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Profitable and reliable EV charging infrastructure: A time-series power flow model for improved voltage and power stability

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ABSTRACT

Efficient and sustainable planning of Electric Vehicle (EV) charging infrastructure requires balancing technical, economic, and environmental factors. Existing EV Charging Station (EVCS) designs often overlook user convenience and grid reliability, while failing to account for uncertainties, which can lead to inefficiencies and suboptimal system performance. This study presents an intelligent approach for profitable and reliable EV charging infrastructure using a Time-Series Power Flow (TSPF) model to enhance voltage and power stability. The proposed method integrates the Opposition-Based Botox Optimization Algorithm (OBOA) and Spatio-Temporal Field Neural Network (STFNN), referred to as the OBOA-STFNN technique. The BOA optimizes the siting and sizing of EVCSs to balance operator profit, grid stability, and user convenience, while STFNN predicts individual EV charging behavior and station demand. The effectiveness of the technique is evaluated in MATLAB and compared with Particle Swarm Optimization (PSO), Modified Snake Optimization (MSO), and Convolutional Neural Network (CNN) approaches. Simulation results demonstrate that the OBOA-STFNN method significantly reduces energy consumption to 38.74 MWh and energy loss to 418 MWh, while achieving a lower optimal cost, mean, and standard deviation, along with reduced total computation time. These results highlight the superior efficiency, reliability, and practicality of the proposed approach for EVCS planning and operation.

1. Introduction

1.1. Background

For addressing both economic and environmental problems in conventional fossil-fueled transportation, transportation electrification is necessary [1]. The use of EVs can be put to good use to decrease fossil fuel use, decrease air pollution, and ensure mobility in cities [2]. The planning of an appropriate Electric Vehicle Charging Station (EVCS) is very important for promoting EV adoption [3]. The flow of traffic, driving habits, and efficiency of both transportation and electrical power utility networks are directly affected by the distribution and capacity of EVCSs [4]. The EV charging takes a lot longer in comparison to that of conventional fuel filling, and hence [25-28], more charging stations would be required to be installed to make it as easily accessible as it is at petrol stations [5]. The servicing time is dependent on the number of charging points for a particular station, while the total number of stations determines the capacity of the electrical equipment to be used for supplying electricity to stations for charging of EVs [6]. Incorrect positioning or size of EVCSs may pose threats to the power grid, such as voltage instability, peak demand, power losses, bus voltage variation and reduced reliability [7]. Also, the poor location of the stations may increase the travelling time of the drivers and change the traffic patterns [8]. Thus, location and capacity optimisation of EVCS is crucial in order to have an efficient, reliable, and sustainable operation of the transportation system and the electrical grid [9,10].

1.2. Literature review

In the literature, various research works were available related to various techniques and aspects. A few of these were reviewed.

Nafeh et al. [11] have suggested the Modified Snake Optimization

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(MSO) algorithm to size grid-connected PV-battery systems to be used in fast-charging stations. They performed a study that incorporated techno-economic analysis and energy management strategy to provide energy balance and reduce total system costs. The strategy has shown to be effective in the optimization of system components with economic viability in diverse pricing strategies.

Muthukannan and Karthikaikannan [12] have presented Particle Swarm Optimization (PSO) to solve the concurrent location of EV charging stations and shunt capacitors. The research was intended to minimize the losses of power, stability of voltages, and coverage in traffic networks. The location and rating of charging stations and capacitors were part of the control variables to optimize grid performance and user convenience of EVs.

Monikandan et al. [13] have introduced Convolutional Neural Networks (CNNs) to streamline EV charging towards minimizing the operational costs and multi-year capacity growth planning. Renewable energy sources, micro-turbines, and battery storage were included in the model, and EV waiting times and the growing load demand were considered. Validation of performance was done on the statistical indices, including mean squared error, correlation coefficient, and mean absolute error.

Turkoglu et al. [14] have developed a method to address the uncertainties in residential load and EV demand, Temporal Convolutional Networks (TCN), and Mixed-Integer Quadratically Constrained Programming (MIQCP). They included Vehicle-to-Grid (V2G) technology as a Virtual Power Plant (VPP) to develop EVs and power grid synergy in maximizing EV profit, minimizing active power loss, and minimizing voltage drops.

Xu et al. [15] have suggested an elaborate model comprising of solar, wind, and battery energy storage and EV charging stations. The study planned renewable energy production with EV charging using machine-learning demand forecasting, enhancing operational performance, grid resiliency, and sustainability and helping to integrate clean energy.

Ramul et al. [16] have introduced the system of Hybrid Fuzzy-Multi-Agent Deep Reinforcement Learning (HF-MADRL) of intrusion detection and mitigation at several layers of EVCS. The method performed Gaussian thresholding and fuzzy C-Means clustering to improve security and adaptive response of EV charging networks.

Amir et al. [17] have introduced an Intelligent Energy Management System (IEMS) of PV-based EV charging stations. The system predicted the solar production and EV load, optimized energy between the PV, the grid, and the battery storage, and minimized the peak power demand. The research attempted to resolve the issues of periodical solar irradiance and battery state-of-charge control, which enhanced the reliability and efficiency of EVCS activities.

He et al. [18] have introduced a multi-objective planning model for EVCS based on the spatial-temporal distribution of EV charging demand and traffic-grid coupling. To simulate EV movement patterns, a real-time traffic model was first created using the real road network. After that, point of interest data analysis was used to divide the planning region. Ultimately, an ideal EVCS planning model was created with the goal of reducing overall expenses, user discontent, and voltage variations. Review of literature survey is shown in Table 1.

Table 1
Review of Literature Survey.

Techniques	Objective	Features	Limitations
Modified Snake Optimization (MSO), Metaheuristic Optimization [11]	Minimize system cost, Ensure energy balance	Techno-economic study, PV-battery grid for EV fast charging	No detailed analysis of data for dynamic load
Particle Swarm Optimization (PSO) [12]	Maximize coverage, Minimize loss, Improve voltage profile	EV charging station placement, Shunt capacitors for loss reduction	Limited scalability for large systems
Convolutional Neural Network (CNN) [13]	Reduce cost of installation, Reduce operational cost	Capacity expansion with EV charging, Battery energy storage	Queuing delay not thoroughly modeled
Mixed-Integer Quadratically Constrained Programming (MIQCP), Temporal Convolutional Network (TCN) [14]	Optimize power grid integration with EVs	EV integration with VPP, Multi-objective optimization	Limited focus on grid infrastructure limitations
Machine Learning-based Forecasting [15]	Improve clean energy charging efficiency, Ensure system reliability	Integration of EV charging, PV, Wind, Storage systems	Reliant on data; complex for small-scale grids
Hybrid Fuzzy-Multi-Agent Deep Reinforcement Learning (HF-MADRL) [16]	Enhance cybersecurity for EVCS, Detect and mitigate hybrid attacks	Intrusion detection, Adaptive mechanisms, Resilience	Requires advanced infrastructure and adaptation
Intelligent Energy Management Scheme (IEMS), Adaptive Neuro-Fuzzy Control [17]	Optimize power flow between PV, grid, and EV storage	Power flow optimization, Solar-based EV charging	Involves complex forecasting and data handling
Multi-objective EVCS Planning [18]	Minimize cost, user dissatisfaction, and voltage fluctuations	Region partitioning, optimal EVCS planning	Limited consideration of dynamic load variations

1.3. Research Gap and motivation

The generic analysis of the recent studies reveals that one of the significant sides of the sustainable transportation and efficient distribution of power and convenience of users is the optimal location and size of EVCSs. The performance of applications in this field is usually hampered by the difficulty of controlling the operator's profitability, energy losses reduction, and the stability of the grid voltage. The optimal sites and capacity of EVCSs in dynamic EV behavior and time variation in demand are very difficult to determine. This issue has been solved by numerous scholars employing different methods like Modified Snake Optimization (MSO), Particle Swarm Optimization (PSO), Temporal Convolutional Network (TCN), and Convolutional Neural Networks (CNN). Nonetheless, MSO has weaknesses in the rapid converging and inefficient energy management, PSO has inefficiency in timely converging and managing spatio-temporal uncertainties, and CNN, though being efficient in the prediction of demand, is inefficient in terms of energy efficiency and grid stability. Current technologies do not aim at uniting economic, technical, and user-centric goals at the same time. These limitations have led to very few approaches with comprehensive coverage in the literature, and it is these limitations that have inspired the creation of the proposed research work.

This study is novel because it proposes an intelligent and combined OBOA-STFNN as the optimal solution for placements and sizing EV charging stations. Unlike conventional methods, the proposed approach simultaneously addresses economic, technical, and user-centric objectives, including profitability, energy efficiency, grid voltage stability, and user convenience. The combination of the Opposition-Based Botox Optimization Algorithm (OBOA) to optimally site and size EV charging equipment with the Spatio-Temporal Field Neural Network (STFNN) to precisely predict EV charging demand makes the approach effective in addressing the uncertainties in EV behavior and the time-dependent changes in load. Also, it is possible to introduce Time-Series Power Flow (TSPF) to better predict and control the power flows and provide greater reliability and less wastage of energy. This holistic model is cost-effective, more efficient in energy consumption, uses less energy, and

4.1. Discussion

The combination of BOA and STFNN with TSPF analysis enhances the robustness and adaptability of the proposed method, making it a powerful tool for addressing the complexities of EV integration and power system uncertainties. This method outperforms existing techniques by achieving significant improvements in performance metrics, as demonstrated through Total computational time and energy loss. Specifically, the proposed method achieves the lower optimal cost of 5885.32$, which is superior to MSO, is 6547.24$, PSO, is 5913.02$, and CNN, is 5980.23 $, indicating higher economic benefits. OBOA-STFNN method demonstrates the most efficiency by consuming only 38.74 Mwh, significantly less than MSO at51.58 Mwh, PSO at 64.48 Mwh, an CNNat 76.62 Mwh,the SD of the proposed method is 0.0364, and Mean is 1.724, which indicates better system performances. Additionally, Energy loss of the proposed method is 418 Mwh while for MSO its 446 Mwh, for PSO its 471 Mwh and for CNN its 470 Mwh indicating higher efficiency. For the proposed method, Total computation time is also low with 1326 s, while for MSO its 1630 s, for PSO its 1598 s and 1432 s for CNN, showcasing improved computational efficiency. Overall, the proposed approach not only minimizes energy lossand energy consumption but also significantly improves energy usage, battery performance, and optimal cost. This results in improved throughput, higher energy efficiency, faster transmission rates, and reduced system latency, making OBOA-STFNN a highly effective and comprehensive solution for the placement and sizing of EV charging stations.

5. Conclusion

This study introduces an opposition-based OBOA-STFNN that will be used to optimally locate and size the electric vehicle charging stations. Solving this problem is possible with the introduction of the TSPF model, which allows making the correct prediction of power demand, detecting the possible overload situations in advance, whereas OBOA and STFNN provide efficient solutions to the temporal variations and uncertainties in EV charging. The proposed solution enables accurate determination of the optimal location of the charging stations and the correct capacity of the chargers, and thus maximizes the returns of the investment and minimizes the waiting time of the users. The proposed approach has been implemented in MATLAB and compared with some of the existing approaches. Its findings indicate that the proposed solution is an optimal cost of a much lower value of 5885.32$ that is lower than the respective costs of MSO, PSO, and CNN. Also, the proposed approach has a high level of statistical activity with a mean of 1.724 and a standard deviation of 0.0364, which validates the robustness and reliability of the approach. The proposed model can be considered superior to the existing approaches in terms of optimal cost, energy consumption, and computer performance. The future work will be associated with practical work and confirmation of the proposed framework, pilot-scale launching of EV charging stations in real-life distribution networks. It will include real-time grid measurements and on-site EV charging data, and hardware-in-the-loop testing to evaluate the viability of the practice and the robustness of its operation. Also, the partnership with utility operators and urban planners will be considered to assess regulatory, economic, and infrastructural limitations, thus simplifying the implementation of the proposed approach on a large scale in the actual working conditions.

CRediT authorship contribution statement

M. Senthilkumar: Writing – original draft, Methodology, Conceptualization. **R. Saravanan:** Supervision. **V. Madhu Kumar:** Supervision. **G.G. Raja Sekhar:** Supervision.

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Not Applicable.

Consent for publication

Not Applicable.

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

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Data availability

No data was used for the research described in the article.

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