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Optimized Energy Management System using Grey Wolf Optimization for Smart Microgrid

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***Abstract*— The evolution of industrialization and population increases the electricity demand for various commercial and residential applications, which encumbers the centralized electricity grid. Also, a centralized electricity grid uses limited and expensive fossil fuels for power generation, which is unreliable, less scalable, less secure, has high pollutant emissions, and poor energy management. Nowadays, microgrids increase the flexibility and reliability of electrical grid systems by using clean energy sources such as wind, solar, power, or hydropower. Microgrid manages to provide electricity in remote areas where centralized utility grids are not served. This paper offers the energy management system (EMS) for intelligent microgrids (SMG) using the Grey Wolf Optimization Algorithm (GWO). The GWO can handle the multiple input variables and multi-objective functions to provide the power to load in islanded mode (IM) and grid-connected mode (GCM)of operation. The GWO-based EMS performs better than the traditional state of arts.**

***Index Terms*— Energy Management System, Renewable Energy, Smart Micro Grid, Artificial Intelligence, Solar Power.**

I. INTRODUCTION

A microgrid is a small-scale and modern centralized electricity system that uses renewable energy sources (RESs), has cheap architecture, decreases pollutant emissions, and is reliable. Its operation is divided into three phases: power generation, distribution, and control at the local level. It can work in GCM or IM [1,2].

Nowadays, utility grids use fossil fuels for electricity production, which contributes to the emission of pollutants that lead to global warming and air pollution. Generalized Utility grids have several disadvantages, such as high cost, unreliable electricity, low electrical efficiency, low power quality, poor scalability, small security, poor energy control, and ecological hazards [3]. Microgrid operations can be controlled at different levels, such as the device level, network level, supervisory level, and grid interaction, as shown in Fig. 1.

Microgrid operation can be controlled using hardware modules such as switches, breakers, controllers, etc., or computer programs to automate the programmable controllers or processors. Nowadays, machine learning, DL, and optimization techniques are more popular for controlling microgrids because of their skill to acquire from formerly accessible data [4-7].At the device level, connectors, control inverters, load controllers, static switches, rotary diesel generator controllers, breakers, and protection devices can be controlled using hardware or software [5]. Energy management in MGS largely depends upon the control of energy generation, transmission, storage,

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and distribution switching. Previously, several artificial intelligence algorithms and optimization techniques have been adopted in microgrids to control the generation, distribution, and power management [8-12].

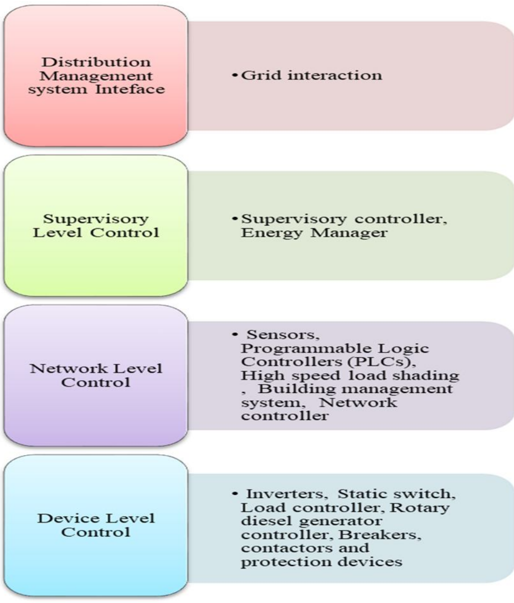

Figure. 1. Micro-grid control at different levels

Wang et al. [13] used intelligent multi-layer supervision in their research to schedule loads, balance power, and generate PV in DC microgrids without any restrictions. This multi-layer supervision consists of an operating layer, an energy management layer, a prediction layer, and a user interface layer. Pablo In [14] authors united the MGS with the grid effect to boost the MGS competence. It provides both active and reactive power facilities. There is no provision for load profiles or load capabilities. Next, Bingnan Jiang et al. [15] have a low-cost, energy-efficient, innovative MGS based on the particle swarm algorithm (PSO) with distributed energy management (DEM) and dynamic demand response (DR). Vanadium redox batteries (VRBs) and Micro combined heat and power systems (μCHPs) are controlled regarding energy consumption and operation using intelligent hierarchical agent-based methodologies dubbed DR and DEM. Later on, George Kyriakarakos et al. [16] detailed the scheme and testing of a poly-generation MGS system using a fuzzy logic energy management system (FLEMS). The MGS comprises a metal hydride tank, solar, wind turbine, fuel cell, battery bank, proton exchange membrane (PEM), and PEM electrolyzer. In [17], researchers presented the multi-objective Glowworm Swarm Optimization (GSO) algorithm, which was used to manage the dispersed MGS, which enhanced load balancing and energy optimization.

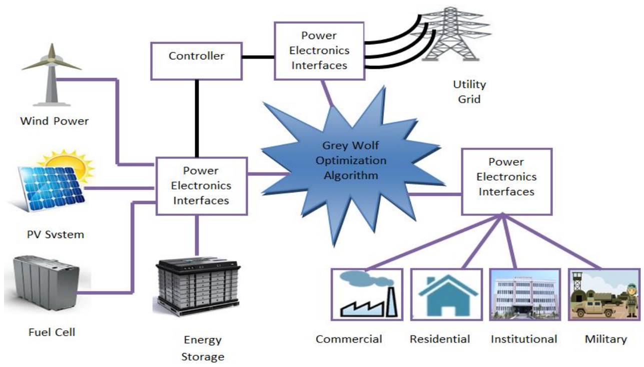

Figure. 2. Block diagram of GWO-based EMS scheme for SMG

Furthermore, Authors in [18] developed an intelligent dynamic Energy management system (I-DEMS) using modified dynamic programming and reinforcement learning to manage variable and unpredictable power sources like wind and solar. This uses thermal power generation and backup battery energy sources to overcome the problem of unpredictability in RES. Thermal power is more expensive, less autonomous, and less ecologically

beneficial since it is produced. Then, employing GPRS to collect information for grid-level control, M. Sharifzadeh et al. [19] used the particle swarm approach to electrify remote settlements. Subsequently, in [20], the authors designed the SMG for the energy-producing, storing, and distribution scheme utilizing an engineering game theory-based technique (EGT). Fuzzy logic has shown simpler approach for EMS but shows less reliability for real time implementation [21].
The Internet of Things (IoT) plays a crucial role in collecting various parameters of the microgrid system and remote control of the power flow and functions of the microgrid. Soft computing approaches have shown greater flexibility in attaining energy management systems. The IOT-based system helps in load profile collection, load profile analysis, power system stability assessment, and control of various appliances [22-25].
Recently, deep learning (DL) techniques have attracted researchers' attention to the use of DL architectures for energy management systems in microgrids. Various DL frameworks have been successfully presented for the EMS systems for intelligent microgrid. The deep learning approaches have shown faster convergence, faster decision-making capability, capability to handle multiple variables for control, higher accuracy, and better performance than traditional machine learning approaches [25-30].
The paper is prepared as follows: section II gives a detailed introduction to the microgrid system, describes and compares various components of the microgrid system, and sections III and IV focus on the GWO-based EMS for SMGs. Next, section IV discusses the results and discussions. The final section concludes the survey and mentions the prospects of intelligent microgrid systems.

II. MICRO GRID ARCHITECTURE

As shown in Fig. 2, the microgrid consists of three major components: power generation, distribution, and control. Microgrids can be AC or DC in nature, depending upon the type of generation source used. For example, Solar PV generates DC power, whereas wind turbines generate AC power. The power obtained from the generator can be converted from AC-DC or DC-AC or stored in energy storage devices using power electronics interfaces.

A. Power Generation

Microgrids are operated at the local level, and for power generation, diesel engines, fuel cells, micro-turbines, and RES such as wind, solar, or hydro-turbines are used. Diesel engines are less preferred in the grid because of higher pollutant emission and noise generation [6]. Fuel cells and micro-turbines are expensive. Thus, RES, such as wind, solar, and hydro-turbines, are famous for power generation because of zero fuel cost and zero pollutant emission[7,9]. The summary of different power sources used in micrograms is given in Table I.

TABLE I . POWER GENERATION COMPONENTS OF MICRO-GRID

Generation Type	**Source**	**Advantages**	**Disadvantages**
Diesel Engine [6]	● Diesel (Fossil fuel)	● Instant startup ● Portable ● Load following ● Good option for combined heat and power (CHP)	● Emission of Nitrogen Oxide ● Emission of Greenhouse gas ● Noise generation
Fuel Cell [7-8]	● Solid Oxide ● Phosphoric Acid ● Molten carbonate ● Alkaline ● Low PEM	● Portable, ● Zero onsite emission, ● CHP capable	● Expensive ● Low lifespan
Micro-turbine [9]	-	● Portable ● Low emission ● CHP capable	● Emission of greenhouse gas
Renewable Generation [9]	● Solar PV cells ● Wind turbines ● Small hydro turbines	● Zero fuel cost ● Zero emission ● Energy storage is possible	● Not portable in available form ● Variable and not controllable energy

B. Energy Storage

As renewable power generation is variable and unavailable all day, storing the power when the primary utility grid is ON and the microgrid is in standby mode is necessary. The power is stored at the source side and load side. This stored power is used in emergency conditions or in high-demand conditions. Solar PV cells' power is DC power and can be stored in the batteries by regulating the voltage using a DC-DC converter. In contrast, a wind turbine generates AC power, which needs to be converted from AC to DC using an inverter before storing it [10,11]. A summary of the various storage systems used in the microgrid system is given in Table II.

TABLE II. ENERGY STORAGE COMPONENTS IN MICRO-GRID

Storage type	**Advantages**	**Disadvantages**
• Battery • (Lead acid, Sodium sulfur, Lithium ion, Nickel Cadmium) [10]	• Portable • Recharging capability	• Limited lifespan • Expensive • Hard to dispose waste • Low charge-discharge cycle
• Regenerative Fuel Cell • (Poly-sulphide Bromide, Zinc Bromide, Vanadium Redox) [10]	• Continuous operation at high load • Simple to discharge without any damage	• Low lifespan • Expensive
• Flywheels [11]	• Higher charge-discharge cycle • Faster response • High Efficiency	• High losses • Limited discharge time

B. Power Electronics Interfaces

Power electronics play a crucial role in microgrids as power generated from solar PV panels is DC, and wind turbine generates AC power, which is variable. Therefore, various power electronics interfaces are required to convert DC-AC conversions, unregulated DC/AC to regulated DC/AC conversion and DC-AC-DC conversion. There is a need for quick switching of static disconnect switch (SDS) on the over-voltage, over-frequency, under-voltage, under-frequency, and over-current using programming [12]. Regular utility grids are AC grids; therefore, an inverter is needed to convert the DC power obtained from the solar PV cells, fuel cells, and batteries into AC power. Low-voltage DC grids are generally used in residential applications, whereas hybrid AC-DC grids are popular in data centers and maritime applications [4].

III. GREY WOLF OPTIMIZATION-BASED EMS

The characteristics of a wolf include strong, full teeth, spiky tails, and living and hunting in groups. 5–12 people make up an average group. Their native habitats include the plains, hills, and woodlands of Asian countries, Europe, and North America. Canis lupus, the grey wolf, is a member of the Canidae genus.

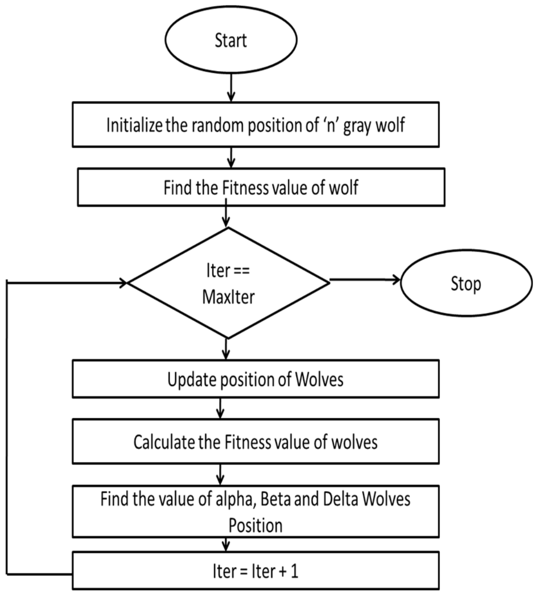

Figure. 3. Flowchart of GWO-based EMS for SMG

Grey wolves are regarded as apex predators at the top of the food chain. To create a computational representation of the social hierarchy of wolves, we use the alpha (α) as the fittest answer while developing GWO. Therefore, beta (β) and delta (δ) are the second and third best options. It is believed that the remaining alternatives are omega (ω). α, β, and δ serve as the hunting (optimization) guidelines for the GWO method. The ω wolves follow these three wolves.

The flowchart of GWO-based EMS for SMG is shown in Fig. 3. The GWO considers the power difference, cost difference, SOC, and SOH for switching the battery, FC, and power switching of the grid. The GWO generates the optimized solution to satisfy the load demand while minimizing the cost of the supplied power. The GWO considers the cost of power per KW. The fitness function is dependent on the total power cost. At the minimum cost of the solution, the solution is considered best.

- *Input variable*: Power Difference, Cost Difference, State of Charging (SOC) and State of Hydrogen (SOH)
- *Output Variables*: Battery Control, FC control, and power to Grid transfer control
- Fitness function is based on power utilization
- Based on the best fitness function, the algorithm will decide whether to switch the input power source, charge/discharge the battery, control the fuel cell on/off, and transfer power to the grid.

IV. Experimental Results And Discussion

The anticipated method is simulated using MATLAB and Simulink. Fig. 4 illustrates the load demand for the operation of the GCM and IM. Energy transfer to and from the utility grid is allowed in GCM mode. The most significant load demand during operation is anticipated to be 4.2 MW. In IM, the EMS only provides power to the necessary loads. The highest critical load requirement in this mode is projected to be 2.1 MW.

The Simulink model is revealed in Fig. 5. This section provides the challenges of implementing MGS.

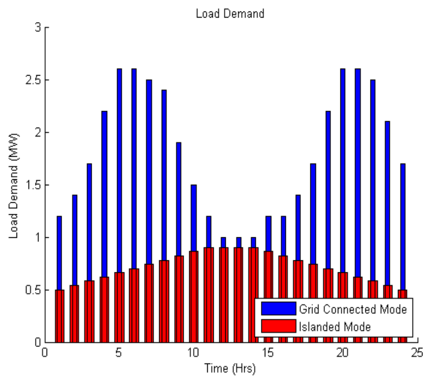

Figure. 4. Load Demand in GCM and IM

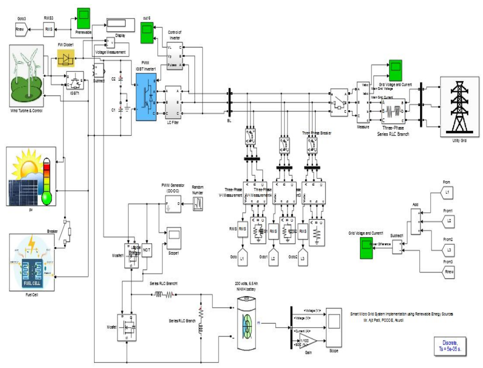

Figure. 5. Simulink model of SMG

The EMS result for the GCM utilizing the GWO technique is shown in Fig. 6. It demonstrates that the suggested EMS system can supply load power at all times of the day. Because renewable energy is readily available, it supplies the system with electricity during periods of high demand. Midday is when the energy from renewable sources is most abundant, raising microgrid power compared to load demand. During this time, electricity is fed into the utility grid. To meet the fluctuating load requirement, batteries are continually charged and discharged.

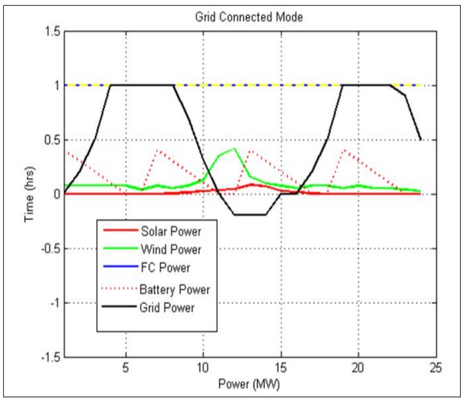

Figure. 6. GWO-based EMS for GCM

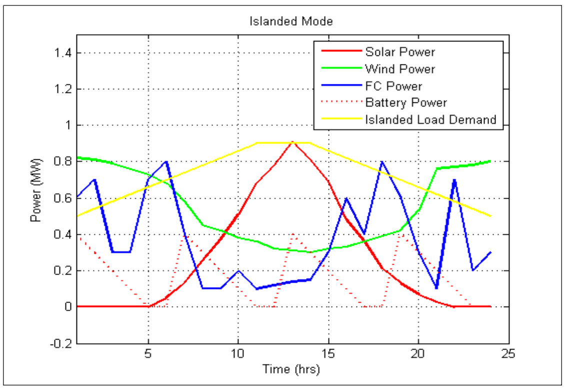

Figure. 7. GWO-based EMS for IM mode

When power is solely supplied to the critical loads, the efficiency of the suggested GWO-based EMS system for IM operation is shown in Fig. 7. Since it is impossible to transmit electricity to or from the utility grid while in operation, essential loads' power needs are met by standalone generators that are currently on the market, such as fuel cells and diesel generators. It demonstrates the low-cost, continuous up-and-down ramping feature of these standalone generators. The power cost profile for the GCM and IM modes, respectively, is shown in Figs. 8 and 9. Compared to the PSO-based EMS scheme, it is discovered that the GWO-based EMS offers superior price effectiveness.

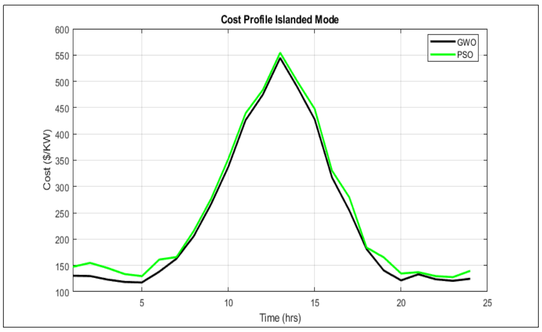

Figure. 9. Cost profile comparison of GWO and PSO for IM

The system results are validated by considering the critical loads. One load is considered critical and requires continuous power. The critical load is a high priority in the system, and power provision to the critical load is preferred compared with the average load. In IM, GWO provides 92% power to the critical load. Because of the constraint optimization problem, overall supplied power using modified GWO is lower than that of GWO. Overall supplied power using PSO is lower than GWO as GWO supports multi-objective and multivariable and provides better solutions for constraint optimization problems. IM has lower load demand; thus, overall supplied power is more than GCM.GCM, the GWO delivers 100 % power to the critical load, whereas PSO provides 78.50% power. Overall supplied power using PSO is lower than modified GWO as GWO supports multi-objective, multivariable, and provides better solutions for constraint optimization problems. GCM has high load demand; thus, overall supplied power is less than IM. Tables III and IV provide the results for power supplied to critical load in IM and GCM mode.

TABLE III. % POWER SUPPLIED TO CRITICAL LOAD IN IM MODE

Critical Load	GWO	PSO
Load-1 (Critical Load)	**92%**	90%
Load-2 (Normal Load)	96%	100%
Load-3 (Normal Load)	100%	95%
Load-4 (Normal Load)	98%	82%
Total Power Supplied	96.50	91.75%

TABLE IV. % POWER SUPPLIED TO CRITICAL LOAD IN GCM MODE

Critical Load	GWO	PSO
Load-1 (Critical Load)	90%	**85%**
Load-2 (Normal Load)	95%	100%
Load-3 (Normal Load)	95%	72.50%
Load-4 (Normal Load)	96%	57.50%
Total Power Supplied	94.00%	78.75%

V. CONCLUSION

This paper presents the GWO-based EMS for the SMG, consisting of PV panels, wind power, and fuel cells. The EMS focuses on the total energy provision and total cost of the power. Smart microgrids provide energy efficiency, improved power quality, scalability, efficient energy management, and reliability of the electricity systems. GWO is developed for the IM and GCM operations .Considering critical load, the GWO returns the best result at the lowest cost in either the IM or GCM mode of operation. With lower operating costs, the suggested algorithm in GCM offers flexibility in the autonomous switching of disseminated generators and flexibility in the automatic buying and selling of electricity. The plan may use diesel generators and fuel cells in IM operation, ramping down and up to meet the power requirements of critical loads while minimizing expenses. GWO offers EMS that is straightforward, quick, and affordable while taking many goals into account.

EMS is crucial in the GCM because of its high load requirement and preference for critical loads over IM operation. Because GWO may provide several optimal solutions and performs better when applied to constraint optimization problems, it outperforms the classic PSO optimization method. In the future, the main emphasis may be on deploying intelligent SMG systems built on deep learning and GWO optimization for smarter EMS. In future, deep learning techniques can be used for efficient EMS of smart microgrid [31-35] to enhance the reliability and efficiency of system.

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