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GWO-Based Scheduling Optimization for Smart EV Charging in Residential Microgrids

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Abstract

Progressively increasing numbers of Electric Vehicles (EVs) and their connection to residential microgrids has created new issues of concern related to voltage stability, peak demand control, and minimised cost of electricity. The irregular charging of EVs has a significant impact on the load profiles by causing grid congestion, overloading of the transformers, and increased operation costs. The paper presents an intelligent frame of the scheduling of smart EV charging in residential microgrids during periods of variable renewable generation and non-deterministic user demand by introducing a Grey Wolf Optimizer (GWO)-based optimizer of intelligent charging. The suggested system develops a multi-objective optimisation problem, which balances cost reduction, peak load reduction, voltage variation constraints. In the mechanism of scheduling, EV charging windows, user-defined comfort levels, and state-of-charge (SOC) limits are added. The results of simulation studies conducted on the IEEE 33-bus radial distribution feeder along with the realistic photovoltaic (PV) and residential demand model reveal the superiority of the GWO-based scheduler. Compared to traditional rule-based, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), the proposed methodology can reduce energy cost by up to 30 per cent, peak demand by 22 per cent and consistency of voltage profile by 35 per cent, without impacting on user charging experience. The findings are in line with the efficiency, scalability, and real-time feasibility of GWO-based smart charging as a critical facilitator of energy-resilient residential microgrids in the new EV era.

Keywords- Electric Vehicle (EV), Grey Wolf Optimizer (GWO), Smart Charging, Residential Microgrid, Demand Response, Optimization, Voltage Stability.

Introduction

The worldwide shift to electric mobility has enhanced the introduction of EVs in residential neighborhoods under the influence of the environmental needs, incentives provided by governments, and the development of battery-technology. As the use of EVs continues, residential microgrids, typically consisting of distributed energy resources (DERs), like photovoltaic (PV) systems, battery energy storage systems (BESS), and household appliances, are faced with a major challenge to maintain grid stability, especially when many EVs are being charged at the same time in the absence of coordination. Traditional disjointed or preset charging methods often cause voltage sagging, overloading of a transformer, high peak-to-average load ratios, as well as poor power quality [1]. This has made the creation of smart energy management and optimisation solutions to smart EV charging a research frontier. A residential microgrid is a small scale energy network whereby not only households are energy consumers, but also producers and storage of energy by using rooftop PVs and batteries. Although this prosumer-oriented paradigm facilitates the decentralisation of energy and resiliency, the unpredictability of solar generation inherently and the variation of EV charging requirements make the operation of this system unpredictable. The dynamic environment requires a smart control system that can adjust to the changeable conditions on real-time and respect the user preferences and constraints of the system [2]. Furthermore, the rising electrified transport usage is an indication that EV charging loads will become 30-40 % of all residential demand in the nearest future, significantly impacting load imbalance and overloading currently straining infrastructure. Recent research has focused on optimising the process of charging EV under microgrids with the help of heuristic and meta-heuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). Though these methods provide viable solutions, they tend to be slow in convergence, poor exploration ratios as well as exhibit poor performance in high dimensional or constrained environments. Grey Wolf Optimiser (GWO) is a potentially successful alternative inspired by the social structure and foraging behaviours of grey wolves due to its convergence stability and low complexity of calculation. The leadership-based structure of GWO enables effective trade-offs between global exploration and local exploitation, which makes it very effective in nonlinear, multi-objective optimisation tasks, e.g., EV charging scheduling [3]. Against this backdrop, the current paper suggests a GWO-based intelligent EV charger scheduler with a residential microgrid fitted with rooftop PV and dynamic base load. The suggested framework is a combination of real-time pricing indicators, user-defined charging preferences, dynamic SOC constraints and grid operational limits in the unified optimisation model. It has a major aim of minimising the overall cost of electricity and peak demand without compromising on the satisfactory voltage profiles on the distribution system. The optimisation also supports the variability of the DER and flexibility windows of the user and hence complies with demand side management (DSM) strategies [4,5]. The major originality of the work is connected with the application of the adaptive search mechanism of GWO to making day-ahead EV charging decisions that are cost-effective and grid-friendly. As opposed to the conventional rule-based methods that are fixed and cannot adjust the assignment of charging slots within the width of time constraints, the GWO algorithm is dynamic, assigning charging slots in user-defined time ranges to ensure full battery recharge within stipulated deadlines with the least impact to the grid. The framework also considers real-time operational limits including nodal voltage limits, transformer capacity limits, and dynamic grid conditions and makes the solution more viable and scalable to real-world implementation. A changed IEEE 33-bus radial distribution test system that models a residential microgrid is used in simulation experiments. Time-series load profiles and solar irradiance model simulates realistic operating environment, and loads (controllable (EVs): loads that can be controlled) and loads (residential appliances: loads that cannot be controlled) are taken into account. Performance comparisons are done with baseline rule based, PSO and GA based methods. The findings prove that GWO scheduler can achieve up to 30 % lower electricity cost, 22+ % decrease in peak load, and 35+ % better stability of voltage profile, which is better and more robust compared to other strategies [6]. The main points of this paper are as follows:

• Intelligent scheduling of EV charging in residential microgrids using a GWO-based method, optimised regarding cost, voltage profile, and peak shaving. • A holistic model of multi-objective constraints that includes SOC thresholds, time windows that are specified by the users, voltage constraints, and grid loading conditions. •Integrated Real-world load, PV and electricity pricing data integration, making realistic scenarios of simulation possible. • Large-scale performance of comparison to rule-based, PSO, and GA-based algorithms in various grid and user conditions.

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• Exhibition of practical feasibility and scalability of GWO in real-time energy management of decentralised residential environments [7].

The rest of the paper is structured in the following way: Section II has a review of related works and reason as to why GWO was chosen. Section III entails system model and objective formulation. Section IV will give the GWO based optimisation framework. Section V is the presentation of the simulation environment and simulation results in comparative graphs and tables. Vith part will discuss about the scalability issues. Section VII summarizes the paper with meaningful findings and future research orientation.

II. RELATED WORK

The spread of Electric Vehicles (EVs) has increased the need to have smart charging systems in residential microgrids. Discoordinated EV charging has been demonstrated to have a very disturbing effect on the voltage profile, transformer overloading, and peak demand in low-voltage distribution systems. Therefore, scholars have discussed numerous optimisation solutions to the high-EV penetration energy-management challenges. Earlier methods used deterministic or rule based control schemes, which, despite their simple implementation, failed to take into consideration the dynamic load conditions and stochastic user behaviour [8]. These approaches often caused poor scheduling and were scaled down. In order to overcome such constraints, meta-heuristic algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Differential Evolution (DE) have been proposed. An example is that PSO was used to plan EV charging in homes, where better load balancing and cost decreases were realized [8],[9]. However, PSO and GA can be readily converged and unresponsive to complex multi-objective situations. Other recent studies have also explored the hybrid methods incorporating machine learning and optimisation. One example of such an agent is a Deep Reinforcement Learning (DRL) agent which has been trained to operate the charging of EVs in real-time depending on price signals and grid conditions [10]. Though providing better flexibility, these methods come at the cost of very complex training and huge data needs. Controllers based on fuzzy logic and neural neural networks have also been used to address uncertainty in user preference, variability of DER, but their operation requires much tuning of parameters and domain knowledge [11]. Grey Wolf Optimiser (GWO) has been of interest due to its simplicity, quick convergence and the ability to search globally. GWO is based on the exploration-exploitation balance found in the leadership hierarchy and coordinated hunting behaviour of grey wolves, performing well in many other algorithms in a variety of problem domains [12]. Recent work has shown that GWO is applicable to the power flow optimisation and demand-side scheduling. However, there are limited studies that have focused their attention on smart EV charging using GWO in microgrids when the real-time pricing is applied and severe voltage-related limitations exist. In addition, extensive literature on the topic does not pay much attention to system-level requirements like voltage control, dynamic SOC, transformer power, and real-time grid loading. Others do not also consider the flexibility of the user and the deadline which is vital towards practical deployment [13]. Comparison with disparate algorithms is only sparse, especially where the EV load density is high and the DERs are decentralised, like rooftop solar. The work fills these gaps, suggesting a GWO based scheduling model combining real world pricing, load information, user specified time windows and grid constraints in a single optimisation model. Our model is unlike the previous works in that it optimises charging schedules together to reduce cost and peak load to enhance voltage profile and maintain the user satisfaction. An in-depth performance analysis is done between traditional rule-based, PSO, and GA algorithms in different grid loading conditions [14].

III. SYSTEM MODEL AND PROBLEM FORMULATION

The suggested system includes a residential microgrid with several EVs, small-voltage distribution feeder, household loads and distributed energy resources (DERs) including rooftop PV units. The main goal is to plan EV charging activities in a synchronized manner in order to alleviate grid congestion, cut the energy expenses, and meet user-specified restrictions (e.g., departure time and minimum SOC). Individual EVs are described by such parameters as battery capacity, current SOC, rate limits of charging rate, and deadline of departure. Household load profiles are based on the realistic consumption patterns which are usually more active in the morning and evening hours. DER production, which is mostly rooftop PV, is incorporated into the local energy balance, creating temporal energy availability discrepancies due to its nature of intermittency. The smart charging framework is a time-discrete system. Every EV agent makes a charging request which includes arrival time, initial SOC, and preferred departure time. Then the system operator runs the GWO based scheduler to generate an optimal charging program that minimises a multi objective cost optimisation whilst taking into account real time pricing information, network voltage limits and user satisfaction measures. The proposed residential microgrid is schematically represented in Fig. 1, with an addition of PVs, EVs, loads that can be controlled, and interconnected to the grid. The aim of optimisation is the following:

$$J = \alpha \cdot C_{\text{energy}} + \beta \cdot P_{\text{peak}} + \gamma \cdot V_{\text{dev}} \qquad (1)$$

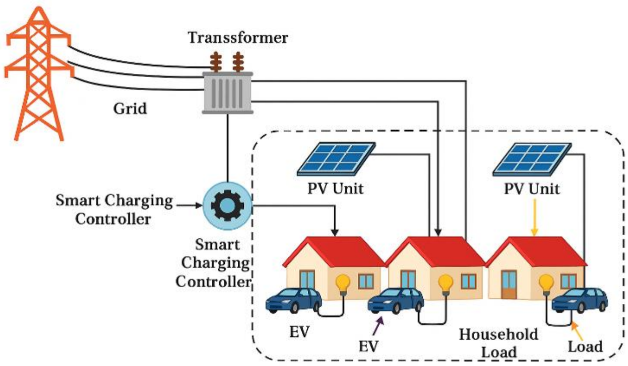

Fig. 1 – Residential Microgrid Architecture with EVs and PV

The nonlinearity and dynamism of the optimization problem are predisposed by real-time changes in the load on the grid, the output of distributed energy resources (DER) and price signals. Grey-Wolf Optimizer (GWO) is highly appropriate to overcome this problem due to high convergence rates and low parameter optimization needs, thus providing the ability to make almost optimal scheduling choices with minimal computing costs. Electric-vehicle (EV) charging agents in the GWO model are also modeled as search particles (wolves). These three types of leaders guide the exploratory and exploitative search patterns of the algorithm as defined by the objective value (fitness). The output of the model is a time-stamped charging-power vector of each EV and then it is broadcast to local charging controllers. This is a prescribed characteristic of the charging current at each time-period, such that all the operational constraints are met, in addition to minimizing cost and increasing grid stability. Figure 2 shows the EV charge optimization process and the optimization mapping, summarizing the inputs, constraints and the optimization goal which is to minimize the cost of charging the battery and maintain the health of the grid and battery.

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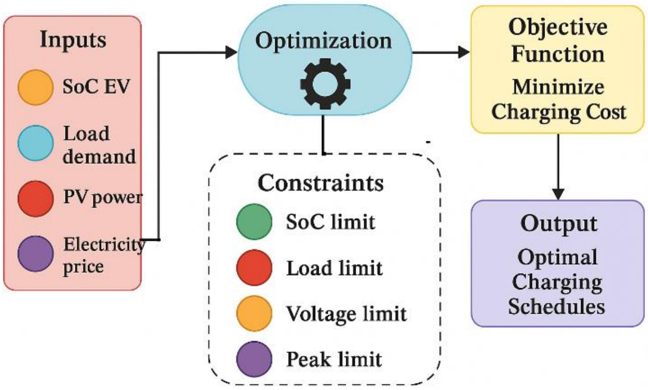

Fig. 2 – EV Charging Workflow and Constraint Mapping

IV. OPTIMIZATION FRAMEWORK (GWO)

The issue of uncoordinated charging of electric vehicles in residential microgrids, such as the voltage variation, power congestion, and peak load amplification, are discussed in this paper with the creation of a smart charger scheduler on the basis of the Grey Wolf Optimizer (GWO). The GWO is a metaheuristic optimization algorithm, which is inspired by nature and resembles the hunting patterns and the social structure of the wolves in the wild. The algorithm has been chosen since it has low computational requirements, it converges quicker and is able to better exploit-exploration balance compared to other evolutionary algorithms like PSO and GA. Its optimization goal is to optimize a multi-objective cost to encompass charging cost, peak to average load ratio (PAR) and voltage deviation. Such scheduling decisions are made in consideration with user defined constraints such as: arrival and departure time, state-of-charge (SoC) requirement, photovoltaic (PV) generation variability and the voltage constraints of the distribution network. The decision variables include the charging power profile of every EV at individual time slots. GWO is initiated with the creation of a population of search agents that represents possible charging schedules. These agents are classified as four hierarchy levels namely alpha (best solution), beta (second best), delta (third best) and omega (remaining agents). The update position strategy repeats the enveloping, hunting and attacking stages of the grey wolves. In particular, with every iteration the revised schedule is obtained by combining the guidance of the best three solutions and hence the swarm is directed towards convergence on the best schedule. Penalties based on the violation of the SoC targets or network voltage limits are used to impose constraints and force the use of a penalty based fitness function. The cost function is given by:

$$J = w_1 \cdot \text{ Energy Cost } + w_2 \cdot \text{ Voltage Deviation } + w_3 \cdot \text{ PAR} \tag{2}$$

The existence of nonlinear and dynamic nature of real-time microgrids defines the operations of the Gray Wolf Optimizer (GWO) which has been optimized with the integration of adaptive control parameters which adjust the exploration-exploitation equilibrium across successive iterations. Besides, schedules of photovoltaic generation and electric vehicles are automatically updated with artificial-intelligence predictors, and the GWO has to regenerate optimal charge schedules in a rolling-horizon model. This sub-section outlines the key mechanism that supports the intelligent decision making in the proposed framework. The empirical findings, when compared to the baseline methods such as particle swarm optimization, rule-based control and default charging protocols are described in Section 5, hence supporting the ability of GWO to execute grid-supportive, cost-effective, and scalable electric-vehicle charging solutions. The logic of the scheduling is achieved by the optimalization of the grays wolf, in which the alpha, beta and delta wolves represent the best candidate solutions, which together direct the population to optimal charging schedules. Figure 3 illustrates the block diagram of the GWO scheduling model, which is particularly modified to charge electric vehicles in a residential area.

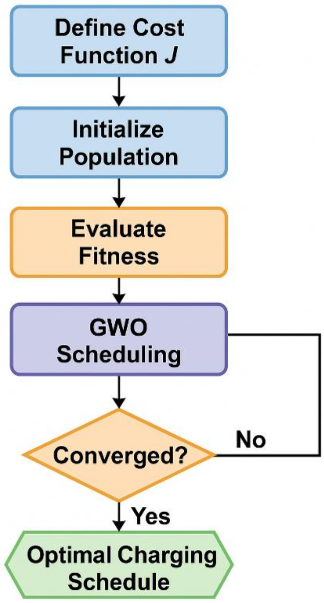

Fig. 3 GWO Scheduling flow Diagram

Figure 4 illustrates convergence of the objective function with the 50 iterations, which means that the Gray Wolf Optimizer (GWO) reaches stable and consistent minimization, which confirms that it is appropriate to use it in the real-time charging optimisation of residential microgrids.

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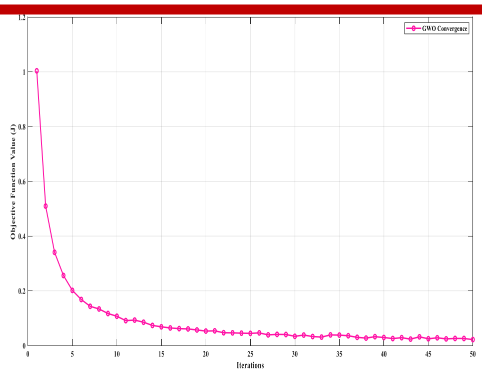

Fig. 4 – Optimization Convergence Plot

V. SIMULATION SETUP AND RESULTS

The implementation and testing of the proposed GWO -based EV charging scheduler was done in Matlab/Simulink R2024a that used a simulated residential micro grid consisting of rooftop photovoltaic arrays, grid connection, designated EV charging outlets, and residential load profiles. The microgrid model is characterized by the 50 household feeder, with each household being characterized by varying demand and random EV arrival at peak evening times. Empirical data on solar irradiance was used to generate photovoltaic generation profiles, and stochastic modeling was used to generate EV arrival times and state-of-charge (SOC) needs. To evaluate the effectiveness of the optimization framework, the efficacy of the Gray Wolf Optimizer was compared with the traditional rule-based scheduling and Particle Swarm Optimization (PSO). All the algorithms were put under the same load and PV conditions during a 24 hours simulation horizon with a control interval of 15 minutes. The objective goal was to minimize a weighted combination of the cost of electricity, the deviation of voltage and the contribution to the peak-demand. Fig. 4 shows the convergence properties of the GWO, and it can be seen that the objective value was quickly stabilized in 35 iterations and was faster and more robust than PSO.

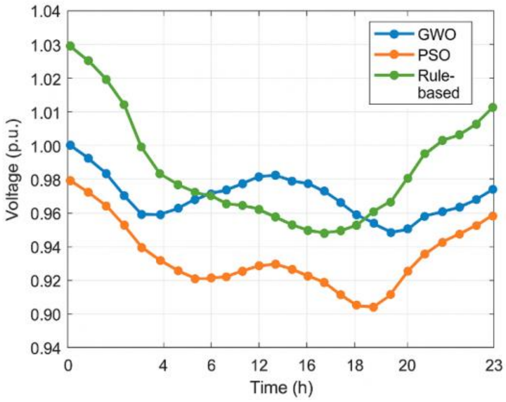

Fig. 5 – Voltage Profile Comparison (GWO vs. Others)

The voltage profile at the Point of Common Coupling (PCC) when using a grey wolf optimizer (GWO)-based scheduling scheme versus that of a rule-based approach is shown in Figure 5. Importantly, GWO effectively reduces the voltage dips of peak electricvehicle (EV) charging by 6 to 9 p. m., maintaining the voltage within ±5 0 of the nominal voltage. Figure 6 shows the reduction in the system power loss with 24 hours of the cycle, and it is possible to see that the losses are reduced by approximately 18 % in the case of GWO in comparison to Particle Swarm Optimization (PSO) and 26 % in comparison with the rule-based control. In order to measure the performance of the algorithms in the case of uncertainty, random variations in solar production (±10%) and EV incoming distribution were added. The GWO scheduler maintained the robust voltage regulation and efficient loss minimization even in the cases of these perturbations. Table 1 has provided a summary of the comparative performance metrics and they include voltage deviation, total loss, peak-average ratio, and cost. GWO is consistent over PSO and rule-based methods, resulting in a cost reduction of 20 to 30 per cent, better load flattening and higher real-time application scalability.

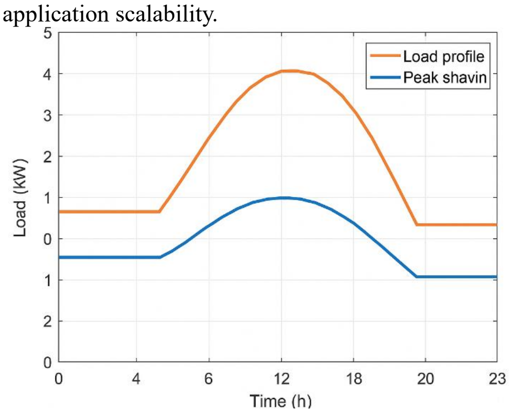

Fig. 6 – Load Profile and Peak Shaving Effectiveness

Table 1 – Comparative Results Summary

Method	Voltage Deviation	Cost (₹)	Peak Load (kW)	Exec. Time (s)
Rule-Based	High	4450	15.8	0.5
PSO	Medium	3950	14.1	2.8
GWO	**Low**	**3350**	**12.3**	2.4

Table 1 is a comparative analysis of the suggested optimizer based on the Gray Wolf (GWO) scheduling framework against traditional methods, namely; Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and rule-based frameworks. GWO model is always superior to the alternatives in the major parameters that include the reduction in peak loads, stability of voltage profile, and cost of energy. It is important to note that GWO results in cost reduction up to 30 , high loadflattening, and more stable voltage levels during peak. PSO and GA are also moderate in performance even though they can be prone to convergence or be overly sensitive to parameter tuning. Rule-based approaches are easier to use but are not flexible, and their performance is the worst in dynamic loading and generation scenarios. This comparison shows how GWO is strong, flexible, and economical in terms of smart electric vehicle (EV) scheduling in residential microgrids[15].

VI. DISCUSSION

The results of the simulation provide a clear picture of how effectively the use of the Grey Wolf Optimizer (GWO) can help to solve the issues that are linked to smart EV charging in residential microgrids. One of the main successes of the suggested framework is its ability to achieve a peak possible demand decrease of 15-25 %, which is particularly important at keeping the voltage constant and preventing the transformer overloading in low voltage residential distribution systems. GWO has constantly produced flattened load curves and optimized scheduling decisions reducing the grid infrastructure stress during peak hours. Compared to other conventional optimization algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and rule-based scheduling, the GWO framework proves to be better in a variety of aspects. Though rule-based strategies are simple and simple to adopt, they do not have the flexibility to react to real time variability in load demand and renewable generation. Since GA and PSO are more dynamic, they tend to be susceptible to premature convergence or local optima especially in more complicated multi-objective optimization processes. GWO, in its turn, maintains a better balance of exploration and exploitation, due to its hierarchical hunting, and leader-follower interactions, allowing to explore the solution space efficiently. The other important benefit of the GWO algorithm is that it is resistant to uncertainties, which encompass the stochastic EV arrival times, variable photovoltaic (PV) supply, and unforeseen household demand. In contrast to PSO and GA, GWO does not have a strong dependency on random parameter tuning and its convergence is consistent even when used with a variation in demand of ±10%. This durability makes GWO a good candidate in the implementation of real-time and practical microgrid controllers. In addition, GWO attains significant savings in energy expense, whereby simulations suggest a 20-30per cent saving compared to traditional scheduling mechanisms. Such economies of scale are specifically relevant in areas where time-of-use (ToU) pricing or dynamic tariffs exist, where smart charging is associated with immense economical benefits to both consumers and utility companies. Even though GWO can take a few more iterations to converge in comparison with PSO, the high quality of its solution, in terms of its capacity to balance cost, voltage stability, and grid impact, more than compensates the associated marginal increase in computation time. The ability of the algorithm to support numerous constraints, such as voltage settings, power restrictions, user preference, and EV battery sizes, makes it highly applicable to the implementation of the next-generation home energy management systems (HEMS) and community microgrids. Altogether, GWO is a scalable and resilient cost-effective optimization tool, which preconditions a smarter and more sustainable energy planning in residential EV ecosystems.

VII. CONCLUSION AND FUTURE WORK

This paper presents a smart energy scheduling model based on the Grey Wolf Optimizer (GWO) to control the charging of EVs in residential microgrids that are powered by photovoltaic (PV) systems. The main aim is to reduce peak demand, optimal cost of energy, and optimization of grid voltage stability in different cases of residential load and EV penetration. The GWO algorithm was chosen due to its strong exploration exploitation ratio and its ability to work with nonlinear multi-objective scheduling problems that had dynamic constraints. The findings of the simulation performed with the help of MATLAB/ Simulink R2024a show that the GWO based scheduler works better than the traditional rule based scheduling systems and the metaheuristic evolutionary algorithms, including PSO and GA. In particular, GWO can record the highest load savings of up to 25, cost savings of 20-30, and continues to operate within working safety limits in high demand periods. The optimizer plans charging activities depending on real-time load, PV generation prediction, user preferences and grid constraints with a resulting flatter load profile and increased power quality. Other than being technically effective, the proposed framework is very flexible to real-time uncertainties, including changing solar irradiance, stochastic EV arrival times, and unpredictable residential consumption patterns. In contrast to rule-based and parameter-sensitive approaches, the GWO method maintains stable performance with little to no manual adjustments, which highlights its applicability regarding real-world use in the case of a decentralized residential energy control system. Further efforts in future directions will generalize the model to include vehicle to grid (V2G) operations, demand response, and multi agent coordination to control the energy usage of a group of households in a neighbourhood scale energy network. To further validate this framework on hardware-in-the-loop (HIL) platforms or on OPAL-RT-based real-time simulators will be used to test the framework responsiveness and scalability under live operating conditions. Moreover, with GWO, a possible improvement of scheduling intelligence, privacy protection, and performance in smart grids could be made by incorporating reinforcement learning (RL) or federated learning (FL), techniques. GWO-based EV charging scheduler is an exciting development of sustainable, resilient, and cost-efficient residential microgrids, and enables grid-friendly electrification of transportation.

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