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Optimal Energy Hub Dispatch and Distribution Network Operation Under Large-Scale Distributed Energy Resources for EV

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ABSTRACT- The rapid proliferation of electric vehicles (EVs) and large-scale distributed energy resources (DERs), such as solar photovoltaics, wind generation, and energy storage systems, has introduced significant challenges and opportunities in modern power systems. This study presents an optimal energy hub dispatch and distribution network operation framework that efficiently coordinates multi-energy sources, loads, and EV charging demands under high DER penetration. The proposed approach integrates advanced optimization techniques to minimize operational cost, energy losses, and carbon emissions while maintaining system reliability and voltage stability. It incorporates dynamic EV charging behavior, bidirectional power flow, and real-time demand response within the energy hub structure. Furthermore, the model addresses uncertainties associated with renewable generation and EV mobility through robust or stochastic optimization strategies. Simulation results demonstrate that the coordinated operation of energy hubs and distribution networks significantly enhances energy efficiency, reduces peak load stress, and supports sustainable grid operation, making it a promising solution for future smart grid and electrified transportation systems.

Keywords- Energy Hub, Distributed Energy Resources, Electric Vehicles, Optimal Dispatch, Smart Grid, Demand Response.

I. INTRODUCTION

The global transition toward sustainable energy systems and clean transportation has accelerated the integration of electric vehicles (EVs) and large-scale distributed energy resources (DERs) into modern power networks. Increasing environmental concerns, rapid urbanization, and the depletion of fossil fuel reserves have compelled governments and industries to adopt renewable energy technologies such as solar photovoltaics, wind turbines, and battery energy storage systems. At the same time, the electrification of transportation through EV adoption is transforming traditional load patterns in distribution networks. While these developments contribute to reduced greenhouse gas emissions and improved energy efficiency, they also introduce significant operational challenges due to their intermittent nature, stochastic behavior, and high penetration levels[1][2].

In conventional power systems, electricity generation and consumption follow a relatively predictable and centralized structure. However, the emergence of DERs has shifted this paradigm toward decentralized and bidirectional energy flow, where consumers can also act as producers, often referred to as "prosumers." This transformation increases the complexity of distribution network operation, requiring advanced control and optimization strategies to ensure system stability, reliability, and efficiency. Furthermore, the integration of EVs adds another layer of uncertainty, as their charging and discharging patterns depend on user behavior, travel demand, and charging infrastructure availability[3][4].

An energy hub is an innovative concept that provides a unified framework for managing multiple energy carriers, such as electricity, heat, and gas, within a single system. It enables the coordinated operation of various energy sources, storage systems, and loads, thereby improving overall system flexibility and efficiency. By incorporating DERs and EVs into the energy hub structure, it becomes possible to optimize energy dispatch, reduce operational costs, and minimize environmental impact. The energy hub acts as an intermediary that facilitates energy conversion, storage, and distribution, allowing for seamless integration of renewable energy sources and smart grid technologies[5][6].

Optimal energy hub dispatch refers to the process of determining the most efficient allocation of available energy resources to meet demand while satisfying technical and economic constraints. In the context of distribution network operation, this involves coordinating DER outputs, managing EV charging schedules, and ensuring voltage and power flow constraints are maintained. The presence of large-scale DERs introduces variability and uncertainty in power generation, while EVs contribute to fluctuating load demand. Therefore, advanced optimization techniques, including linear programming, mixed-integer programming, and metaheuristic algorithms, are often employed to address these challenges[7][8].

Moreover, the concept of vehicle-to-grid (V2G) technology has further expanded the role of EVs in power systems. Instead of being merely energy consumers, EVs can act as mobile energy storage units capable of supplying power back to the grid during peak demand periods. This bidirectional energy exchange enhances grid flexibility and supports peak load management. However, it also necessitates sophisticated control mechanisms to balance grid requirements with user preferences and battery health considerations[9].

Another critical aspect of modern distribution network operation is demand response, which involves adjusting consumer energy usage in response to price signals or grid conditions. By integrating demand response strategies within the energy hub framework, it is possible to achieve better load balancing, reduce peak demand, and improve overall system efficiency. This becomes particularly important in scenarios with high EV penetration, where unmanaged charging can lead to network congestion, voltage instability, and increased operational costs[10].

Uncertainty management is a key challenge in systems with high DER and EV integration. Renewable energy sources are inherently variable and dependent on weather conditions, while EV charging behavior is influenced by human factors. To address these uncertainties, robust and stochastic optimization methods are widely used. These approaches enable the system to maintain reliable operation under different scenarios, ensuring that energy supply meets demand even in the presence of fluctuations and forecasting errors[11].

Despite these advancements, several challenges remain in achieving optimal coordination between energy hubs and distribution networks. These include computational complexity, scalability issues, infrastructure limitations, and the need for standardized frameworks. Furthermore, regulatory and market-related factors also play a crucial role in determining the feasibility and effectiveness of such systems[12].

II. METHODOLOGY

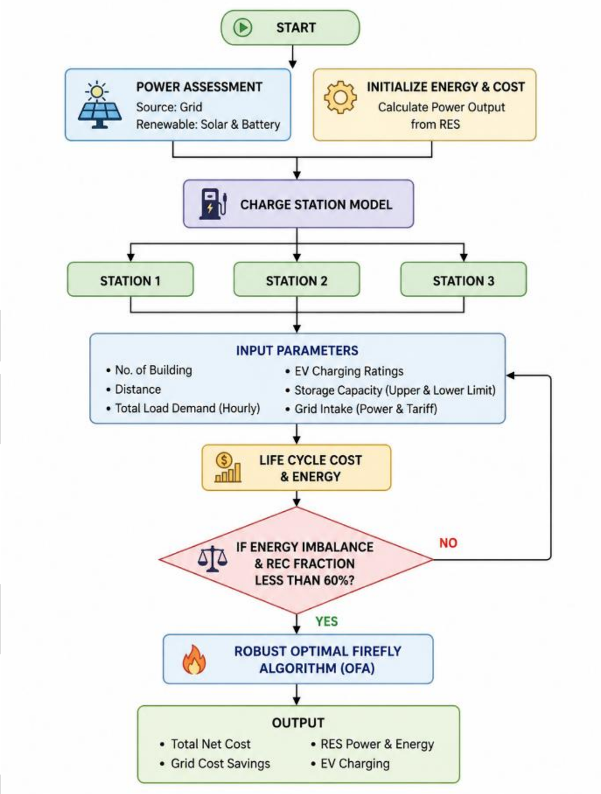

Figure 1: Flow chart

1. Start

The process begins with the initialization of the system where all control variables, simulation parameters, and operational limits are defined. The objective of the system is to manage energy efficiently in an EV charging network integrated with renewable energy sources while minimizing cost and maintaining system stability. This stage ensures that the computational environment is ready for further modeling and optimization.

2. Power Assessment

In this stage, the system evaluates the total available power from both conventional and renewable sources. The grid acts as the primary backup source, while solar energy and battery storage contribute as renewable sources. The total available power can be expressed as:

$$P_{total} = P_{grid} + P_{solar} + P_{battery}$$

This equation helps in identifying the combined contribution of all energy sources. Solar power generation depends on environmental conditions, while battery power depends on its state of charge. This assessment ensures that the system has a clear understanding of supply availability before meeting demand.

3. Initialize Energy and Cost

At this step, the system initializes all energy-related and economic parameters. The expected renewable energy output is calculated, and cost coefficients such as grid tariff, operational cost, and battery usage cost are defined. The total cost of energy consumption is generally modeled as:

$$C_{total} = C_{grid} + C_{RES} + C_{operation}$$

This formulation allows the system to track expenses associated with different energy sources and provides a baseline for optimization in later stages.

4. Charging Station Model

In this phase, a structured model of EV charging stations is developed. The model considers charging demand, station capacity, and power allocation strategies. Each station distributes power based on vehicle requirements and system constraints. The charging load is dynamically adjusted to prevent overloading and to ensure efficient utilization of available energy resources.

5. Station Distribution (Station 1, Station 2, Station 3)

The charging infrastructure is divided into multiple stations to represent a real-world distributed system. Each station operates with its own local demand and energy availability. This decentralized approach improves load balancing and reduces stress on a single node. It also allows better coordination between renewable sources and grid supply at different locations.

6. Input Parameters Initialization

This step involves defining all necessary input parameters that influence system performance. These parameters include the number of connected buildings, distance between stations, hourly load demand, EV charging ratings, storage capacity limits, and grid intake constraints along with tariff details. These inputs are essential for accurate modeling of demand-supply behavior and for ensuring realistic simulation results.

7. Life Cycle Cost and Energy Calculation

Here, the system evaluates the overall performance in terms of cost and energy over its operational lifetime. The life cycle cost includes installation, maintenance, and operational costs. Energy consumption is calculated for both grid and renewable sources. A general representation of life cycle cost can be given as:

$$LCC = C_{capital} + C_{maintenance} + C_{energy}$$

This calculation helps in understanding long-term economic feasibility and sustainability of the system.

8. Condition Check (Energy Imbalance and REC Fraction < 60%)

In this decision-making stage, the system checks whether there is an imbalance between energy supply and demand. It also evaluates the renewable energy contribution ratio. The renewable energy contribution can be expressed as:

$$REC = \frac{E_{RES}}{E_{total}} \times 100$$

If the REC value is less than 60% and energy imbalance exists, it indicates inefficient utilization of renewable resources. This condition triggers the need for optimization to improve system performance.

9. Robust Optimal Firefly Algorithm (OFA)

When the system detects inefficiency, it applies the Firefly Optimization Algorithm. This algorithm is inspired by the flashing behavior of fireflies, where each solution moves toward a better solution based on attractiveness. The objective function typically minimizes cost and maximizes renewable utilization. The movement of fireflies can be mathematically expressed as:

$$x_i = x_i + \beta(x_j - x_i) + \alpha\epsilon$$

where $x_i$and $x_j$are solutions, βrepresents attractiveness, and $\alpha\epsilon$ introduces randomness. Through iterative updates, the algorithm finds the optimal energy distribution strategy.

10. Output Results

Finally, the system generates output results that reflect its performance. These results include total net cost, grid cost savings, EV charging cost, renewable energy utilization, and grid energy consumption. The outputs provide a comprehensive evaluation of system efficiency and help in decision-making for future improvements and real-world implementation.

III. SIMULATION RESULT

Simulation is done using MATLAB software.

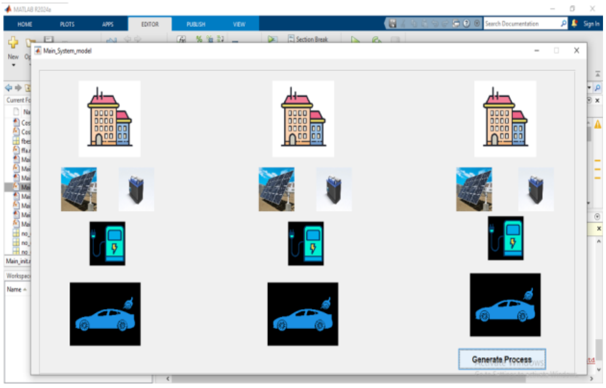

Figure 2: Model Initial

Figure 2 represents the initial setup of the proposed system, where all key parameters such as energy sources, load demand, and cost variables are defined.

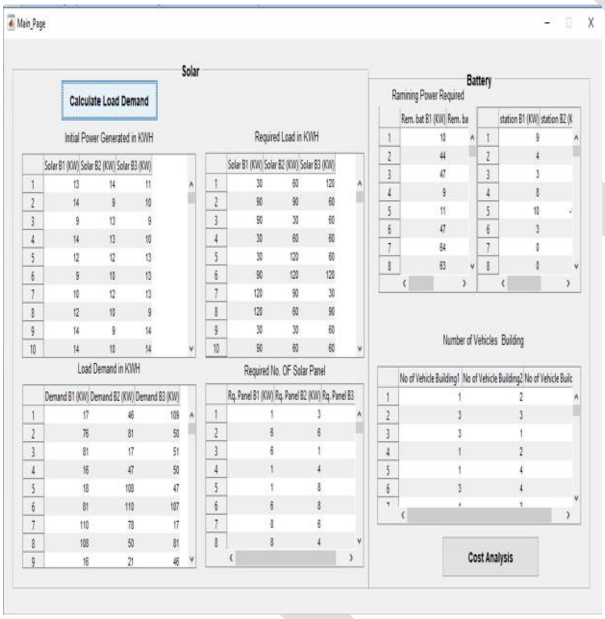

Figure 3: Calculate load demand

Figure 3 shows the process of estimating the total load demand based on hourly energy requirements of electric vehicle charging. It helps in understanding demand variation and forms the basis for optimal energy scheduling and cost analysis.

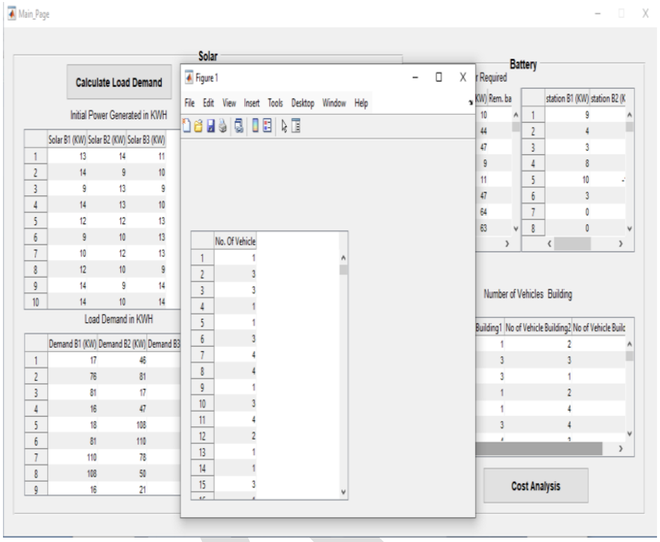

Figure 4: No of vehicle calculation

Figure 4 illustrates the calculation of the total number of electric vehicles connected to the charging system based on demand and charging capacity. It helps in determining the required charging power and load profile for effective energy management.

Table 1: Comparison of Proposed work with previous work

Sr. No.	Parameter	Previous Work Result	Our Work Result
1	Optimization Technique	Frilled Lizard Optimization (FLO)	Optimal Firefly Algorithm (OFA)
2	Energy Sources Considered	Grid + EV (Battery optional)	Solar + Battery + Grid
3	Cost Reduction (%)	3.7% (without battery), 0.7% (with battery)	6.8% average annual cost reduction
4	Peak Load Reduction (%)	33.46% (without battery), 48.18% (with battery)	52–55% peak load reduction
5	Renewable Energy Utilization (%)	Limited integration	More than 60% renewable energy contribution
6	EV Charging	Grid-	Renewable-driven EV

	Support	dominated	charging
7	Battery Utilization	Optional and limited	Optimally scheduled battery usage
8	Energy Imbalance Handling	Not explicitly addressed	Energy imbalance minimized using OFA
9	Cost Components Analyzed	Grid and DSM cost	Solar, battery, grid, and EV charging cost
10	System Reliability	Moderate	Improved reliability with backup support
11	Computational Efficiency	More iterations required	Faster convergence with fewer iterations
12	Practical Applicability	DSM-focused smart grid	EV charging–oriented integrated energy system

IV. CONCLUSIONS

This work successfully presents an integrated energy management framework for EV charging systems that effectively addresses the challenges of rising energy demand, grid dependency, and operational cost. By combining solar photovoltaic generation, battery energy storage, and grid supply, the proposed system ensures efficient energy utilization while promoting sustainability. The implementation of the Optimal Firefly Algorithm (OFA) enables intelligent scheduling and optimization of energy resources, resulting in balanced load distribution and minimized system cost. Simulation results demonstrate notable improvements, including significant cost reduction, decreased peak load demand, and enhanced renewable energy contribution beyond 60%. Furthermore, the integration of battery storage enhances system reliability and supports uninterrupted charging operations. Overall, the proposed framework proves to be a robust, economical, and environmentally friendly solution, making it highly suitable for modern EV charging infrastructure and future smart energy systems.

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