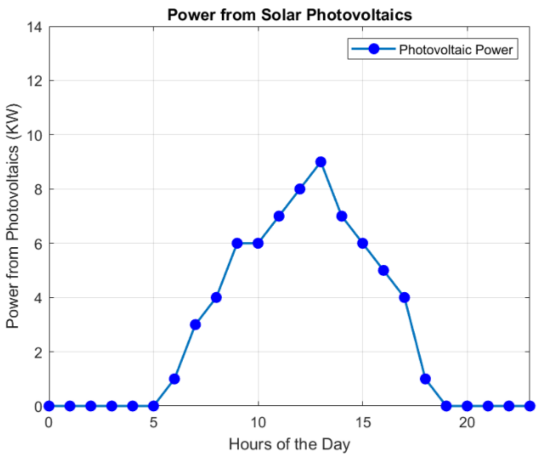

Fig. 7. Photovoltaic power profile of during different hours of the day.

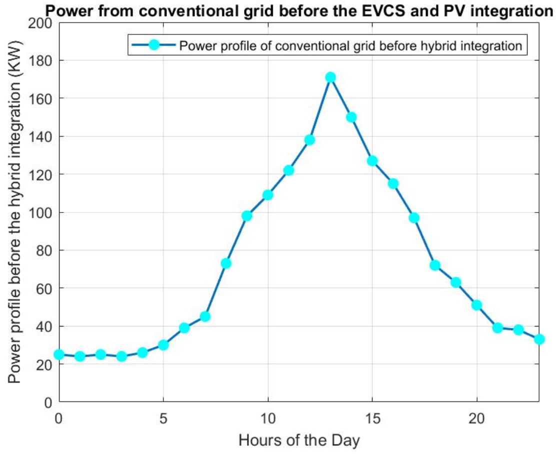

Fig. 8. Power profile of grid without hybrid EVCS integration during different hours of the day.

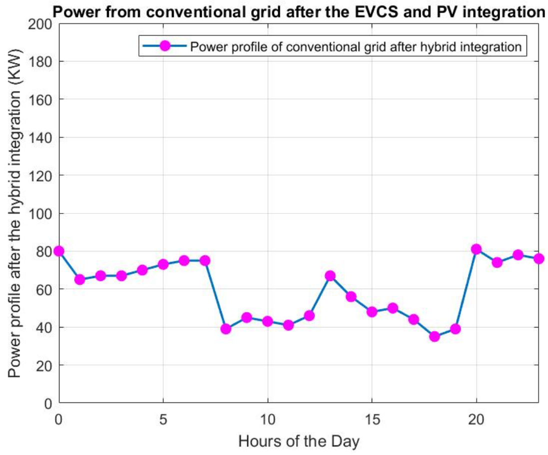

Fig. 9. Power profile of grid with hybrid EVCS integration during different hours of the day.

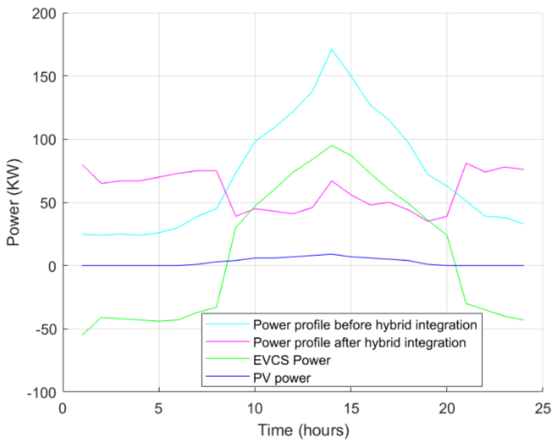

Fig. 10. Merged power and load profiles during different hours of the day.

The Hybrid Genetic Algorithm and Sperm Swarm Optimisation method have shown encouraging results in our Short-Term Load Forecasting Model for Demand Side Management. One important factor that warrants discussion is the performance of this hybrid algorithm. Swarm optimisation and genetic algorithms working together has proven to have many benefits for improving our model's forecast accuracy. With this hybrid technique, the local search effectiveness of swarm optimisation and the global exploration power of GAs are combined. Through extensive testing and validation, we found that the hybrid algorithm not only displayed faster convergence rates than separate algorithms, but also significantly increased prediction accuracy while lowering forecasting mistakes. However, introducing such a sophisticated and cutting-edge strategy also poses certain difficulties. The proper balancing of exploration and exploitation requires careful consideration of crossover and mutation rates, swarm size, and other control factors, which is one of the main issues when fine-tuning hybrid algorithm settings. Additionally, because of the hybrid algorithm's computational complexity, additional research may be needed to determine how well it can be adapted to different datasets and system settings. For our suggested forecasting model to be reliable and scalable, these issues must be resolved.

5. Conclusion

This research article proposes a thorough framework for data-driven DSM in an electric car connected microgrid in light of the urgent problems surrounding conventional fossil fuel vehicles and their related greenhouse gas emissions. The EV charging station was modelled as single energy source with the level of charge of its ESS calculated by hybrid GASSO. Intelligent hybrid optimisation was used to forecast loads connected to the microgrid. Effective DSM was made possible by the efficient optimisations suggested. After applying the specified controller, the analysis of the outcomes depicted a reduction in the amount of electricity provided by conventional sources during the day. In comparison to conventional mathematical modelling methodologies, the proposed technique is found to be less complex, very effective, and capable of producing a more accurate system modelling. Overall, the suggested approach reduces greenhouse gas emissions while also improving microgrid dependability and EV charging station system profitability, which encourages investors to build more EV charging stations.

6. Future Work

There are several opportunities for more study and potential improvements to the suggested methodology. First, it may be investigated to incorporate sophisticated machine learning methods, such as deep learning models like recurrent neural networks (RNNs) or Long Short-Term Memory (LSTM) networks. The accuracy and effectiveness of load forecasting could be further improved by these models in the presence of electric vehicles, energy storage systems, and renewable energy sources, which have demonstrated promising outcomes in a variety of time-series forecasting applications.

Second, our methodology might benefit from a greater emphasis on real-time data sources given the expanding significance of real-time data and the Internet of Things (IoT) in energy management. Smart metres, grid sensors, and other IoT devices can contribute data that is more precise and up to date, improving the accuracy of load forecasting and the control of EVs and ESS.

Also, it could be interesting to investigate how our model scales and adapts for various geographic areas and utility grids. Our model could produce more region-specific load forecasts and DSM strategies by being adjusted to particular geographic characteristics because different locations have different load patterns and different energy resource availability.

Additionally, future study might focus on maximising the allocation and utilisation of energy from RES, seeking to reduce energy waste while maximising the utilisation of renewable sources as sustainability and environmental concerns continue to rise. Last but not least, a fascinating area for future research could be examining how new battery technologies and vehicle-to-grid systems affect load forecasting and DSM. By allowing EVs to send energy back into the grid, for example, V2G systems have the ability to complicate and add additional factors to load forecasting models.

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