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Energy Management System for Microgrid System using Improved Grey Wolf Optimization Algorithm

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Abstract—An Energy Management System (EMS) is indispensable to monitor the power flow and load matching inside a microgrid during grid-connected mode (GCM) and islanded modes (IM) of operation. Many conventional optimization algorithms show poor reliability for real time optimization problem solving where an objective function is non-linear. An optimization technique is necessary to reduce the cost of energy obtained from the grid, generated inside the grid, and consumed by the load. This article presents, an optimization scheme based on the improved Grey wolf optimization (GWO) algorithm that considers replacement of wounded/injured wolves of one pack by strong wolves of other pack for an EMS in micro-grid. The GWO optimization algorithm's effectiveness is demonstrated forGCM and IM operation. The proposed GWO shows fast, lost cost and precise optimization of the real time EMS for the grid connected and islanded micro-grid system.

Keywords- Energy Management System; Grey Wolf Optimization; Microgrid; Smart Microgrid; Optimization Algorithms; Renewable Energy; Electrical engineering.

I. INTRODUCTION

Microgrids (MGs) are the innovative model for the development of the distribution system. MGs are made up of a collection of non-critical and critical loads as well as distributed energy resources such generators, energy storage systems (ESSs), generators and renewable energy sources (RESs). They allow the best possible amalgamation of these subsystems into the power distribution system and guarantee the steadiness of the main grid. The two modes in which MGs operate are islanded mode [1–2] and grid linked mode. When operating in GCM, a microgrid receives electricity from and supplies it to the main (utility) grid in accordance with generation and load requirements, as well as market laws that, among other things, higher efficiency and cost. In the same way, it has the ability to cut off from the primary grid in the event of a serious power quality crisis and to provide power to vital loads [3-4].

The MG is built with a proper monitoring and control scheme to guarantee that it operatescompetently and reliably. The control system schedules and controls all DERs to guarantee the MG's stability, dependability, and cost-effective operation. In the MG, the EMS is critical for controlling power generation and/or flow. The system's design is based on an economic model that identifies running costs and emission functions while also accounting for electricity consumption. Furthermore, an EMS scheme is employed for DGs optimization by lowering working costs while keeping lower hydrocarbon emission [4-5].

The authors of [6] investigated a Genetic Technique (GA) based EMS scheme that could select the best operating strategies while lowering the MG's running costs and emissions. Similarly, particle swarm optimization (PSO) [7], reduced gradient (RG) [8], and the Cuckoo search algorithm (CSA) [9-10]are utilized to obtain the lowest operational cost for MGs in IM. G. Graditi et.al[11] used multi objective Glowwarm Swarm Optimization (GSO) algorithm for the control of the distributed system which produced better load balancing and energy optimization. Further, Ganesh Kumar et.al [12] implemented an intelligent dynamic EMS (I-DEMS) using reinforcement learning and evolutionary adaptive dynamic programming to control variable and uncertain RESs like solar and wind power sources. In this, alternative battery energy sources and thermal power generation has been employed to tackle the problem of vagueness in renewable energy sources. It is less self sustainable, fewer environmental friendly and expensive due to thermal power generation. Subsequently, Sharifzadeh at.al [13] used particle swarm algorithm for the electrification of remote villages which used

GPRS to collect the data for communication at grid level. Next, S. Mei et.al [14] proposed the smart micro grid for the energy generation, energy storage and energy distribution system using Engineering game theory based approach (EGT). Afterwards, Srikanth et.al [15] used wind turbine, PV array and battery to build the smart grid. They used fuzzy logic to control the different control parameters to obtain the energy efficiency.

Y Lee et.al [16] used Harmony Search Algorithm (HSA) and Genetic Algorithm (GA) for the expansion planning and improvement in reliability of micro grid in wind thermal co-generation system. Harmony search performs better than the genetic algorithm but carbon emission increases due use of thermal power. Next, L. Shi et.al [17] implemented the EMS for AC/DC hybrid micro grid to handover the control from PV systems to main grid in night time. It resulted in Seamless operation, minimization of cost and efficient energy management. Later, Georgieva and Dolchinkov [18] used two fuzzy models for the management of solar micro grid system. The first fuzzy model has used for the management of PV battery by fuzzyfying the PV panel power production, battery power and consumed power. The second fuzzy model has been used for the additional energy flow control such as diesel engine or fuel cell. Further, Z. P. Cheng et.al [19] presented EMS for independent DC microgrid system utilizing fuzzy-PI controller to obtain the steadiness in the DC bus voltage. It improved the robustness of the scheme and solved the poor adaptability of conventional PI system. Carli et al. [20] presented model predictive control (MPC) for micro-grid energy scheduling that included controllable as well as non-controllable electrical appliances. It shows better energy scheduling in case of load flexibility.

This paper presents energy and cost efficient EMS based on GWO for GCM and IM operation. The chief offerings of the paper are recapitulated as follow:

- Simulation of pollution free micro grid system that includes fuel cell (FC), photovoltaic generator (PV), wind generator, and battery as energy storage device.
- Implementation of improved GWO based EMS for GCM and IM operation of microgrid system consisting of renewable energy sources.

This research article is structured as follow: Section II provides the description related to the modeling of anticipated microgrid system. Section III focuses on the anticipated GWO based EMS for the microgrid. Section IV gives depiction of experimental results and discussions. Finally, section V offers the conclusion of the work and gives the future direction for improvement in proposed scheme.

II. MODELLING OF MRICROGRID SYSTEM

Figure 1 illustrates the representation of the anticipated EMS for microgrid. The considered microgrid model consists of five distributed generators such as diesel generator, fuel cell, photovoltaic generator, wind generator, and battery set as energy storage device. The distributed generators are connected with the control system for energy management in microgrid for optimal power distribution to the loads.

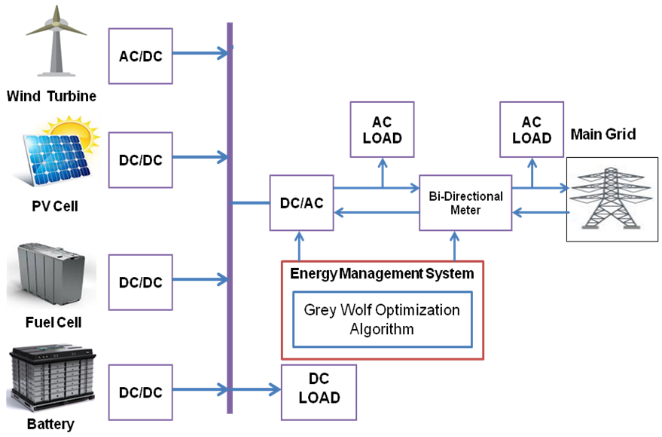

Figure 1.Structure of proposed microgrid system

The anticipated microgrid is connected in GCM and IM operation. In GCM, the microgrid can acquire/sell the power to/from the main grid. Whereas, in IM the main grid is not connected with the microgrid and thus the power transfer flexibility between microgrid and main grid is unavailable. The power generation competence of the independent sourcesand ESSs is described in Table 1.

Table I. SPECIFICATIONS OF THE POWER GENERATORS

Power Generator	Minimum Power (MW)	Maximum Power (MW)
Fuel Cell Generator	0	1
Photovoltaic Generator	0	0.5
Wind Generator	0	0.5
Utility Grid	-1	1
Battery	0.1	0.4

The total cost fitness is computed using equation 1 that encompasses the cost fitness of fuel cell generator, photovoltaic generator, wind generator and battery as given in equation 1. The aim of the suggested EMS is to lessen the cost fitness along with fulfilling the load demand. The best fitness ($\mathrm{Fitness_{Best}}$) is considered as fitness of the alpha wolf ($\mathrm{Fitness_{MG\_X_{\propto}}}$).

$$\mathrm{Fitness_{MG}} = \mathrm{Fit_{FC}} + \mathrm{Fit_{PV}} + \mathrm{Fit_{W}} + \mathrm{Fit_{B}} \tag{1}$$

$$\mathrm{Fitness_{Best}} = \mathrm{Fitness_{MG\_X_{\propto}}} \tag{2}$$

The various parameters related to photovoltaic generator, battery and wind generator considered for the microgrid simulation of anticipated system are given in Table 2.

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Table II. PARAMETER SPECIFICATIONS OF PHOTOVOLTAIC GENERATOR, WIND GENERATOR AND BATTERY

Power Source	**G^e (\$/kW)**	**I^P (\$/kW)**	**r**	**N (years)**
Photovoltaic Generator	0.016	5000	0.09	20
Wind Generator	0.016	1400	0.09	20
Battery	0.016	1000	0.09	20

A. Fuel Cell Generator Cost Function

Equation 3 states that the cost function for FCs is often also thought of as a function of a quadratic approximation.

$$\mathrm{Fit}_{FC} = \alpha_2 + \beta_2 P_{FC} + \gamma_2 (P_{FC})^2 \quad (3)$$

Where, Fit_{FC} is cost function of fuel cell, α_2, β_2, and $\gamma_2$depicts for the FC cost coefficients, and P_{FC} represents the power generated by FC. The cost coefficients for FC α_1, β_1, and γ_1 are set to 9.00\$/hrs, 0.306\$/hrs, and 0.000315\$/hrs respectively [6][21][22].

B. Photovoltaic Generator Cost Function

The cost function for PV generator is given by equation 4 and 5.

$$\mathrm{Fit}_{PV} = aI^P P_{PV} + G^e P_{PV} \quad (4)$$

$$a = \frac{r}{(1-(1+r)^N)} \quad (5)$$

Where, P_{PV}denotes the PV power (MW), Fit_{PV} is cost fitness function of PV generator, a represents annuitization coefficient, r denotes interest rate, N stands for investment lifetime (N=20), I^P denotesratio of investment cost to installation per unit power (\$/kW, G^epresents maintenance and operation cost per unit of PV energy (\$/kW). The power profile of the solar energy for 24 hrs. duration is illustrated in Figure 2.

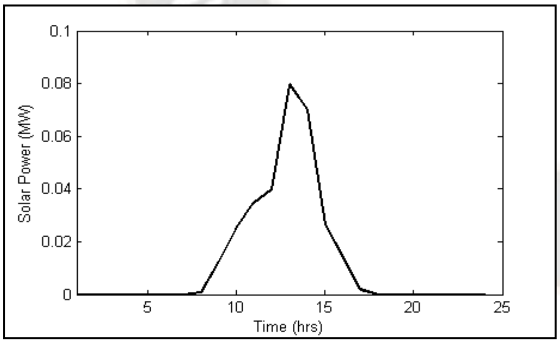

Figure 2. Solar power profile for single day

C. Wind Generator Cost Function

The cost function for wind generator is given by equation 6.

$$\mathrm{Fit}_{W} = aI^P P_{W} + G^e P_{W} \quad (6)$$

Where, $P_W$denotes the wind power (MW), Fit_W is cost function of wind generator, a represents annuitization coefficient, r denotes interest rate, N stands for investment lifetime (N=20), I^P denotes ratio of investment amount to installation per unit wind power (\$/kW, G^e presents maintenance and operation cost per unit of wind energy (\$/kW). The power profile of the wind energy for 24 hr duration is shown in Figure 3.

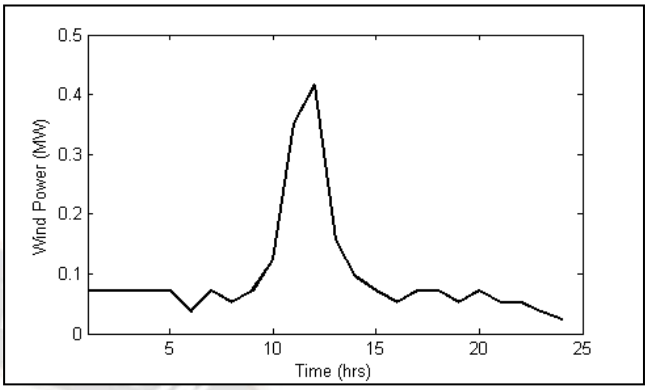

Figure 3. Wind power profile for single day

D. Battery Cost Function

The anticipated microgrid system considers 500kW battery where the changing mode of the battery is considered as the load of about 3MW. The battery cost function is described in equation 7.

$$\mathrm{Fit}_{B} = aI^P P_{B} + G^e P_{B} \quad (7)$$

Where, $P_B$represents the battery power (MW), Fit_B is battery cost function, a depictsannuitization coefficient, I^P denotes ratio of investment amount to installation per unit battery power (\$/kW, G^epresents maintenance and operation cost per unit of battery energy (\$/kW).

E. Constraint Function

The constraint functions are necessary to achieve the expected energy management of microgrid system. For the GCM, the total microgrid power ($P_{generated}$) is different than the load demand (P_{Load}) as given in equation 8.

$$P_{generated} \neq P_{Load} \quad (8)$$

The total microgrid power is given by equation 9. The power difference between microgrid generated power and power supplied to the load can be given by equation 10.

$$P_{generated} = P_{DG} + P_{FC} + P_{PV} + P_W + P_B \quad (9)$$

$$P_{diff} = P_{generated} - P_{Load} \quad (10)$$

If $P_{diff}$is positive then the power is fed (sell) to the utility grid and when the P_{diff} is negative then the power is received (buy) from the grid. For the IM of operation, the microgrid power is same as load requirement, and hence the power is provided to the critical loads only as given in equation 11.

$$P_{generated} = P_{Load} \quad (11)$$

The power generation of every generator (j) generates the power in between the specified minimum (P_{min}) and maximum range (P_{max}) as given in equation 12.

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$$P_{min} \le P_j \le P_{max} \tag{12}$$

III. IMPROVED GREY WOLF OPTIMIZATION (IGWO)

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn. A grey wolf is member of the canidae family. As apex predators, grey wolves are at the apex of the food chain. A pack is what grey wolves desire. 5–12 wolves make up the usual pack size. It's extremely remarkable how well they follow the social dominance structure. A male and a female serve as the alphas, or leaders. Hunting, sleeping arrangements, and waking hours are among the many responsibilities mostly handled by the alpha. The alpha's choices are made for the pack.

Generally some alpha wolves follow the other members in the pack in democratic behavior. During meetings, the entire pack lowers its tail to signal the presence of the alpha. Since the pack must obey the alpha wolf's orders, he or she is also referred to as the dominant wolf. To mate, a wolf must be the alpha of the pack. Unexpectedly, the alpha is frequently not the most physically capable wolf of the pack, but rather the one who is most adept at leading it. In hunting, a pack's rules and organization and rules are extremely significant than their strength [23–24].

The grey wolf hierarchy's second rank is beta those supports alpha in decision-making and other responsibilities related to pack. When alpha wolves dies due to any reason, the beta wolf (male or female), is the most likely contender to take over as alpha. Although the beta wolf ought to obey the alpha, they should also respect the alpha. The beta reinforces the alpha's instructions and provides feedback to the alpha throughout the pack, acting as both an advisor to the alpha and a pack disciplinarian. The least powerful grey wolf is Omega. As a scapegoat, the omega is brought up. The last to be allowed to eat is an omega wolf, who must constantly submit to their superiors.

Although the omega might seem like a minor player in the pack, it has been observed that if the omega were to go missing, the entire pack would experience internal conflict and problems. This is because all of the wolves' rage and anger was released by the omega (s). All of the pack will be happy as a result, and the dominance structure will remain in place. In exceptional circumstances, the omega can also look after the pack.

If a wolf is not one of the alpha, beta, or omega species, it is regarded as subordinate (delta). Delta wolves rule the omega, despite the fact that they must submit to alpha and beta wolves. Scouts, senior citizens, hunters, sentinels, and caregivers are all members of this group. The task of monitoring the boundaries of the territory is that of the scouts, who are also responsible for warning the pack of any danger. Protective guards assure the security of the pack. Wolves who have previously served as alpha or beta are considered elders. Huntsmen assist the alphas and betas by capturing prey and supplying food for the pack. The pack's caregivers must then take care of the weak, hurt, and wounded wolves [25–26].

Grey wolves show strong social characteristics and hierarchy while hunting in group. The major steps of grey wolf hunting are described as follow:

• Pursuing, encircling, and pestering the prey until it bec omes steady

• Tracking, persuing, and approaching the prey

• Make an attack on the prey

Equation 13–14 represents the prey as a group of grey wolves surrounding it after searching it.

$$\vec{E} = \left|\vec{O}.\overrightarrow{X_p}(i) - \vec{X}(i)\right| \tag{13}$$

$$\vec{X}(i+1) = \overrightarrow{X_p}(i) - \vec{B}.\vec{E} \tag{14}$$

Where, i stands for current iteration, $\vec{O}$ represents the coefficient vector describing the barrier in hunting pathway while wolves approaching towards the prey as given in equation 15, $\vec{B}$ denotes the coefficient vector describing distance between two wolves as given in equation 16, $\overrightarrow{X_p}$ depictthe prey's locationand $\vec{X}$ describes the location of grey wolf.

$$\vec{O} = 2 \times \overrightarrow{r_2} \tag{15}$$

$$\vec{B} = 2 \times \vec{l} \times \overrightarrow{r_1} - \vec{l} \tag{16}$$

Where, the component $\vec{l}$ decreases linearly from 2 to 0 at every iterations and $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are arbitrary vectors selectedin the range [0, 1]. Following the victim's encirclement, the wolvesα, β and δ lead the other pack members in an assault on the prey. Out of the three wolves, α wolf makes the best choice. Equation 17-23 serves as a mathematical representation of the grey wolf's hunting behaviour.

$$\overrightarrow{E_\alpha} = \left|\overrightarrow{O_1}.\overrightarrow{X_\alpha}(i) - \vec{X}(i)\right| \tag{17}$$

$$\overrightarrow{E_\beta} = \left|\overrightarrow{O_2}.\overrightarrow{X_\beta}(i) - \vec{X}(i)\right| \tag{18}$$

$$\overrightarrow{E_\delta} = \left|\overrightarrow{O_3}.\overrightarrow{X_\delta}(i) - \vec{X}(i)\right| \tag{19}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha}(i) - \overrightarrow{B_1}.\overrightarrow{E_\alpha} \tag{20}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta}(i) - \overrightarrow{B_2}.\overrightarrow{E_\beta} \tag{21}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta}(i) - \overrightarrow{B_3}.\overrightarrow{E_\delta} \tag{22}$$

$$\vec{X}(i+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{23}$$

Generalize GWO sometimes fails to provide the better optimization because of unchanging pack of GWO. Some GWO packs underperform due to poor fitness of some members (wounded/injured/weak wolf) which degrades the overall fitness of the pack. This work presents replacement of

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weak wolf strategy to enhance the pack's performance. The pack with low fitness chooses the strong member from the other weak pack to enhance the performance. So, along with updating the position of existing wolves of the pack, some packs are newly formed by using replacement of weak wolf strategy. The position of 70% pack is updated as per generalized GWO and 30% packs are used for new pack generation using proposed scheme. In real life scenario, strong wolf takes the place of the injured or weak member of the same pack or the other pack for survival. The weak members are considered as the treat to the packs strength. The replacement of weak member strategy of one pack by strong members of other pack is illustrated in Figure 4.

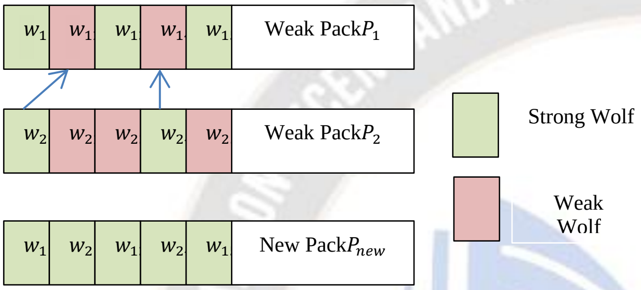

Figure 4. Improved GWO weak wolf replacement strategy

The algorithm for the GWO based EMS for the microgrid is given as:

Step 1: Initialization Phase
Initialize the grey wolf population Xi (i = 1, 2, ..., n)
Initialize a, A, and C
M: Mode of operation (GCM/IM)
N: Number of energy sources
Initialize costing parameters of the generators
Initialize the distributed generator parameters
Step 2: Compute the fitness for each grey wolfusing equation 1
$X_{\propto}$ = *Best wolf*
X_{β} =*Second best wolf*
X_{δ} =*Third best wolf*
Step 3: while (iter < Maximum iterations)
for everywolf (search agent)
Arbitrary initialize r_1*and*r_2
Update the location of the present wolf using equations 17-23
Generate new wolf pack using proposed replacement strategy
Update a,B and O
Compute the fitness of all wolves
Update $X_{\propto}$, X_{β}, *and* X_{δ}
iter=iter+1
return $X_{\propto}$*(Best Solution)*

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed EMS scheme is implemented using MATLAB/Simulink by considering GCM and IM for 24 hour duration with variable load power requirement.

Grid Connected Mode (GCM): During the GCM, the power transfer to and from utility grid is enabled. The maximum load demand during the GCM operation is assumed as 4.2MW.

Islanded Mode (IM): In IM, the EMS supply power to the critical loads only. The maximum critical load demand during this mode is assumed as 2.1MW.The load demand profile for the IM and GCM given in Figure 5.

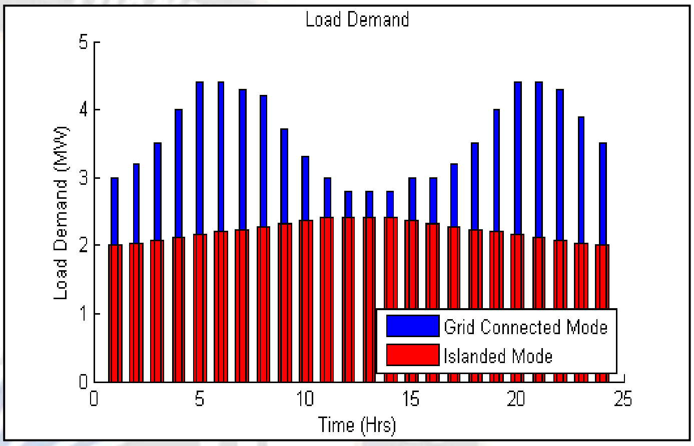

Figure 5.Load profile for GCM and IM

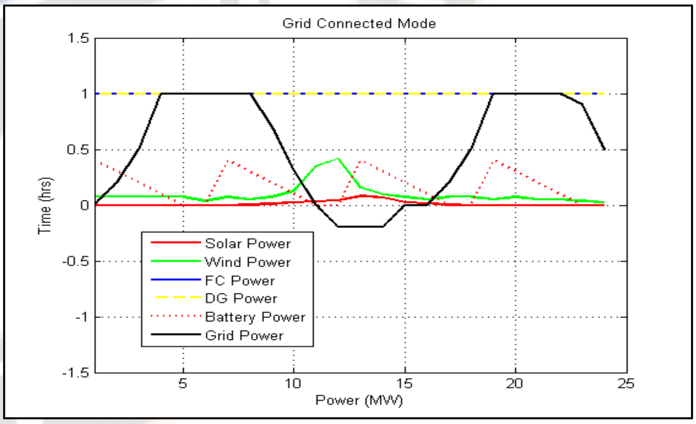

Figure 6.IGWO based EMS output for GCM operation

Figure 6 illustrates the EMS output for the GCM using GWO algorithm. It shows that the anticipated EMS system is capable to provide the load power during the all period of the day. It provides the power to the grid during the peak time because of availability of the renewable power. During midday hours the energy obtained due to renewable energy sources is larger which causes increase in microgrid power compared with load demand, thus for this duration the power is fed to utility grid. The battery charging and discharging takes place continuously to fulfill the variable load demand.

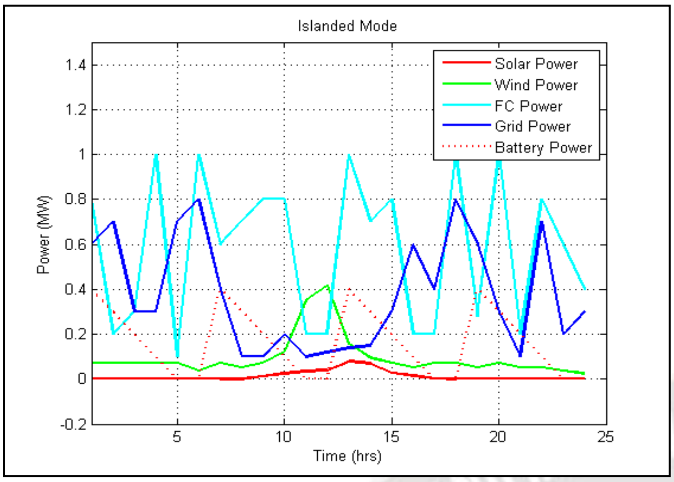

Figure 7.IGWO based EMS output for IM operation

Figure 7 illustrates the results of GWO based EMS system for IM operation when power is provided to the critical loads only. In IM operation, the power transfer to/from utility grid is not possible; therefore, the available independent generators such as diesel generator and fuel cells are used for fulfilling the power demand of the critical loads. It shows continuous up-down ramping nature of these independent generators with minimum cost. In future deep learning algorithms can be utilized for performance improvement [27-31].

V. CONCLUSIONS

Thus, the Grey Wolf Optimization based EMS is presented for the GCM and IM operation. The algorithm provides the optimal solution with minimum cost either in GCM or IM of operation for different load power requirement. In GCM, the proposed algorithm provides flexibility in automatic dispatching of distributed generators and flexibility for automatic buy/sell power to/from with reduced operation cost. In IM, offered EMS scheme is capable of using fuel cell by ramping up and down to fulfill the power requirement of critical loads while reducing the cost. The proposed system provides 98.50% average load demand fulfillment under various critical conditions for the islanded mode whereas it provides 100% load demand fulfillment under grid connected mode of operation. In future, the outcomes of the anticipated system can be enhanced further with the use of real time solar and wind meteorological data.

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