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RESEARCH ARTICLE

Neuro-Fuzzy and Networks-Based Data Driven Model for Multi-Charging Scenarios of Plug-in-Electric Vehicles

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ABSTRACT In recent times, significant progress has been achieved in the domain of intelligent and eco-friendly transportation. Electric mobility emerges as a viable and effective solution, offering cost-efficient means of transportation. However, the rise in fuel expenses, climate change, and unregulated charging of electric vehicles (EVs) have necessitated a transformative shift in the operation of smart grids. The exponential rise in EV charging requirements has the potential to adversely affect power grids, resulting in peak demand, grid overload, energy hub emissions, and possible infrastructure overburden. This study presents a predictive cost model that utilizes a hybrid search and rescue (SAR) and adaptive neuro-fuzzy interface system (ANFIS), denoted as the SAR-ANFIS approach. The model is designed to effectively model complex dynamic energy emission dispatch scenarios that are integrated with transient charging loads. These scenarios include peak, off-peak, electric power research institute (EPRI), and stochastic scenarios. The proposed methodology aims to minimize the cost of charging scenarios while providing policymakers with a tool to create financial budgets for forthcoming electric vehicle loads. This is achieved through the use of a fuzzy model that has the ability to predict costs. The ANFIS exhibits robust predictive capabilities owing to its aptitude for acquiring and representing intricate non-linear associations between input and output variables. The incorporation of ANFIS into a SAR algorithm results in improved predictive capacity through the optimization of the learning process, enhancement of model accuracy, and facilitation of efficient parameter tuning. The integration of ANFIS and SAR algorithms enhances predictive accuracy and robustness by leveraging the former's adaptive and learning capabilities and the latter's global search and optimization capabilities. The model considers various charging strategies and dispatch constraints within an energy hub. The attainment of the 24-hour pricing scheme is achieved by solving a minimum-cost optimization problem, which serves as the initial training data for the development of the proposed model using an adaptive neuro-fuzzy approach. The proposed approach effectively coordinates the various charging behaviours of electric vehicles, including those identified by the EPRI, as well as stochastic, peak, and off-peak charging, at the system level. The proposed methodology offers several advantages, including the facilitation of coordination among various charging scenarios for EVs and the creation of a cost prediction model that can assist policymakers in devising budgetary plans for future EV loads. One of the benefits of this technology is its capacity for autonomy, which enables vehicle owners to charge their electric vehicles in a cost-effective manner, regardless of the specific scenario they find themselves in. Furthermore, the suggested plan has the potential to mitigate the release of greenhouse gases from the power generation sector, thereby facilitating the establishment of a viable charging network that is environmentally sustainable. The present study examines the efficacy of the SAR-ANFIS approach and model on a standardized test system across a range of load profiles.

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INDEX TERMS Neuro-fuzzy, charging scenarios, cost prediction model, electric vehicles, optimization, economic emission dispatch.

I. INTRODUCTION

The use of fossil fuels in the transportation and energy sectors is a reliable indicator of economic growth. However, owing to the rapid depletion of fossil fuels and due to the increase of greenhouse emissions, countries are being compelled to look for other options. To meet with the future energy and environmental challenges, scientists and engineers are continuously working to develop new and emerging technologies [1], [2], [3]. Among these, plug-in electric vehicles (EVs) are a vibrant solution which can eliminate the growing concerns about energy security and dependency on imported fossil fuels [4]. Global power grids have become more complex as energy consumption is increasing, making the generation units as essential components of the electric power system. In essence, supplying a power system with clean electricity at the lowest feasible cost can be a difficult operation that is fully dependent on the grid supervision [5].

When it comes to economic dispatch (EDs), the purpose is to optimize the operating cost of electricity generation within the dispatch centers [6], [7]. The traditional works have looked into a variety of strategies for reducing the total cost of power production. EDs are one of the most promising and cost-effective solutions for efficiently and safely delivering the high performance energy to clients [8]. The integration of system stability constraints in the context of optimum distribution of powers has become a significant problem in the modern grid operation, as power networks are expanding day by day and system demand is increasing for new type of electric loads such as EVs. Additionally, to deliver energy to EV users with fine quality and at a reasonable cost, computational intelligence is an important, reliable, and viable choice as observed in [9]. A primary goal of dynamic EDs (DEDs) is to disseminate the time-based load demand among generators to meet the various linear and nonlinear constraints. Toady's societies are concerned about the environmental impact of power plants and their emissions. For clean environment, a number of laws have been passed, requiring power plants to reduce emissions of polluting gases, particularly sulphur dioxides (SO_x) and nitrogen oxides (NO_x) [10], [11]. The induction of air emission function of power plants in DEDs has made models more complex and revealed multi-objective optimization, known as combined DEDs (CDEDs).

Sustainable mobility demands the use of diversified vehicles, consisting of both conventional internal combustion based automobiles and those employing clean energies, including plug-in and semi-hybrids EVs. In contrast with combustion based automobiles, EVs have several additional benefits for sustainable transportation. For instance, they are remarkably quiet, require no routine maintenance (oil and filters), having three times more torque, and emit almost no carbon emission [12]. Rising performance in green system initiatives and smart consumption has catapulted EVs to the forefront of the sustainable transportation [13]. The widespread utility of EVs offers hope for mitigating climate change and fostering a more environmentally sustainable transportation infrastructure [14]. Nevertheless, there have been significant constraints for integrating EVs and semi-hybrid EVs into transit networks such as charging power infrastructures, energy security management for EVs, and smart routing systems [15].

The use of EVs in the transit systems of advanced countries has significantly for reduced the pollution. Consequently, various communities of scientists, engineers, and technologists around the globe are working to produce efficient cars that have large capacity of the battery storage system [16]. EVs depend primarily on rechargeable batteries to conserve electric power while simultaneously validating the energy requirements. Modern transportation systems have made an effort to regulate vehicle charging or discharging plans, based on the system load profile and the variation in electricity prices. When integrating EVs with CDEDs, the problem becomes more multi-dimensional and complicated because charging loads are large and they fluctuate over time, depending upon the charging scenarios. Another crucial aspect is that the power demands for EVs are mobile in nature and may be high during peak charging hours, further complicating the system design of DEDs and load demands in urban locations [17].

Numerous research works have examined the impact of charging EVs through an electric infrastructure. According to Ye et al. [18], the widespread use of EVs will have a substantial effect on the generation and delivery of power. Xie et al. [19] examined the potential consequences of EVs charging load on the energy grids and determined that even low penetration rates of EVs can result in new peak loads if the energizing load profile is not distributed over the off-peak period. Taking into account the current load, the ambient temperature, and the time of day, the work of [20] estimated the optimal time to charge EVs. This assumption skewed the results and led to gloomy outcomes in the majority of these studies, which assumed that all EVs are charged simultaneously from a completely depleted state. In [21], a probabilistic power flow estimation was developed to simulate the whole charging load requirement for EVs.

The charging load of EVs depends on the type of battery, its capacity, and the vehicle's maximum range. There are a number of factors that influence the amount of energy for charging of EVs, including how far the vehicle travels in a day, where it is charged, and when it is charged. It is vital to consider the distribution of charging loads across the system from the electric grid analysis and design perspectives. The work in [22] presents a multi-objective model (with EVs as a mobile load along with generation) for analyzing the effect of charge-discharge capability on the economic effectiveness over a micro-grid system. Yang et al. [23] developed an adaptive optimization method for the scheduling of charging of EVs. The integration of renewable energy into the architecture was used for charging and discharging to offset the renewable power penalty costs. A non-cooperative iterative technique through which an EV seeks the lowest possible charging pattern using the dynamic pricing schemes has been discussed in [24]. According to Ahn and Lee [25], an optimal distributed charging strategy is one in which distributed EVs power banks obtain a simple instruction from a centralized grid controller and use that command to determine their own individual charging patterns. In this strategy, the global best solution of a linear optimization model is achieved, with a valley-filling effect that is close to the global optimal solution. The owner's willingness to give up the charging autonomy for an EV in exchange for device-level objectives is critical to the success of a command-based strategy because it does not necessitate a complex bidirectional network.

The sales of EVs have experienced a substantial surge in recent years, with a notable rise observed worldwide. Furthermore, several nations have initiated comprehensive carbon reduction strategies. The widespread implementation of EVs on a wider basis and the need for extended journey distances have resulted in a demand for increased battery pack capacity. The authors of [26] have proposed a fuzzy inference approach that takes into account the uncertainty and independence of the accessible power, needed SoC, and duration of dwell from both the electrical structure and EV realms. This approach then integrates these factors into ranked control parameters. The work of [27] found that the most effective solution is contingent upon the selection control parameter, that is acquired via the fuzzy fusion process. This process integrates various distinct and precarious preliminary cost trends as well as SoC ingredients from both the power hub as well as EV realms. Neural networks are proficient at acquiring sequences and recording nonlinear connections, whereas fuzzy logic facilitates the portrayal of unclear and ambiguous information. Through the use of these methodologies, it is possible to construct resilient algorithms that take into consideration the random characteristics of the energy lines and proficiently handle the unpredictability that arises from charging EVs [28].

The above mentioned literature shows that the ability to connect EVs to the energy production hubs has created new challenges in the power system management. To increase smart grid security, the majority of power production hubs are developing load projection models to conduct safe and dependable electricity dispatch operations. The flaw with the existing methods is that they tend to concentrate on local points and lack in a robust global search methodology for upcoming future EVs loads. Additionally, as use of EVs rises, unprecedented stress on power systems can increase which further can affect the energy distribution networks [29] and [30].

This paper introduces a predictive model based on SAR-ANFIS for forecasting the optimal charging patterns costs of plug-in EVs. The proposed SAR-ANFIS model is a new fuzzy model that combines the optimization capability of search and rescue algorithm (SAR) with the prediction capability of adaptive neural fuzzy interference system (ANFIS) to address the above-mentioned issues. The scheme is more reliable and cost-effective because it not only deals with the DEDs model while taking transient charging patterns of EVs into account, but also forecasts an optimal cost for the future dynamic EVs load. The plan enables utility management and policymakers to enhance or modify their complex dispatch system in order to quickly meet the load demands of mobile EVs. In addition, owing to the characteristics of deep learning, inference capability, and ease of embedding, the approach is better suited for addressing multidimensional, constrained real-world problems. Furthermore, the scheme enables energy dispatch operators to easily compute upcoming loads with the aid of a trained predictive model. Based on the preceding discussions, the primary contributions and novelties of the study are summarized as follows:

1) Compared to [31], [32], [33], [34], a predictive cost model, based on hybrid SAR-ANFIS approach, is provided to model complex DEDs integrated with transient charging loads scenarios (peak, off-peak, EPRI and stochastic). The developed approach will achieve the lowest possible operational fuel cost and greenhouse gasses emissions for all charging situations. The DEDs models provide valuable insights and data that can inform policy formulation and long-term energy planning. The implementation of DEDs models can offer significant contributions in terms of informing regulation formulation and facilitating prospective energy scheduling. The outcomes of the analyses conducted by DED can be utilized by legislators to make well-informed judgements regarding energy policies, infrastructure expansion, and the allocation of resources towards novel power production techniques. Moreover, in comparison to prior research, we incorporate the ANFIS model, which facilitates comprehension of usage trends for forthcoming EVs and discernment of prospects for demand-side control by legislators. The implementation of the ANFIS prediction model enables policymakers to make well-informed decisions, develop efficient procedures, and establish prospective tariff schemes for forthcoming loads.
2) In comparison to the previous DEDs models in [31], [32], [33], [34], a more complex and multi-constrained model is developed by incorporating spinning reserve (SR) limitations to further extend the practicability of smart grids operations. The SRs can be used to keep the frequency under control, to create reserve power losses, and to feed a large number of EVs in the event of disconnection. Compared to earlier works,

their inclusion in the optimization process helps strike a balance between economic efficiency, grid stability, and environmental sustainability, leading to a more sustainable and environmentally friendly power system.

3) The developed approach for multi-constrained DEDs model achieves excellent optimization performance at a low computational cost. Additionally, it demonstrates improved convergence (see details in Section "Test AND RESULTS") and execution speed when compared to the currently available state-of-the-art algorithms [31], [32] (see also [35], [36], [37], and [38]).
4) In contrast to [31] and [32], a large-scale test system is considered for investigating feasibility of the proposed approach, and performance of SAR-ANFIS has been evaluated by modifying load curves to simulate future EVs participation. The developed fuzzy-framework eliminates the need for re-simulation of the whole optimization paradigm and provides a quick operational cost estimate for an increased EVs load.

II. SYSTEM MODELING

A. DYNAMIC ENERGY AND EMISSION DISPATCH MODELS

The mathematical expression for cost of a unit is given by

$$C_{n,\tau}(P_{n,\tau}) = u_n + v_n P_{n,\tau} + w_n P^2_{n,\tau}, \tag{1}$$

where u_n, v_n and w_n represent the cost coefficients of the n^{th} plant [39]. $C_{n,\tau}$ represents the fuel cost and $P_{n,\tau}$ denotes the active generated power of the n^{th} unit at time τ. The objective function of dynamic DEDs can be written as [40]

$$J_1(P_{n,\tau}) = \sum\nolimits_{\tau=1}^{24} \sum\nolimits_{n=1}^{N_{ep}} C_{n,\tau}(P_{n,\tau}). \tag{2}$$

Here, N_{ep} denotes the number of engaged plants. Thermal plants are sophisticated machines and consist of multiple valves for the smooth operation of steam opening. The mechanized valve opening system produces rippling effect, leading to valve-point loading effect (VPLE) [6], [40] given by

$$\begin{aligned} C_{n,\tau}(P_{n,\tau}) &= u_n + v_n P_{n,\tau} + w_n P^2_{n,\tau} \\ &\quad + \left| E_i \sin(F_i(P^{\min}_{n,\tau} - P_{n,\tau})) \right|. \end{aligned} \tag{3}$$

The load-demand equality constraint can be modelled [41] as

$$\sum\nolimits_{n=1}^{N_{ep}} P_{n,\tau} = P_{LD,\tau}, \tag{4}$$

$$P_{LD,\tau} = P_{NL,\tau} + P_{EVs,\tau} + P_{LL,\tau}, \tag{5}$$

where $P_{NL,\tau}$ indicates the connected network load demand for time instance τ which can be residential or industrial load depending upon the network geographic position. $P_{EVs,\tau}$ is the load of electric vehicles connected to network for charging (the detail of which will be provided later). $P_{LL,\tau}$ denotes the line-loss loads due to transmission lines. Technically, every generator must be operated in a certain range [40], given by

$$P^{min}_{n,\tau} \leq P_{n,\tau} \leq P^{max}_{n,\tau}. \tag{6}$$

The peak power handling limitation in the load distribution problem can be written as

$$\left| P_{L,f,K} \right| \leq P^{max}_{L,f,K}, \quad K = 1, 2, \ldots, L. \tag{7}$$

Due to technical constraints, committed units are unable to generate electricity in certain zones between their lowest and highest production levels. These zones are known as restricted zones, which has the following form [40], [42]:

$$P_{n,\tau} \in \begin{cases} P^{min}_{n,\tau} \leq P_{n,\tau} \leq P_{n,\tau^L}, \\ P^U_{n,\tau,j-1} \leq P_{n,\tau} \leq P^L_{n,\tau,j}, \; j = 2, 3, \ldots.., Z_n, \\ P^U_{n,\tau,Z_n} \leq P_{n,\tau} \leq P^{max}_{n,\tau}. \end{cases} \tag{8}$$

The spinning reserves (SRs) are the amount of idle capacity in online energy assets that can be used in case of emergency to prevent the system collapse over a specified time period. The EVs are costly and the failure or voltage drop in lines can affect the chargers connected to utility lines. Any damage to EVs by the service provider can impose legal penalties. The mathematical expression for SRs has the form

$$\sum\nolimits_{n=1}^{N_{ep}} S_n \geq S_{R,full}. \tag{9}$$

Ramp-up and ramp-down restrictions apply to the power units to prevent oscillations [41]. Consequently, we have

$$P_{n,\tau} - P_{n,\tau-1} \leq RU_n, P_{n,\tau-1} - P_{n,\tau} \geq RD_n. \tag{10}$$

Without a doubt, one of the most pressing issues confronting humanity now is the climate change due to industrial emissions. When fossil fuels are used to generate the electricity, several different substances are released into the air, causing greenhouse effect and smog like conditions [43]. The cost of preventing the atmospheric emission by all engaged plants is also taken into account in this paper. The corresponding cost function, for the environmental effects [41], [44], is given by

$$J_2\left(P_{\tau,r}\right) = \sum_{\tau=1}^{24} \sum_{n=1}^{N_{ep}} \left(E_{n,\tau}\left(P_{n,\tau}\right) + \zeta_n \exp\left(\lambda_n P_{\tau,rn}\right)\right), \tag{11}$$

where $E_{n,\tau}(P_{n,\tau}) = \mathrm{A}_n + \mathrm{B}_n P_{n,\tau} + \mathrm{C}_n P^2_{n,\tau}$, and A_n, B_n, C_n, ζ_n and λ_n are emission coefficients of the n^{th} plant. Now the combined energy and emission dispatch mathematical expression using (2) and (11) is $\min\left(J_1\left(P_{n,\tau}\right) + \mathcal{K}(J_2\left(P_{\tau,r}\right))\right)$ where $\mathcal{K} \in [0, 1]$.

B. IMPACT OF EVs ON ENERGY GRIDS

Integration of EVs with energy system can cause failures and equipment damage, if EVs charging characteristics are not properly accounted. These failures occur when a large number of EVs are interfered with electricity systems during peak hours of operation. Typically, a charger located at home consumes 20 − 25 KW and can be fitted in the consumer energy lines. While the supercharger, used for the commercial purposes, consumes 120 − 150 KW energy, depending upon the vehicle type. Both of these devices cause abrupt variations and occasionally spikes in the load graphs. By implementing effective supervision and synchronization between e-mobiles and the generation system, modern power systems aspire to reduce the power demand surges.

1) EVs CHARGING LEVELS

Charging of EVs involves three levels which depend upon the vehicle type and usage purpose. Since more energy is supplied to the EVs at the top scale of charging, the charging process is faster at the higher level of charging. Different EVs are charged at different speed on each level since each EVs can accept different level of power from the charger. Whenever an EV is plugged in, a communication process takes place prior to the charger's operation. In this communication, the EVs requests the maximum amount of power that the station can deliver and that the vehicle can accept from the charging station.

Level 1 charging is accomplished through the use of a standard 120-volt household outlet. By connecting the charging equipment to a standard wall outlet, any EVs or plug-in hybrid EVs can be recharged on Level 1. Level 1 charging is the most inefficient method of charging for EVs. It increases range by 3 to 5 miles per hour, depending on the vehicle and push consistent tension on energy grids [45]. For daily EVs charging, Level 2 is preferred depending on the power output of the Level 2 charger and the maximum charge rate of the EVs. Level 2 chargers have a maximum power output of 80 A. However, it necessitates a 100 A $208 - 240$ V dedicated circuit. A 40 A charger is capable of delivering 9.6 KW while a 48 A charger can charge at 11.5 KW to the EVs [21]. A Level 3 charger can charge EVs at a rate ranging from 20 miles/minute, making it the fastest charging method available. The power consumption is significantly higher than that of other charging levels, and this level is always used for commercial purposes [46].

2) DYNAMIC CHARGING SCENARIOS

Specifically, there are four different charging techniques available for EVs: The EPRI charging scenario (based on driving habits), off-peak charging, peak charging, and stochastic scenario [31]. In general, the utilization of multi-charging scenarios is of paramount importance in enhancing the connectivity of EVs with energy hubs. Through the utilization of intelligent charging methodologies and the exploitation of expert tools, the potential adverse effects of EV charging on the energy grid can be mitigated while simultaneously optimizing the advantages of green mobility. The information pertaining to multiple charging scenarios are outlined as follows:

1) **EPRI:** The EPRI is one of the leading and prestigious group in the field of EVs research and other related areas. When accounting for the pollution caused by automotive, EPRI uses the cumulative multivariate distribution of the charging profiles. This charging scenario results in a 7-hour period between 22 and 4 A.M. during the night when more than 60% of the power is consumed. On other times, a minimal rate charge has been set aside for charging purposes.
   The EPRI charging scenario endeavours to achieve equilibrium between the exigencies of EV drivers and the prerequisites of the energy hubs. The EPRI framework makes it easier for EV charging infrastructure to work well together by including grid-interactive exchange standards, demand response functions, and time-based charging methods. This integration aims to enhance the stability and resilience of energy delivery networks.
2) **Off-peak:** An off-peak charging scenario is considered based on the estimated demand for EVs. The off-peak charging scenario for EVs provides an incentive for EV proprietors to charge their automobiles during moments of reduced energy demand, which usually occur during times of low demand. The implementation of this particular approach aids in the equilibrium of the power system by mitigating the occurrence of demand-driven periods and averting potential strain on the electrical network. The utilization of time-based pricing frameworks, such as time-of-use (TOU) prices, is a common strategy for off-peak charging profiles. This approach provides the EV proprietors with reduced energy costs throughout such times, resulting in reduced expenses. Three charging stages are completed with about 18.5 percent energy among 23 and 2 hours, 9% energy within 2 and 4 hours, and remaining energy until 6 o'clock. Charging of EVs during non-charging hours is prohibited, which makes an ideal situation for energy grids. As compared to off-peak, the peak charging has a seamless charging graph, which has three distinct degrees of power to ensure the supply of electricity to EVs. This is a more severe scenario than the previous ones, because EVs consume the most energy between the hours of 13 and 20.
3) **Stochastic:** Given the uncertainty associated with the charging of EVs, the stochastic charging scenario incorporates a random profile. The integration of stochastic components into the EV charging process enhances its adaptability and responsiveness to dynamic grid constraints, thereby promoting grid reliability and optimal resource utilization. Typically, it models the probability distribution function as a Gaussian distribution with a mean of 5%. The likelihood of stochastic charging varies between 1.1% to 9.7%. This value fluctuates randomly regardless of peak or off-peak loads.
4) **Peak:** The charging patterns for EVs are designed to prioritise the powering of these kinds of automobiles during times of elevated consumer demand, which usually occur during peak hours. The objective of this approach is to optimise the utilization of sustainable power resources and the power grid during periods of significant accessibility. Incentivizing or granting priority utilization of charging facilities during times of high demand through peak charging scenarios may

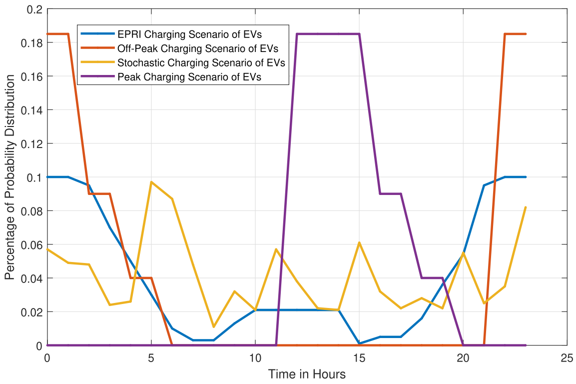

FIGURE 1. Distribution curve for various charging scenarios.

motivate EV proprietors to support grid stability and long-term viability.

The load changes associated with each of the four scenarios presented are shown in Figure 1. These profiles assume a constant level of demand for energy generated $P_{EVs,\tau}$. Despite the presented scenarios, the research problem appears more complex and multidimensional. The primary objective of this research is to develop a data-driven SAR-ANFIS model for energy hubs integrated with EVs load by considering multiple charging scenarios. The evaluation indicates that the proposed model achieves an optimal cost for the operation of energy hubs by satisfying generator system constraints with greater precision than other advanced approaches in terms of robustness, predictability, and computational budget.

III. OPTIMIZATION FRAMEWORK

To achieve the research objective, we need an optimizer capable of calculating the best operational optimal cost for generation machine and the best combinations of power to meet the charging load demand of EVs for the various Section II scenarios. In this section, we will introduce an EVs multi-charging optimization framework and a data-driven prediction model.

A. SEARCH AND RESCUE ALGORITHM (SAR)

The SAR model has been applied (i) for investigating a dispatch problem and (ii) for attaining an initial data set for training the proposed fuzzy model for the cost prediction. In SAR model, the humans locus for obtaining solution of an optimization problem is considered, and a clue found in that position indicates the solution's suitability. A better solution corresponds to a more significant clue, and vice versa.

1) CLUE

Individuals in the group collect clues and information during a search operation. Several clues have been left by participants of the group to aid the search for more significant clues. However, their data are used to enhance the search operation. We assume that the location of the left clues are saved in a memory matrix S in the model, and the positions of humans are feed in a position matrix T. The dimensions of both S and T matrices are considered as identical. $G \times H$ matrices are used in this case, where G represents the problem's dimension and H represents the number of participants. The matrix A_{cm} contains the locations of all of the clues that were discovered. T and S are matrices that make up this matrix, which can be created using (12). The clue matrix serves as the foundation for all current panacea in both the individual and societal stages of SAR, and it is an integral ingredient of SAR. T, S and A_{cm} matrices are updated during each of the human search phase.

$$A_{cm} = \begin{bmatrix} T \\ S \end{bmatrix} = \begin{bmatrix} T_{11} & \cdots & T_{1H} \\ \vdots & \ddots & \vdots \\ T_{G1} & \cdots & T_{GH} \\ S_{11} & \cdots & S_{1H} \\ \vdots & \ddots & \vdots \\ S_{G1} & \cdots & S_{GH} \end{bmatrix}. \tag{12}$$

For the G^{th} human, T_{G1} is the position of the first dimension. Furthermore, the position of the D^{th} dimension for the first memory is represented by the S_{1H}. Humans search can be divided into two phases, referred to as the social phase and the individual phase.

2) SOCIAL PHASE

Here, (13) is used to determine the search direction based on the previous explanations as well as the inclusion of a random clue among the previously discovered clues.

$$SH_q = \left(T_q - C_w\right), w \neq q, \tag{13}$$

where T_q denotes the q^{th} human position, C_w is the w^{th} clue position and SH_q indicates the q^{th} human search direction. w is a randomly generated integer number in the range 1 to $2N$. C_w is equal to T_q when $q = w$, and w is chosen so that $w \neq q$. The members of the group will refrain from searching for a site more than once. As a result, it is critical that the search should be performed in such a way that the activity of the team members toward one another is kept to a minimum level during the entire process. If you move T_q in the manner of (13), you should not change its dimensions at all. The binomial crossover operator has been used to implement this limitation. Clues around and across the SH_q path are explored, if it is assessed that the evaluated clue merits more attention than the relevant clue to the present location. Otherwise, the search will be expanded to include the area around the current location as well as in the direction of SH_q. The following mathematical relation can be used to model the social phase:

$$T'_{q,\kappa} = \begin{cases} \begin{cases} C_{w,\kappa} + RL \times (T_{q,\kappa} - C_{w,\kappa}), \text{ if} f(C_w) > f(T_q), \\ T_{q,\kappa} + RL \times (T_{q,\kappa} - C_{w,\kappa}) \text{ otherwise}, \end{cases} \\ \text{if } \kappa = \kappa_{\text{random}}, \\ \\ T_{q,\kappa} \text{ otherwise.} \end{cases} \tag{14}$$

Here, $T'_{q,\kappa}$ denotes the q^{th} human's new position in the κ^{th} dimension. $C_{w,\kappa}$ denotes the κ^{th} dimension's position relative to the w clue. $f(C_w)$ and $f(T_q)$ represent the values of the objective function for the solutions C_w and T_q, respectively. RL is a uniformly distributed random number in the range $[-1, 1]$. Random integer number κ_{random} is used to guarantee that $T'_{q,\kappa}$ have one minimum dimension from $T_{q,\kappa}$ and κ_{random} varies according to dimension, but RL remains constant across all dimensions. By using (14), we can figure out where the q^{th} human is now in all three dimensions.

3) DISTINCT PHASE

During the individual phase, people look for clues in and around their immediate surroundings, building on the social phase concept of connecting disparate hints. The new human q^{th} position is represented in (15) below.

$$T'_q = T_q + \upsilon \times (C_w - C_m),\ q \neq w \neq m, \tag{15}$$

where w and m are two random integers that fall within the range from 1 to $2N$. It is important to keep track of the other clues in such a way that it holds $q \neq w \neq m$. The values of υ ranges from 0 to 1, and during the the individual phase, people look for clues in and around their immediate surroundings on the social phase concept of connecting disparate hints.

4) BOUNDARY CONTROL

Individual and social phases should produce solutions that are located within the solution space. Otherwise, the modified q^{th} position can be given as

$$T'_{q,\kappa} = \begin{cases} \left(\frac{T_{q,\kappa}+T_\kappa^{\max}}{2}\right) \text{ if, } T'_{q,\kappa} > T_\kappa^{\max}, \\ \left(\frac{T_{q,\kappa}+T_\kappa^{\min}}{2}\right) \text{ if, } T'_{q,\kappa} < T_\kappa^{\min}, \end{cases} \tag{16}$$

where $T_\kappa^{\max}$ and $T_\kappa^{\min}$ are the maximum and minimum cutoff limits for the κ^{th} dimension, respectively.

5) LOCATION AND UPDATED INFORMATION

During each iteration of the search, the members of the group will follow the above-mentioned two phases, and the position and location in formations are updated as

$$UL_{NR} = \begin{cases} T_q & \text{if } f(T'_q) > f(T_q), \\ UL_{NR} & \text{Otherwise,} \end{cases} \tag{17}$$

$$T_q = \begin{cases} T'_q & \text{if } f(T'_q) > f(T_q), \\ T_q & \text{Otherwise,} \end{cases} \tag{18}$$

where UL_{NR} denotes the memory matrix position of the L^{th} stored clue. L is a randomly generated integer from 1 to N.

6) STRANDING CLUES

It is very important for SAR teams to get there quickly. As a result, the actions must be performed in such a way that the maximum amount of space is searched in the least amount of time possible. So, a group member who has scanned the area and found no more significant clues leaves and moves to another position. To simulate this behaviour, the ineffective scanned multitude (ISM) can be updated as

$$ISM_q = \begin{cases} ISM_q + 1 \text{ if } f(T'_q) > f(T_q), \\ 0 \ \text{ otherwise.} \end{cases} \tag{19}$$

Here ISM_q denotes the amount of instant that q^{th} human has failed to uncover more significant clues, after trying several times. When the ISM for a human exceeds the maximum failure number MFN, the following relation is used to replace the current solution in the scanned area.

$$T_{q,\kappa} = T_\kappa^{\min} + RL_2 \times \left(T_\kappa^{\max} - T_\kappa^{\min}\right), \tag{20}$$

where RL_2 is uniformly distributed between 0 and 1.

7) LIMITATION HANDLING PROCEDURE

The e-constrained technique is used to compare the SAR for constrained optimization problems and modifications in (14), (17), (18) and (19) will be as follows.

$$T'_{q,\kappa} = \begin{cases} \begin{cases} C_{w,\kappa} + RL(T_{q,\kappa} - C_{w,\kappa}), \text{ if } f(C_w) \text{ better than } T_q, \\ T_{q,\kappa} + RL(T_{q,\kappa} - C_{w,\kappa}) \ \text{ otherwise,} \\ \text{if } \kappa = \kappa_{\text{random}}, \end{cases} \\ T_{q,\kappa} \ \text{ otherwise.} \end{cases} \tag{21}$$

$$UL_{NR} = \begin{cases} T'_q \text{ if } (T'_q) \text{ better than } T_q, \\ UL_{NR} \ \text{ Otherwise.} \end{cases} \tag{22}$$

$$T_q = \begin{cases} T'_q \text{ if } (T'_q) \text{ better than } T_q, \\ T_q \ \text{ Otherwise.} \end{cases} \tag{23}$$

$$ISM_q = \begin{cases} 0 \text{ if } (T'_q) \text{ better than } T_q, \\ ISM_q + 1 \ \text{ otherwise.} \end{cases} \tag{24}$$

B. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) is an interesting fuzzy approach, which is often utilized for the system identification and function approximation problems. Fuzzy logic theorem was originally proposed by Zadeh [47] to describe complex engineering problems, which became very popular and has been applied successfully to a variety of problems, especially control systems, automation engineering, and renewable power systems. Here, we recommend to utilize the fuzzy system approach to resolve the inherent uncertainties and vagueness found in dispatch operations [48]. For modelling ANFIS, data analysis procedures are often based on assembling a training set of statistical values of the unknown function that is to be approximated. Here, we have used the Sugeno model to build fuzzy rules from input-output data.

The Sugeno fuzzy model tries to build a structured strategy that is adaptable to all data sets to generate fuzzy rules from a specific input-output data set. The following is a typical Sugeno fuzzy rule example [48], [49], [50], [51], [52], [53]: **If** Y_1 is Z and Y_2 is $X then V = f(Y_1, Y_2)$, where Z, X are fuzzy sets of linked function V. The standard

ANFIS cannot handle huge inputs without incurring significant processing costs and losing its casual inference. The membership function selection is also a vibrant issue in the traditional ANFIS approach. A neural network is able to adapt to the environment as it learns through input-output and self-organizes itself. In this study, we propose the use of adaptive neuro-fuzzy inference system (ANFIS) framework to learn from SAR as self-organize network structure to predict the best optimum operating cost of power generating units for change in loads, as mentioned in (5).

Inspired by the capabilities of SAR and features of ANFIS, we aim to develop a hybrid model that can efficiently solve the energy dispatch problem keeping in view the future integration of EVs in energy hubs.

IV. PROPOSED HYBRID SAR-ANFIS MODELING

This section details the modelling procedure for the proposed SAR-ANFIS model. SAR is being used in this study to enhance ANFIS predication accurately for upcoming EVs load. In other words, SAR is applied to determine the lowest possible cost while satisfying the system constraints. The SAR results are validated by comparing them to various sophisticated methods; and after updating the test system, the SAR data is sent to ANFIS for constructing an accurate cost prediction model for incoming EVs loads. Algorithm IV-B depicts the suggested step-by-step approach, whereas Figure 2 depicts the total operation.

A. ARCHITECTURE

In the ANFIS, the input space is mapped to the output space using neural network learning algorithms and fuzzy reasoning. ANFIS has both fuzzy and adaptive neural network capabilities, and it is widely used in many applications such as modeling of complex system identification models and prediction of wind speed and solar irradiation in power systems. ANFIS is well-suited to learning, evaluation, and classification. Adaptive rule bases can be constructed by using numerical data or expert knowledge to extract fuzzy rules. Furthermore, it is capable of tuning the complex process of converting human intelligence into fuzzy systems. Let us assume that our cost prediction framework has an information source x with different scenarios of load distribution and one output z, that is, optimum cost of operation. The fuzzy rule set can be expressed as follow [50].

$$\begin{aligned} &\text{If } x \text{ is } MF_1 \text{ then } z_1 = e_1x + r_1,\\ &\text{If } x \text{ is } MF_2 \text{ then } z_2 = e_2x + r_2,\\ &\text{If } x \text{ is } MF_3 \text{ then } z_3 = e_3x + r_3. \end{aligned} \tag{25}$$

Here e_i is the linear parameter, and our SAR-ANFIS based cost prediction model is shown in Figure 2. The description of various layers in the architecture is provided below.

1) INPUT (LAYER-1)

Each node of this layer makes membership limits to which they have a spot with all of the legitimate fuzzy sets using membership function presented by

$$\nabla_{1,i} = \mu_{MF_i}(x) \;\; for \;\; i = 1, 2, 3. \tag{26}$$

2) RULES (LAYER-2)

In this layer, results of the comparing degrees received from the Layer 1 are tested for the fuzzy rules.

3) LAYER-3

The node capacity of this layer registers the commitment of each i^{th} rule toward the complete results.

4) OUTPUT (LAYER-4)

This layer registers the general result by adding every one of the approaching signal from Layer-3.

The utilization of fuzzy logic is of paramount importance in the framework, as it significantly enhances its capacity to effectively manage data that is characterized by uncertainty and imprecision. Fuzzy logic facilitates the expression and handling of imprecise notions, thereby facilitating the resolution of intricate problems. It also empowers the process of making choices in complicated structures. The selection of the input settings within the fuzzy logic framework is a meticulous process aimed at capturing the appropriate factors that exert an impact on the behaviour of the entire system. The aforementioned inputs, namely consumption of electricity, electrical charging trends, and energy conditions, are expressed through the utilization of linguistic parameters as well as membership functions [54], [55]. The resultant variables of the fuzzy logic designs are formulated with the intention of furnishing significant and practicable outcomes. The framework utilizes fuzzy rules as well as inference processes to produce outcomes that determine the most efficient electrical charging tactics, control grid load, and optimal costs [56]. Based on the supervised learning, the proposed SAR-ANFIS network has been trained to approximate unknown functions, based on training data, which is loaded from the cost obtained by SAR. Then, we find the precise value of the optimum cost, based on those loads.

B. LOGICAL STEPS for SAR-ANFIS

The following logical stages outline the development of the SAR-ANFIS framework for cost prediction.

1) **Step-1:** The initial step in the process is referred to as initialization. During this step, we initialize the SAR algorithm to minimize the objective function mentioned in equations (2) and (11), while also considering the constraints presented in equations (3)-(10). Additionally, we incorporate the charging load demand power $P_{EVs,\tau}$ distributions of EVs, such as EPRI, stochastic, peak, and off-peak, as well as the $P_{NL,\tau}$ as described in [32].
2) **Step-2:** The achieved values are assessed based on predefined criteria to determine their compliance. In the event of any violations, the clue matrix (equation (12)) is updated to generate new solutions using the social

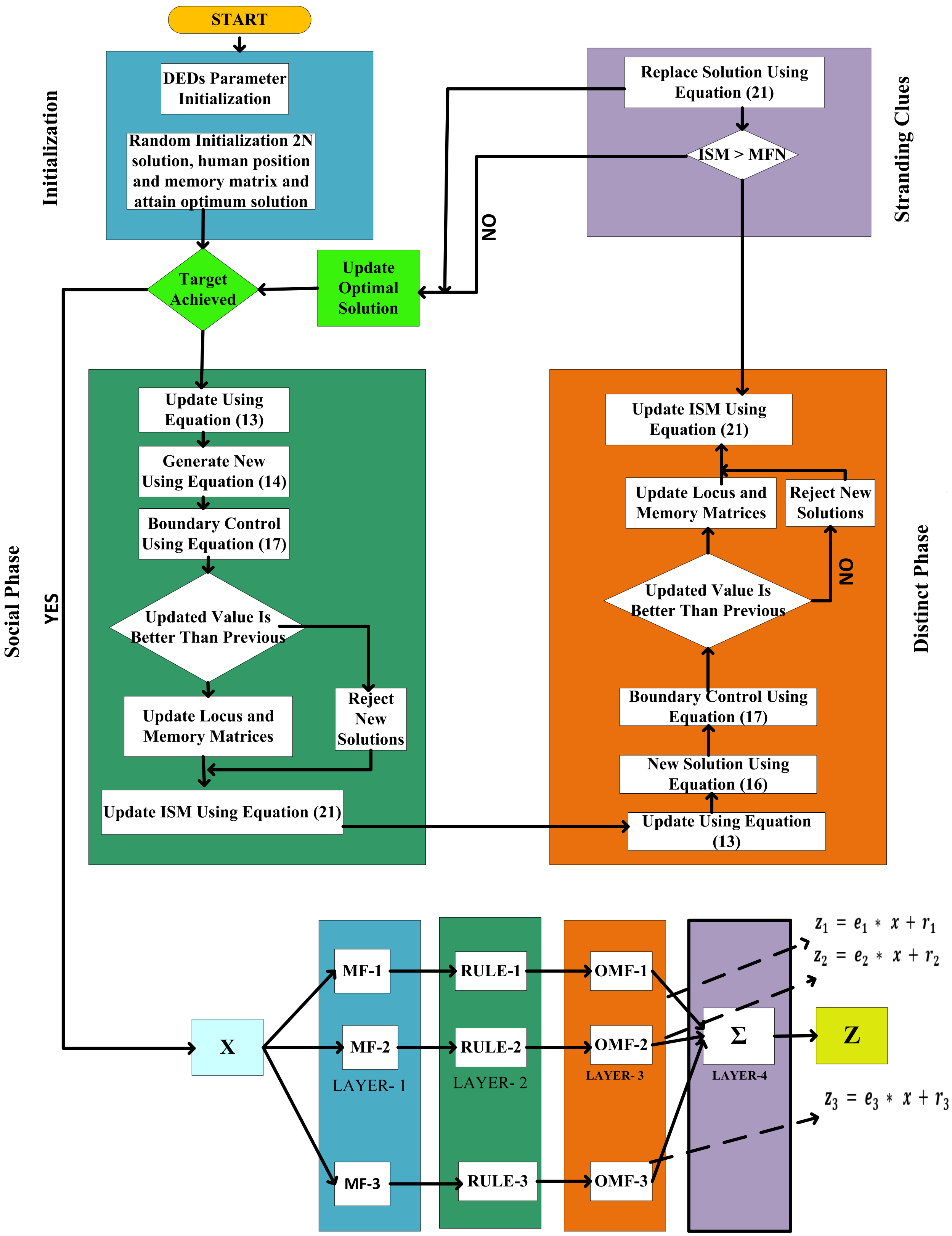

FIGURE 2. SAR-ANFIS cost prediction architecture.

phase equations (equations (13) and (14)). Subsequently, the updated values for cost and system limitations are validated (equation (19)) to ensure optimal performance.
3) **Step-3:** The updated schedule for generator power allocation is allocated to distinct phases, as represented by equation (15).
4) **Step-4:** The newly generated solutions from the distinct phases are incorporated while considering the condition of stranding clues, resulting in the replacement of the current solutions.
5) **Step-5:** In this step, we perform result validation by first examining the constraints through the computation of the total power and the system limitations of each unit. If the system adheres to the specified limitations, the objective results are recorded. However, if the system fails to meet the constraints, we repeat Step 1 using new solutions.
6) **Step-6:** The test system load curves undergo modification to incorporate the load from EVs. Subsequently, we repeat Step 1 to Step 5 to generate a sample data set (based on generators production limits) for ANFIS-based cost prediction.
7) **Step-7:** The optimal results obtained from SAR are standardized for compatibility with the ANFIS model. The data is then divided into training and testing sets for further analysis and evaluation.
8) **Step-8:** The training data is utilized to feed the ANFIS model, with careful selection of the appropriate fuzzy parameters. The system is then trained for a specific number of epochs, typically up to 500, to optimize its performance.
9) **Step-8:** Testing and prediction are conducted by evaluating the root mean square error and verifying the results against the SAR outputs. This assessment provides a quantitative measure of the accuracy and reliability of the ANFIS model in predicting the desired outcomes.

The SAR-ANFIS is beneficial in several ways and can be applied in various fields due to its ability to combine the strengths of brain computing and machine learning [57], [58], [59], [60]. For instance, it predicts the optimal cost for EVs dynamic charging load change. Second, it reduces the system's complexity since policymakers can estimate optimal costs while using the same energy infrastructure and planning the energy budget. The results of the SAR-ANFIS model are compared with other advanced techniques for efficacy and applicability.

Algorithm 1 Pseudo code for SAR-ANFIS prediction model

Input: $min\ \left(J_1\left(P_{n,\tau}\right) + \mathcal{K}(J_2\left(P_{\tau,r}\right))\right)$, where $\mathcal{K} \in [0, 1]$.
Constraints: Equations (3) to (10).
Dynamic charging scenarios and charging levels.
Output: Optimal values of costs, emissions,
and power generations are achieved,
while all constraints for dynamic
charging scenarios of EVs are satisfied.
Initialize population **P** with random solutions
Initialize best solution bestSol as the first solution in **P**
Set iteration counter iter = 0
While iter < maxIterations:
For each solution sol in **P**:
Evaluate the fitness of sol using the ANFIS model
If sol is better than bestSol:
Update bestSol with sol
For each solution sol in **P**:
Generate a new solution solNew using SAR rules
If solNew is better than sol:
Replace sol with solNew
Else:
Replace sol with a random solution in **P**
Increment iter by 1
End While
Return bestSol as the optimal solution
Save optimal for ANFIS
Standardize the saved optimal from SAR.
Standardize the saved best and split data into
training set, checking and testing set from SAR.
Initialize training and create ANFIS
Save ANFIS T_q optimal.
Input the testing data for prediction and error computing.
Start predictive model
Results Validation
END

V. TEST AND RESULTS

To evaluate the efficacy and applicability of the proposed SAR-ANFIS method, a non-convex large-scale fifteen units system is investigated by incorporating contiguous device-level limitations such as VPLE, restricted operating zones and ramp-rate inequalities through different charging scenarios (EPRI, Peak, Off-Peak and Stochastic) of EVs. The objective of the testing is to achieve the lowest possible operational cost level for energy grids while meeting the demands of domestic dynamic loads and industrial EVs loads on grids with a diversity of charging profiles and levels. We also present a cost prediction model by including futuristic load demands of EVs and their impact on energy grids by modifying the load curves. A complex system consisting of 15 units with higher dynamic domestic demand and EVs charging load is deployed over a 24-hour period of time. The input data of thermal plants are selected from [40], [61] with total load demand 60960 MW. The dynamic load demand curve including domestic and EVs four charging distribution is depicted in Figure 3. The test system has considered ninety thousand EVs with limited, moderate and fully hybrid operation. It can be observed from Figure 3 that the minimum instantaneous demand considering 90, 000 EVs lies in between 2, 200 MW to 2, 450 MW. At peak hours the instantaneous demand is between 3, 000 MW to 3, 180 MW which further reveals the higher stress on generation side. The result for this system are presented in Table 1, and it is worth noticing that the stochastic case has the maximum cost 761, 773.18 \$/Day where the least cost is observed in off-peak scenario 749, 320.97 \$/Day. The power generation level of each individual generator attained by SAR-ANFIS is depicted in Figures 4, 5, 6, and 7 for various charging scenarios of EVs load profiles as depicted in Figure 3. It is evident from Figures 4, 5, 6, and 7 that all generators meet the system-level constraints efficiently represented by equations (3) to (10) while achieving optimal power allocation levels. Furthermore, it is important to note that significant operational cost savings can be observed in all scenarios compared to other advanced approaches listed in Table 1. For instance consider the scenario of peak profile as shown in Figure 3, the maximum power demand in this case is 3, 180 MW for hours 15th to 17th. Figure 5 shows that SAR-ANFIS meets the dynamic power demand of 3180 MW for corresponding hours. Also it can be observed, the operational cost for this specific profile (peak) obtained by SAR-ANFIS is 781,315.65. Compared to MARFL, the proposed SAR-ANFIS yields annual savings of approximately 11.25 million dollars. Furthermore, as shown in Figures 4, 5, 6, and 7, the optimal power levels not only reduced the operational expenses but also produced the optimal emissions by consuming less fossil fuels. Also SAR-ANFIS is able to withstand the load profiles of EVs in Figure 3. The results also indicate that reducing operational costs and toxic emissions is a step toward sustainable transportation and a sustainable environment, as evidenced by the ability of SAR-ANFIS to withstand EVs loads. The other profiles with annual cost savings by the proposed SAR-ANFIS are: 7.4 million dollars for stochastic, 11.39 million dollars for off-peak, and 7.4 million dollars for the EPRI load profile. Moreover, the proposed SAR-ANFIS approach exhibits superior convergence capabilities in contrast to other state-of-the-art methodologies, including MAFRL, w-PSO, PSO-CF, and m-TLBO. The graphical evidence presented in Figures 8, 9, 10, and 11 unequivocally showcases the swift attainment of the global optimum by the proposed approach, achieved through a remarkable reduction in the number of iterations required. The simulation results also indicate that SAR-ANFIS not only efficiently tackles the complex instantaneous demand and system limitations and attains least possible operating cost as compared to other heuristic approaches, but also predicts the best optimal cost for the upcoming future EVs load curves shown in Figures 12 and 13. The optimal operational costs for these load profiles are shown in Tables 2 and 3. Moreover, the SAR scheme also yields both high performance and low computational overheads. The computational time for this simulation was found to be is 3.11 seconds as compared to [31], [32], [33], [34].

The simulation results indicate that the proposed SAR-ANFIS method exhibits greater practicality and efficiency when compared to other approaches documented in the literature. In comparison to the various methodologies discussed in [32], namely multiagent fuzzy reinforcement learning approach (MAFRL), weighted particle swarm optimization (w-PSO), particle swarm optimization constriction factor (PSO-CF), and modified teaching-learning-based optimization (m-TLBO), the SAR-ANFIS technique demonstrated the most optimal results in terms of operational fuel cost

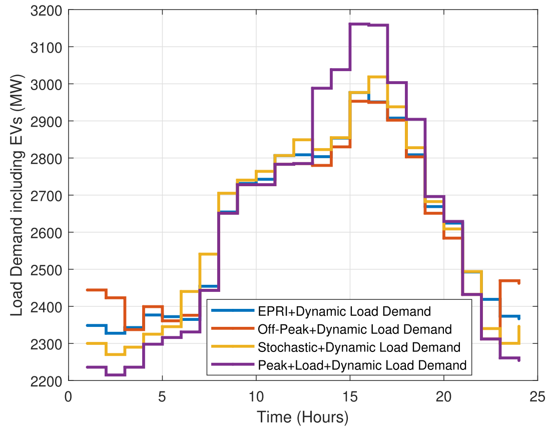

FIGURE 3. DEDs with EVs Load demand for 24 hours committed units for test system.

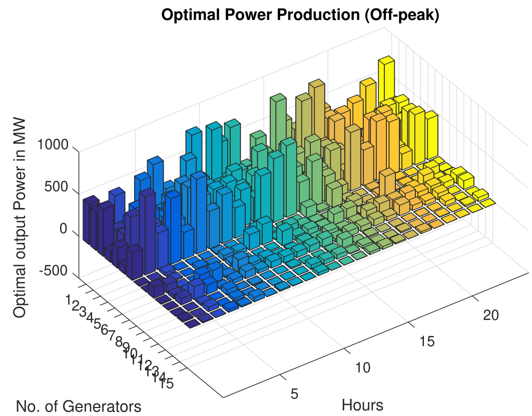

FIGURE 4. Generators response for off-peak charging scenario for test system.

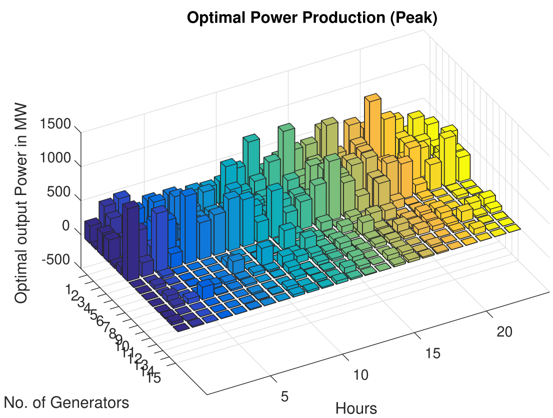

FIGURE 5. Generators response for peak charging scenario for test system.

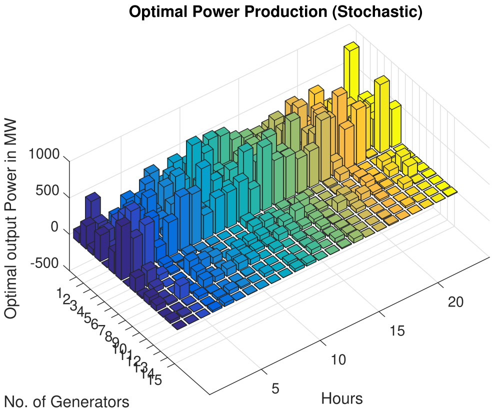

FIGURE 6. Generators response for stochastic charging scenario for test system.

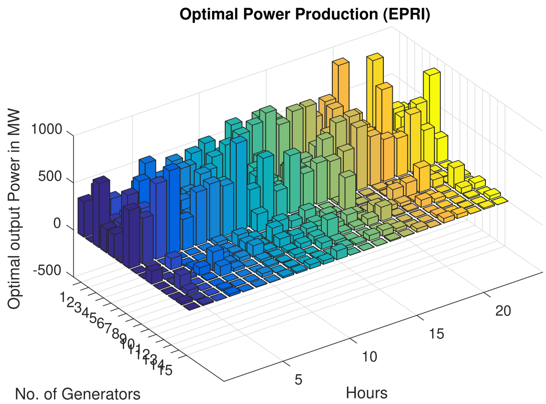

FIGURE 7. Generators response for EPRI charging scenario for test system.

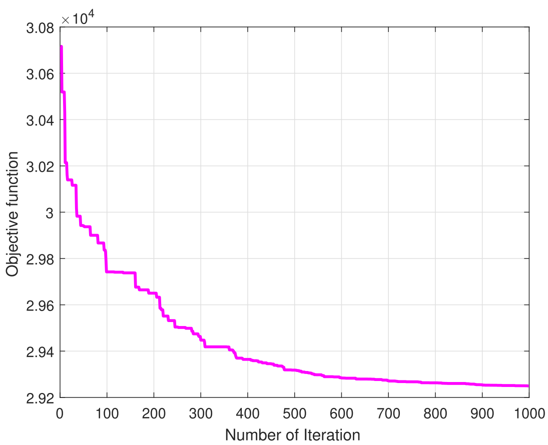

FIGURE 8. SAR-ANFIS convergence behaviour (EPRI).

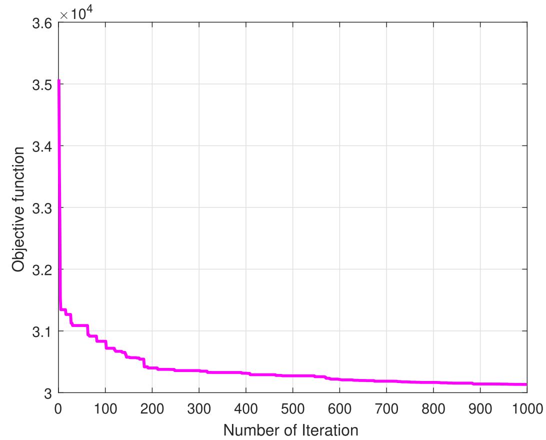

FIGURE 9. SAR-ANFIS convergence behaviour (Off-peak).

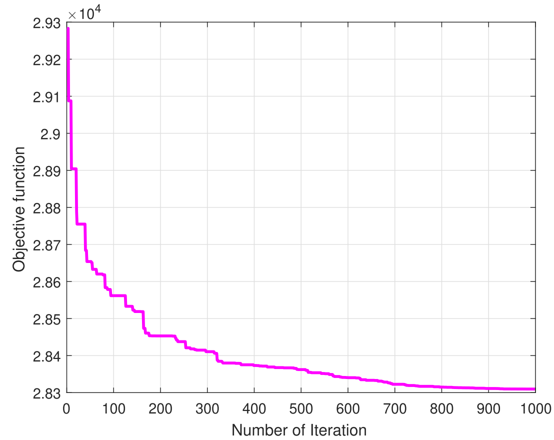

FIGURE 10. SAR-ANFIS convergence behaviour (Peak).

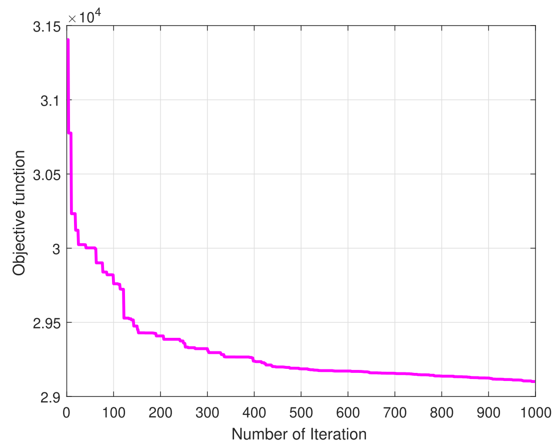

FIGURE 11. SAR-ANFIS convergence behaviour (Stochastic).

and greenhouse gas emissions across all charging scenarios, as evidenced by the data presented in Table 1. It will not only result in saving operational fuel expenses but also reduce environmental harmful emissions and dependency on imported fuels. In comparison with the study in [31], we considered a large-scale test system with fifteen generating units confined by strict system limits. In addition, our study differs from previous research cited in [31], [32], [33], [34] by integrating the ANFIS model. This approach enhances the understanding of usage patterns for future electric vehicles and enables policymakers to identify opportunities for demand-side management. The use of the ANFIS forecasting

TABLE 1. Large-scale DEDs with EVs cost ($/Day) comparison for test system.

Approach	EPRI	Off-Peak
w-PSO	783,004.14	783,650.51
PSO-CF	784,391.24	784,532.96
DE	784,354.55	784,313.52
TLBO	781,644.49	783,002.47
e-TLBO	782,323.93	782,320.70
m-TLBO	781,562.91	781,179.19
SL-TLBO	781,001.23	780,862.82
MAFRL	780,288.72	780,544.82
SAR-ANFIS	759,824.37	749,320.97
Approach	**Peak**	**Stochastic**
w-PSO	783,863.93	784,610.33
PSO-CF	785,851.62	785,491.74
DE	785,512.30	785,273.31
TLBO	784,004.33	783,962.29
e-TLBO	783,383.72	783,280.51
m-TLBO	782,922.74	782,138.87
SL-TLBO	781,961.91	781,459.24
MAFRL	781,315.65	782,415
SAR-ANFIS	750,487.40	761,773.18

model facilitates informed decision-making by policymakers, the creation of streamlined processes, and the formulation of potential tariff structures for future loads. Furthermore, a novel and intricate model has been formulated by integrating the constraints of SR to enhance the feasibility of smart grid operations. SRs have the potential to regulate frequency, mitigate power losses, and facilitate the charging of numerous EVs in the event of a disconnection.

EVs sales have skyrocketed in recent years with significant increase around the globe, and extensive decarbonization plans are being implemented by numerous countries, with the goal of diminishing the use of traditional vehicles [62]. In 2025, it is expected that global production of EVs will reach 14.8 million units [63]. This sudden rise of EVs market also brings challenges to design accurate load prediction models, based on machine learning tools to handle precarious electric loads of EVs in current power generation energy hubs. The management of the energy system, particularly, the generations and transmission networks, will undoubtedly be affected by transition from traditional vehicles to EVs. Researchers have looked at a wide range of challenges caused by EVs penetration to energy grids [64]. Multiple studies have previously examined the EVs penetration consequences in energy grids in terms of precarious load demand, impact on generation cost for EVs charging and system security [65]. According to a recent research [66], the number of people purchasing EVs is expected to rise, reaching as much as 10% of the car market by 2025 and 20% to 30% of the market by 2030. With the adoption of EVs, the sustainable transit system has become a vital component of economic planning, as a

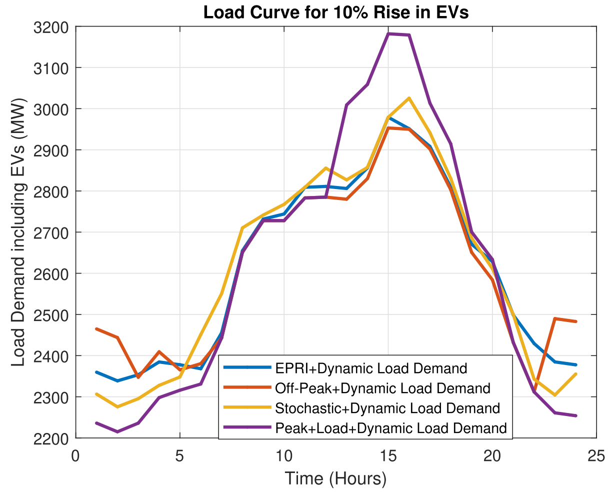

FIGURE 12. DEDs with EVs Load demand for 24 hours year 2025.

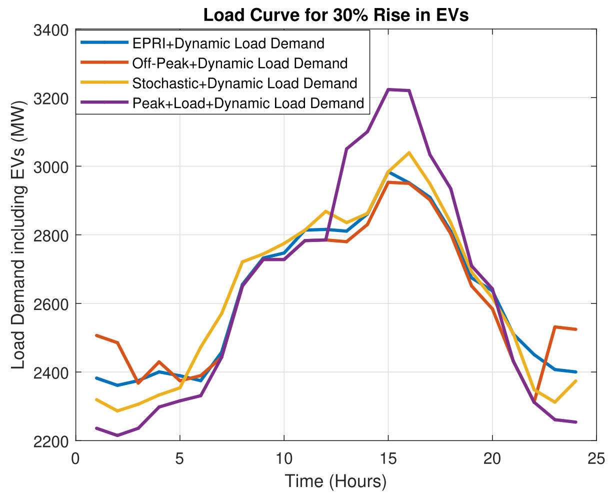

FIGURE 13. DEDs with EVs Load demand for 24 hours year 2030.

variety of sophisticated optimization techniques have been implemented to address the complexity and nonlinearities involved. The developed SAR-ANFIS framework enables industries' administration and legislators to improve or modify their complex dispatch infrastructure in order to fulfil mobile EVs loads quickly and cost-effectively.

Now we have modified the test system for future EVs load. The state of charge is assumed to be 50% with participation ratio (45%, 25%, and 30% for all charging scenarios. The initial EVs load was computed as $9000 \times (15 \times 0.45 + 25 \times 0.25 + 40 \times 0.30) \times 0.5 = 1125$ MW. According to [66], the 10% increase in EVs will increase the load to 1237 MW and with increase of 30% the new load for year 2030 will be 1462 MW. The new modified load curves for years 2025 and 2030 are shown in Figures 12 and 13, respectively.

The dynamic load demand for EVs has been used as the input for the proposed model, and the optimal operating cost has been employed as the output in this study. SAR did a large number of iterations at this point in order to construct

TABLE 2. DEDs with EVs load demand in $/Day for year 2025.

SAR-ANFIS Predictive Cost for 10% EVs Rise			
EPRI	799370.58	Peak	791188.42
Stochastic	771393.03	Off-peak	751255.83

TABLE 3. DEDs with EVs load demand in $/Day for year 2030.

SAR-ANFIS Predictive Cost for 30% EVs Rise			
EPRI	806580.19	Peak	801529.24
Stochastic	793729.85	Off-peak	758002.32

a realistic model, starting with the smallest capacity of the generator as load and progressing to the highest delivery capacity of the powers available. The potential outliers are eliminated following the completion of the analysis. This data set is divided into three subsets, with 50 percent being used for training, 25 percent being used for checking, and 25 percent being used for testing. Following that the data is sent to the SAR-ANFIS model, as indicated in Figure 2. For the sake of simplicity, we have computed the costs of all charging scenarios with the same dynamic load demand, and the prediction results are tabulated in Tables 2 and 3 in $/Day.

VI. CONCLUSION

This paper developed a data-driven ANFIS model for energy hubs integrated with EV loads by considering multiple charging scenarios such as EPRI, off-peak/peak, and stochastic. An optimal cost was determined (EPRI 759,824.37 $/Day, Peak 750,487.40 $/Day, Off-peak 749,320.97 $/Day, and Stochastic 761,773.18 $/Day) for dynamic energy emission dispatch model by fulfilling non-convex confined constraints at the system level via SAR, and then an ANFIS model using a feed-forward multi-layer neural network was trained to predict the cost for all charging scenarios with the increase in load. Furthermore, the SAR-ANFIS has demonstrated that it is an interpretable model structure with several rules to prevent an energy overload. The SAR-ANFIS strategy will benefit not only energy providers in terms of ensuring safe and secure dispatch operations while maintaining quality but also energy auditors and policymakers in terms of forecasting energy costs and tariff plans for future EV load on current distribution networks. The proposed scheme's flexibility enables it to foresee future developments in the field. Even though SAR-ANFIS combines optimization and prediction capabilities to track the best global optimal point, the method has some limitations. For instance, with a large memory matrix, the optimal solution searching capability becomes slower. In addition, the centralized nature of the proposed strategy renders it ineffective against system attacks. In the future, we can modify the model for vehicle-to-grid operations in a distributed manner, where EVs users can sell their vehicles' battery energy to grids during peak utilization times.

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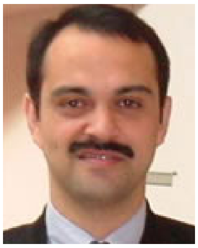

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