IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 16, 2021, accepted November 24, 2021, date of publication November 30, 2021,
date of current version December 16, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3131502

Novel AI Based Energy Management System for Smart Grid With RES Integration

ASTITVA KUMAR[1], (Member, IEEE), **MUHANNAD ALARAJ**[2], (Member, IEEE), **MOHAMMAD RIZWAN**[1], (Senior Member, IEEE), AND **UMA NANGIA**[1], (Member, IEEE)
[1]Department of Electrical Engineering, Delhi Technological University, New Delhi, Delhi 110042, India
[2]Department of Electrical Engineering, College of Engineering, Qassim University, Buraydah, Qassim 52571, Saudi Arabia

Corresponding author: Astitva Kumar (astitvakumar_phd2k16@dtu.ac.in)

ABSTRACT The different energy assets such as solar panels and batteries help electrical engineers to manage and meet the increasing demand. The amalgamation of renewable energy resources with artificial intelligence is the key focus of providing high energy efficiency with alternative sources. This solution will not only meet electricity demand but also help in reducing greenhouse gas emissions as a result the efficient, sustainable and eco-friendly solution can be achieved which would contribute a lot to the smart grid environment. Here, a modified grey wolf optimizer approach is utilized to develop a novel energy management system for SPV-based microgrid considering modern power grid interactions. The proposed approach aims to provide a proficient microgrid that utilizes solar photovoltaic technology, and energy storage systems using an artificial intelligence algorithm-based microgrid control for optimal dispatch of energy in grid-connected systems. The performance of this novel energy management system is validated under sunny day and cloudy day, to emulate the stochastic nature of solar photovoltaic systems. A comparative study with mixed linear programming is also conducted that indicates towards the savings in 23.34% and 45.55% of the rolling cost for a clear and cloudy day respectively.

INDEX TERMS Smart grid, microgrid, renewable energy resources, optimization technique, artificial intelligence, energy storage system.

I. INTRODUCTION

The generation, transmission, and distribution of electrical energy have entered into technological change and reforms globally. Renewable energy-based technologies particularly solar photovoltaic and wind energy conversion systems are invigorated due to their abundant availability and have the potential to provide an eco-friendly and sustainable solution for future power requirements. To accommodate the fluctuating nature of these resources, the operation of power generating systems should be efficient and responsive, thus the concept of the smart grid is playing a key role in such transitions. However, the major challenge lies in the development of a distributed generating system that can cater to the requirements of remote areas. As per the latest data, about 17% of the world's population does not have the access to electricity [1]. This is an alarming situation for the sustainable growth and development of any nation and a renewable energy-based distributed power generating system would be able to provide an alternative solution for this challenging task. Presently, these areas are catered by diesel-based generating systems which are costly and cause significant pollution in the environment. In such a scenario, a hybrid system consisting of more than one renewable energy resources or the concept of microgrid has a tremendous potential to provide electricity access to the 1.2 billion deserving people, who do not have access to constant electricity.

To meet the overgrowing demands of the rising population and increasing comfort levels, power engineers are exploring the use of renewable energy (RE) resources. In recent years, there has been significant growth in the installed capacity of renewables. RE technology has seen a boom because of the continuous decrease in the price of PV panels, easy availability of solar energy, government subsidies, and innovative models in residential and commercial sectors. The integration of RE with MG offers many benefits, still, the challenge is to maintain a low cost of operation, controlling

The associate editor coordinating the review of this manuscript and approving it for publication was Sotirios Goudos.

the intermittent nature of renewables. The working conditions of the RE sources such as WEGS and SPV are considered to be at unity to maximize the objective function i.e. the condition of unit commitment. The adequate size of BESS provides sufficient stability for grid operations in MG, the operating reserves are provided by the DG set, also, these act as the backup supply for emergency operations.

The literature review explaining the concept of energy management system (EMS) integrating renewable energy sources are presented in [2]–[4]. A comprehensive survey on the MG-EMS is discussed by the authors exploring the possibilities of economical optimal energy dispatch [5]. This proposed mixed-integer linear programming (MILP) optimal energy dispatch algorithm results in low cost and reduced CO_2 emission. The reduced emission was obtained while MG was in standalone mode. An imperialist competition model for RE sources and batteries to work in an islanded 24-hour time period to reduce the problem of the high cost of generation and storage [6]. The techniques such as Tabu search (TS) [7], dynamic programming [8], particle swarm optimization (PSO) [9], [10], and PSO-fuzzy [11] are implemented for optimal energy management in islanding mode. The mentioned literature focuses mainly on reliability, supply security, and cost of energy of MG respectively.

In [12] authors have presented a techno-economic analysis for hybrid MG with PV and biomass for rural areas. The afore-mentioned study aims to study the grid-connected MG system because of its various advantages. A grid-connected hybrid MG (HMG) is more reliable and capable of providing electricity along with the reduced operational cost. The optimization techniques implemented for grid-connected MG system are Lyapunov [13], multi-objective cross-entropy [14], fuzzy logic [15], genetic algorithm (GA) [16], [17], chaotic group search optimizer [18] and MILP [19], [20] reduce the cost and increases profitability of the system. The authors have implemented the grey wolf optimization approach for a grid-connected hybrid system (SPV, biogas, and BESS) at a rural site to reduce the cost [21]. In a grid-connected MG, a key component to achieve optimal dispatch of energy is MGC. In the MGC, the ESS state of charge (SoC) in each hour depends on the SoC in the previous hour. Therefore, the ESS SoC every two consecutive hours is correlated, and the optimization problem is subjected to a dynamic constraint. Up to now, two main methods, namely, centralized energy management (CEM) and decentralized energy management (DEM), have been proposed in various literature to solve the MGC problem.

As energy management of the grid connected MG plays a vital role in robust and efficient performance. A novel approach using stochastic programming has been utilized for effective energy management of MG in [22]. This approach addressed the issue of high operational cost and operating reserves adequately. But, lacked technical analysis of the MG performance, hence a distributed framework based grid connected MG was designed for the same [23]. There is scope to study the performance of the MG system with time-varying and controllable loads. The authors have designed the loads according to the user preferences and designed the different components of MG accordingly [24], [25]. The authors have also focused studies on the MG transitions between standalone and grid-connected modes and proposed a nonlinear simplex algorithm for the same [26]. V. Suresh *et al.* analyzed the performance of a practical MG energy management system present at Wroclaw University [27]. The authors proposed a multi-objective optimization using the ant colony technique to find the best global solution. The objective of the system is to minimize the import of power from the main grid resulting in improved self-sufficiency.

It is observed from the above literature, that traditional optimization techniques have been used to develop energy management strategies for MG. The uncertainties and variabilities of the weather conditions, grid, and load play a vital role in determining the performance and the operational cost of MG. Constant deregulation of the modern power system possesses a unique challenge for the new age MG to assess and compute optimal time for the energy exchange. The inadequacy of the objective functions and constraints to address this condition affects their performance. Therefore, a new optimization algorithm should be developed to determine the optimal performance of MG considering the above-mentioned challenges.

From the literature survey, it can be concluded that the MG and its control requires a robust and effective technique to handle the large computational problems. Thus, this paper explores the possibility of modeling an intelligent optimization technique for solving the complex multi-objective function to reduce the operational/rolling cost of the MG. The paper presents a comparative study of this intelligent optimization i.e., modified grey wolf optimizer (MGWO) with the linear programming-based (LP) optimization. The main contribution of this paper is to model a hybrid microgrid energy management system with renewable energy sources and energy storage systems such as a battery. The proposed system is controlled with the help of a novel energy management system based on an AI approach with multi-objective functions. Study of techno-economic comparison of the MGWO based MGC with LP based energy management system. The performance of the proposed EMS is presented for clear day and cloudy day conditions.

The rest of the paper is divided into the following sections: Section II presents the modeling of RES components required for MG such as SPV, ESS and load modelling. Section III gives an insight of the proposed hybrid intelligent energy management system. The results of the proposed model in comparison with other techniques for the clear and cloudy conditions are explained in section IV of the paper. Section V of the paper gives the conclusion to the presented work followed by references.

II. MICROGRID COMPONENTS AND MODELING

HMGs s a system composed of various distributed resources connected in parallel and is capable of performing grid

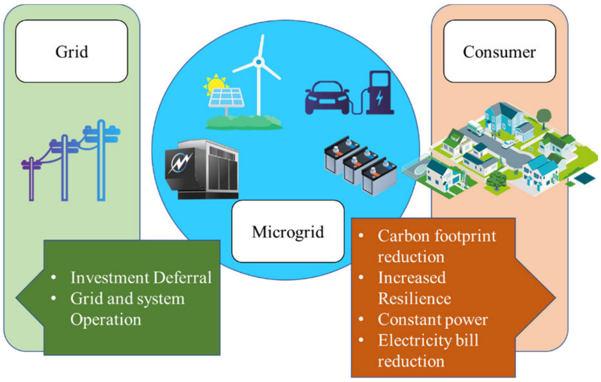

FIGURE 1. Components and function of microgrid.

synchronization and islanding mode operations. The typical framework and components of a microgrid are depicted in Fig. 1. The modern MG comprises of following components: renewable energy sources, diesel generators, batteries, residential and commercial load, electric vehicles, utility grid and a microgrid controller (MGC) for effective and optimal energy dispatch. This MGC is designed to reduce the cost of MG operational cost and enable effective power exchanges between various components as mentioned above.

A. SOLAR PHOTOVOLTAIC SYSTEM (SPV)

Output power of the SPV system can be calculated as defined in (1)

$$P_{pv}(t) = d_{pv} P_{pvr}\left(\frac{G(t)}{G(t)_{stc}}\right) \times \left\{1-\alpha_{pv}\left(T_c(t)-T_{c,stc}(t)\right)\right\} \tag{1}$$

$$T_c(t) = T_a(t) + \left(T_{c,NOCT}-T_{a,NOCT}\right)\left(\frac{G(t)}{G(t)_{NOCT}}\right) \times \left(1-\frac{\eta_{pv}}{0.95}\right) \tag{2}$$

The uncertainty of SPV power output is modeled using the beta distribution function [28].

$$f_b(g) = \frac{g^{\alpha-1}(1-g)^{\beta-1}}{\Gamma(\alpha).\Gamma(\beta)}\Gamma(\alpha+\beta) \tag{3}$$

$$\alpha = \mu\left(\frac{\mu-\mu^2}{\sigma}-1\right) \tag{4}$$

$$\beta = (1-\mu)\left(\frac{\mu-\mu^2}{\sigma}-1\right) \tag{5}$$

$$P_{pv} = \begin{cases} P_{pvr} * \dfrac{g}{g_r}; & 0 < g < g_r \\ P_{pvr}; & g_r < g \end{cases} \tag{6}$$

B. BATTERY ENERGY STORAGE SYSTEM (BESS)

The energy storage is done using a battery system. The primary function of the batteries is storing electricity and dispatching that electrical energy during times of need. The energy change in a battery bank over one hour is given as in (7).

$$E^{bt}(t+1) = E^{bt}(t) + P_C(t).\eta_C(t) - \frac{P_D(t)}{\eta_D(t)} \tag{7}$$

The capacity of the battery bank fades with time as the battery discharges and is known as total capacity fade (E^{bt}_{tcf}) of the battery. This is given by

$$E^{bt}_{tcf}(t+1) = E^{bt}_{tcf}(t) + Z_B.P_D(t) \tag{8}$$

The maximum and minimum state of the charge (SoC) allowed is defined as:

$$SoC = 1 - DoD \tag{9}$$

$$E^{bt}(t) \leq \mathrm{SoC}_{\mathrm{mx}}.N_B - E^{bt}_{tcf}(t) \tag{10}$$

$$E^{bt}(t) \geq N_B(1-DoD) \tag{11}$$

C. LOAD MODELLING

The loads for the selected site are classified in two different classes: i) constant load, and ii) variable load. The variable loads L_{exl}, L_{bld} and L_{mtr} have loading factors k_l, k_b and k_m respectively. These loading factors are a function of time and help in defining the time of use (ToU) of lighting, building, and motor loads [30].

Here, loading factors can be defined by (12), the ratio of A_m/A_i the total number of hours the specific load (motor, building or lights) can be discretely operated. D_{load} defines the task commitment duration in hours for that specific type of load.

$$k_{l/m/b} = 1 - \min\left(\frac{A_m}{A_i} * D_{load}, 1\right) \tag{12}$$

D. ENERGY EXCHANGE/WWWWW/TIME OF USE (ToU)

Power exchanges between the utility grid and SPV+BESS system is governed by time of use (ToU). The proposed Time of Use (ToU) function has three intervals: lower price, normal price, and high price. This ToU function helps in defining a deregulated utility grid. Equation (13) and (14) define the selling and purchase of electricity below,

$$C_s(t) = \mathrm{ToU}\left(C_s^{mkt}(t)\right) \tag{13}$$

$$C_p(t) = \mathrm{ToU}\left(C_p^{mkt}(t)\right) \tag{14}$$

III. PROPOSED STRATEGY FOR MICROGRID CONTROL

The optimal strategy for the microgrid control is presented in this section multi-objective function is defined by (15) and the structure of the proposed MG is depicted in Fig. 2.

A. OBJECTIVE FUNCTION

The proposed MGC aims at unit commitment and regulates the power generated from the proposed MG. The main focus is to control the power generated from RE sources, assess power exchanged from the utility grid, charging and discharging of batteries to meet adequately the load

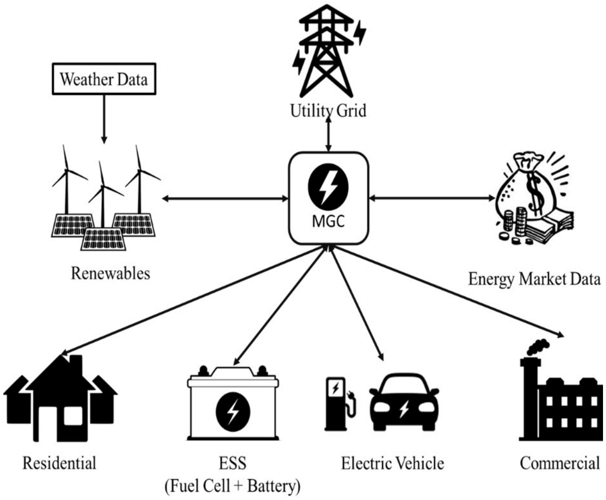

FIGURE 2. Structure of the MG.

requirement while satisfying the constraints. The multi-objective function $f(x)$ is solved using a modified grey wolf optimizer (MGWO) in MATLAB-Simulink Environment.

$$f(x) = \min\left(f_1(C_{res}) + f_2\left(C_{ig}\right) + f_3(C_{bess}) + f_4(C_{gex})\right) \tag{15}$$

$$f_1(C_{res}) = N_{pv}(PV_{ii} + PV_{om}) \tag{16}$$

$$f_2\left(C_{ig}\right) = N_{inv}\left(Inv_{ii} + Inv_{om} + Inv_{rep}\right) \tag{17}$$

$$f_3(C_{ess}) = \varepsilon_{bt}^{op}(P_C(t) - P_D(t)) + C_{wo} \tag{18}$$

$$C_{wo} = \frac{B_{rep}}{N_B.y.\sqrt{\eta\epsilon t}} \tag{19}$$

$$f_4\left(C_{gex}\right) = \sum_{t\in T}\left\{C_p(t)\left[P_{PG}^{ac}(t) + P_{PG}^{dc}(t)\right] - C_s(t)P_{SG}(t)\right\} \tag{20}$$

where, $f_1(C_{res})$ is the cost of renewable energy-based generation, $f_2\left(C_{ig}\right)$ is the cost of starting up generators, switches, and generators, $f_3(C_{ess})$ is the cost of energy storage system, $f_4\left(C_{gex}\right)$ is the cost of energy exchanged from the grid.

B. CONSTRAINTS

The balance between the generation and dispatch is maintained using (21) and (22). The power output of renewable energy sources is maintained within its capacity using (28).

$$P_{PG}^{ac}(t) + \left[P_{pv}^{ac}(t) + P_D(t)\right] = P_L(t) + P_{SG}(t) \tag{21}$$

$$P_{pv}^{dc}(t) + \left[P_{PG}^{dc}(t) + P_{wt}^{dc}(t)\right] = P_C(t) \tag{22}$$

$$P_L \geq L_{cnst} \tag{23}$$

$$P_{pv}^{dc}(t) + P_{pv}^{ac}(t) \leq N_{pv}.P_{pv}(t) \tag{24}$$

The charging and discharging of the battery are limited by the following:

$$P_C(t) \leq N_B.P_B \tag{25}$$

$$P_D(t) \leq N_B.P_B \tag{26}$$

C. MODIFIED GREY WOLF OPTIMIZATION BASED EMS

The main focus of the work is to design MGWO based energy management for MG. The RE sources are stochastic and intermittent, thus do not provide constant electrical power at all times. Hence, it is necessary to control the power from these RE sources. In modern power system. the utility grid is experiencing high penetration of RE sources with higher uncertainties. These variabilities are due to increasing customer awareness and their preferences resulting in variable cost of electricity, and higher exchange of power between grid and RE sources. Thus, designing an optimal energy management strategy is critical for maximizing the comfort, savings and productivity for both consumers and operators. The basic principle for working of the optimal energy management system is the interaction and exchanges of power between different power sources (grid, renewables, generators, and batteries) to meet the load demand as per user's preference.

The developed MGWO based EMS is a two-stage approach for the HMGs. In the first stage, a feasibility analysis is performed for the RE sources for adequate sizing to meet the load demand considering the geophysical parameters. This is followed by a metaheuristic demand management system for optimum management of the proposed MG to reduce the overall cost of electricity. This stage focuses on the interactions from the grid and considers the ToU factor for MGC to act accordingly. Fig. 3 shows the systematic flow of control to manage the MG. Initially, MG with RE sources is assessed for the islanding operation with minimal interaction from the grid, helping in the estimation of the total power generated by RE. The prime aim of the proposed EMS is to maximize the social benefit by recharging the BESS when electricity cost is minimum and export energy to the grid during high ToU.

The proposed optimization technique is a hybrid technique. This is inspired by the movement of grey wolves to attack their prey and the swarming action of birds to reach locations for food. The proposed hybrid algorithm is a modified particle swarm optimization (PSO) with grey wolf optimizer (GWO), thus placing it in between swarm intelligence and evolutionary algorithm [30]. The proposed MGWO mitigates the drawbacks of PSO and GWO. The low convergence rate and low precision accuracy of PSO and GWO respectively, are the major shortcomings of these methods.

GWO is a modern meta-heuristic technique based on hunting and leadership traits of the grey wolf. The major advantages of the GWO are its less storage and computational memory requirement, faster convergence due to continuous reduction of search space and simple implementation with less decision variables. Grey wolves are at top of the food chain symbolizing that they are the apex predators. They prefer to live in a pack of 5 to 20. In GWO the pack is divided into four groups of different hierarchy such as alpha, beta, delta and omega [31]. Fig. 4 clearly shows the position update of grey wolves to attack prey in GWO.

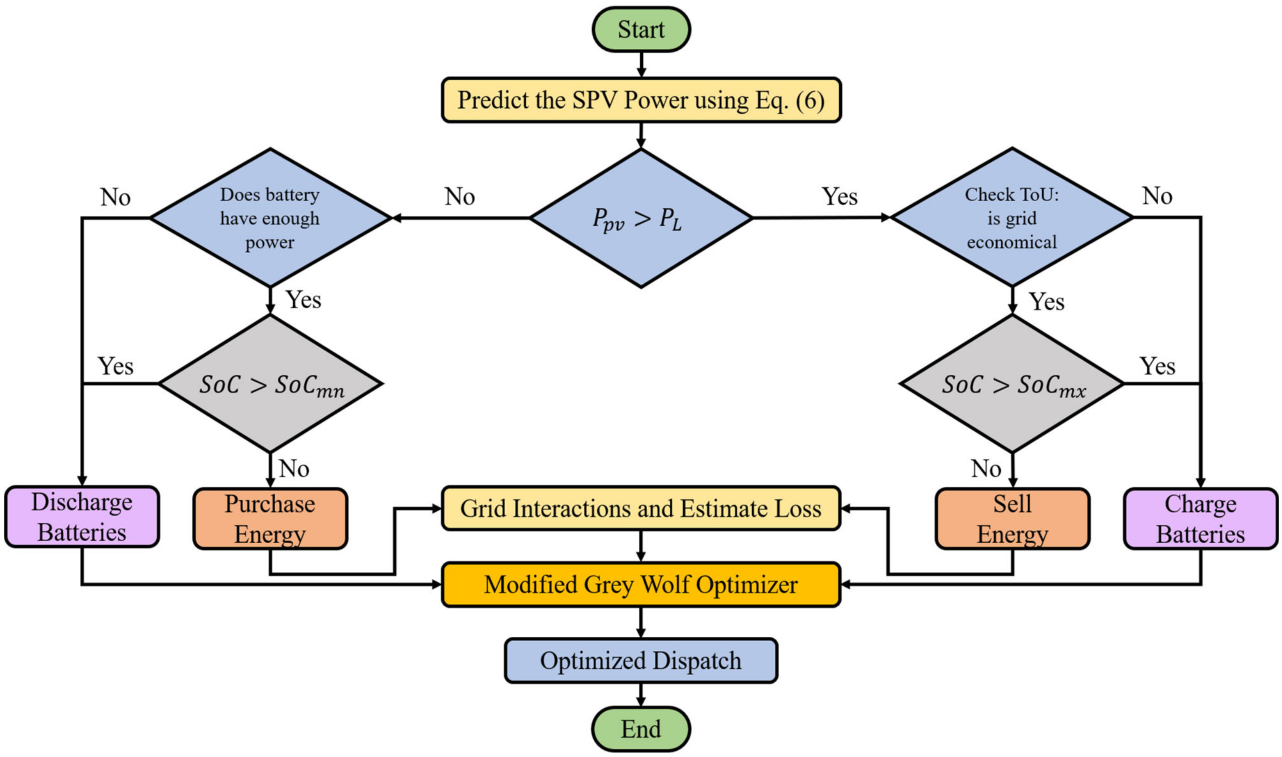

FIGURE 3. Flowchart of proposed hybrid energy management system.

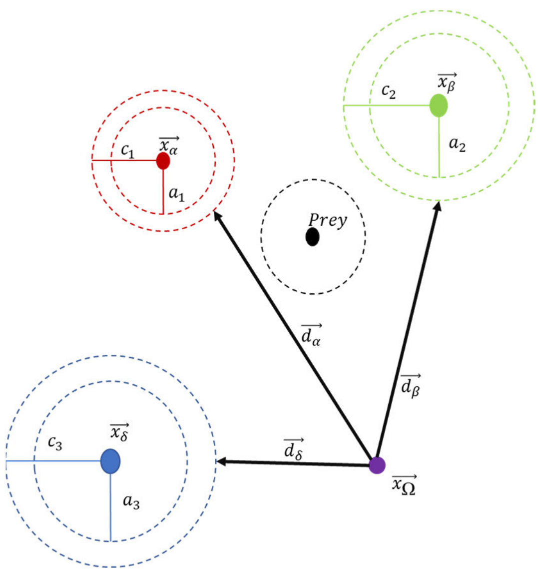

FIGURE 4. Position update of wolves in GWO.

The alphas (α) are at the top periphery of the social hierarchy, thus are the main decision-makers and the rest follow them. The betas (β) are the next in line to become the alphas, they are second to the alpha and help them in decision making or other pack actions. These ensure that the order of α is followed throughout the pack and provides the necessary feedback when required. The third level of the pack is known as the deltas (δ) and always follows the ones before. These are dominated by alphas and betas. If a wolf is not alphas, beta, or delta then it is called omegas (Ω). The main characteristics of grey wolf i.e., hunting, searching, encircling, and attacking its prey is designed with the help of mathematical equations to perform the optimization. A brief outline of the proposed hybrid metaheuristic technique, namely MGWO has presented the flowchart given in Fig. 5. The encircling behavior is depicted in (26) and (27).

$$\vec{d} = \left|\vec{c}.\vec{x_p}(t) - \vec{x}(t)\right| \tag{27}$$

$$\vec{x}(t+1) = \vec{x_p}(t) - \vec{a}.\vec{d} \tag{28}$$

Here, $\vec{d}$ defines the encircling behavior, $\vec{x}$ is the current position of the grey wolf, $\vec{x_p}$ is the position of the prey that has to be hunted, the coefficient vectors $\vec{a}$ and $\vec{c}$ are given as

$$\vec{a} = 2\vec{q}.\overrightarrow{r_{gwo1}} - \vec{q} \tag{29}$$

$$\vec{c} = 2.\overrightarrow{r_{gwo2}} \tag{30}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{31}$$

$$w_{pso}(t) = w_{max} - \frac{(w_{max} - w_{min})}{T} * t \tag{32}$$

$$\begin{aligned} v_i(t+1) = {} & w_{pso}(t) * v_i(t) + c_1.r_{pso1}(x_1 - x_i(t)) \\ & + c_2.r_{pso2}(x_2 - x_i(t)) \\ & + c_3.r_{pso3}(x_3 - x_i(t)) \end{aligned} \tag{33}$$

The exploitation and exploration of MGWO are based on grey wolf optimization and particle swarm optimization

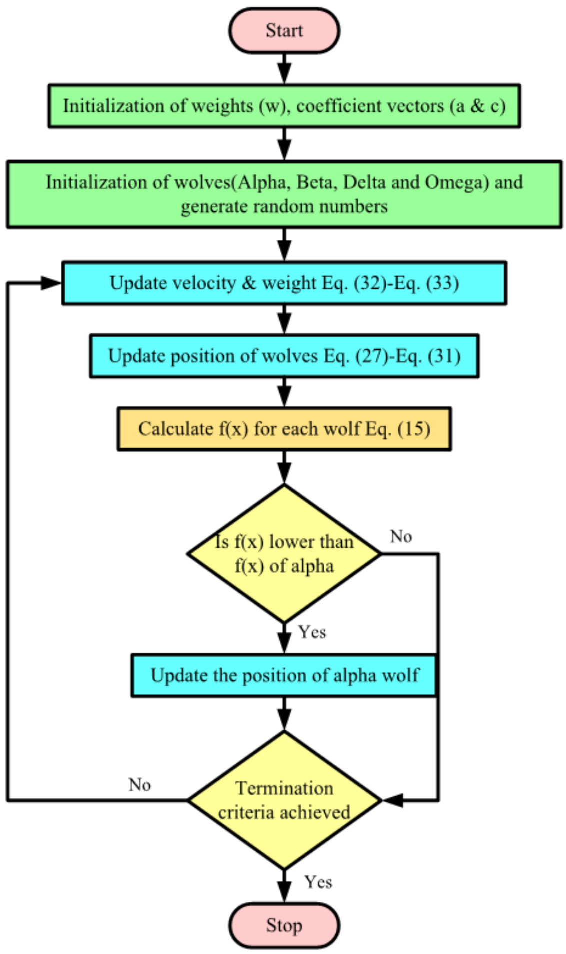

FIGURE 5. Flowchart of the proposed MGWO technique.

TABLE 1. Benchmark functions used to test the performance of proposed MGWO.

FUNCTION	DIMENSION	RANGE	f_{min}
$F_1(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10)$	20	[-5.12, 5.12]	0
$F_2(x) = \sum_{i=1}^{n}(x_i^2)$	20	[-5.12, 5.12]	0
$F_3(x) = \frac{1}{4000}\sum_{i=1}^{n-1}(x_i^2) + \sum_{i=1}^{n-1} cos\left(\frac{x_i^2}{\sqrt{i+1}}\right) + 1$	20	[-500, 500]	0
$F_4(x) = \sum_{i=1}^{n-1} 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$	20	[-30, 30]	0
$F_5(x) = \sum_{i=1}^{n-1}((i+1)x_i^4) + rand[0,1]$	20	[-1.28, 1.28]	0
$F_6(x) = -\sum_{i=1}^{n} x_i \mathrm{SIN}(\sqrt{\lvert x_i \rvert})$	20	[500, 500]	-8829.65
$F_7(x) = 20 + e - 20\, exp\left[0.2\sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i^2}\right] - exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))$	20	[-32, 32]	0
$F_8(x) = (x_2 + x_1^2 - 11)^2 + (x_1 + x_2^2 - 7)^2 + x_1$	2	[-5, 5]	-3.78396
$F_9(x) = \sum_{i=1}^{5} jcos((j+1)x_1 + j)\sum_{i=1}^{5} jcos((j+1)x_2 + j)$	2	[-10, 10]	-186.730

respectively. The modified governing equations for the first 3 wolves are given by (30)-(31). The velocity and position update equation of PSO are shown by (34)-(36).

The proposed MGWO has been tested on various unimodal, multimodal benchmark functions to assess the performance of the hybrid meta-heuristic technique. Table 1 represents various benchmark functions (such as rastragin, sphere, greiwank, rosenbrock, noise, shwefel, ackley, himmelblau and shubert) used to test the capability of the proposed hybrid optimization technique. Table 1 gives an insight into the modality, dimensions, randomness, and minimum value (f_{min}) of various benchmark functions. These benchmark functions are a few of the standard benchmark functions that are considered for performance analysis of the proposed technique. The functions $F_1(x)$ to $F_9(x)$ have been selected after careful observations to provide a good launchpad for testing the credibility of any optimization algorithm.

The drawbacks of PSO and GWO in high dimensional calculation of function is highlighted in Fig. 6 and Table 2. Fig. 6 shows the comparative performance analysis of the proposed MGWO technique with PSO and GWO. Fig. 6 depicts the characteristics of each of the objective functions defined in Table 1, moreover, the performance of the optimization techniques in solving each of the function is represented. The aforementioned characteristic of different functions is given by parameter space in Fig. 6(a)-(i). The performance of each optimization techniques such as, PSO, GWO and MGWO, are depicted in objective space i.e., best solution vs iterations curve. From the objective space curves, it can be concluded that PSO falls in local minima in high and complex dimensional space and along with this for all the benchmark functions its convergence rate is less in comparison with GWO and MGWO. In addition, GWO suffers from low solving precision especially highlighted by benchmark functions $F_3(x)$, $F_5(x)$ and $F_7(x)$, where the MGWO outperforms GWO significantly. Hence, it can be concluded that the proposed MGWO technique is a hybrid meta-heuristic technique with advantages of both PSO and GWO and the shortcomings have been mitigated. The comparison is done considering the behavior of PSO, GWO, and MGWO to give the best solution with respect to the number of iterations required. Furthermore, this technique can be implemented for modeling a robust EMS with high computational capabilities.

IV. RESULTS AND DISCUSSION

In this paper, a novel approach is presented using a hybrid MGWO algorithm that has been proposed to design a hybrid MG for optimal energy management, load management at reduced electricity cost. MG is designed for a test location

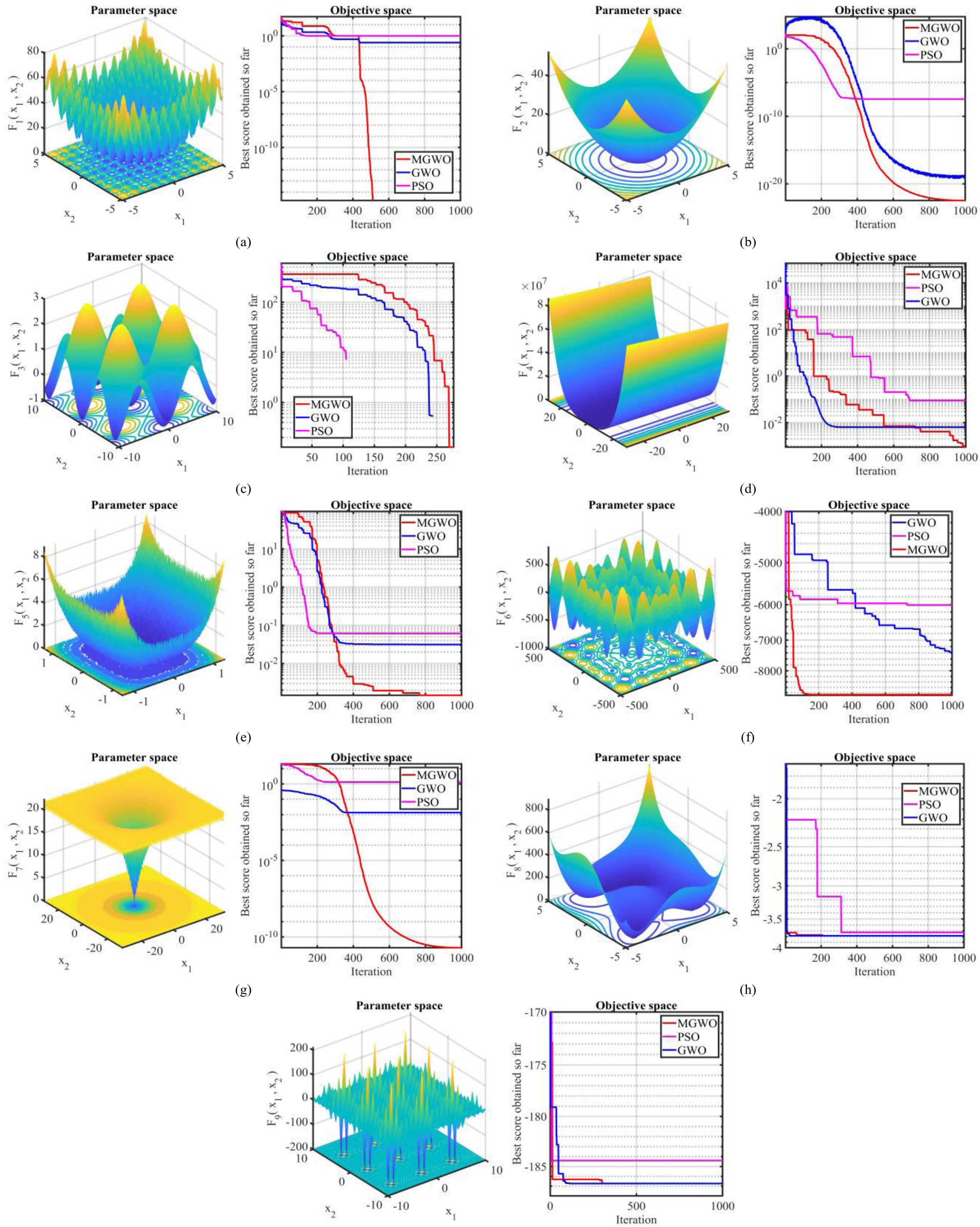

FIGURE 6. The performance of proposed MGWO on different functions (a) Rastragin (b) Sphere (c) Greiwank (d) Rosenbrock (e) Noise (f) Schewefel (g) Ackley (h) Himmelblau (i) Shubert.

TABLE 2. Statistical analysis of PSO, GWO and MGWO.

FUNCTION	STATISTICAL INDICATORS	TECHNIQUES		
		PSO	GWO	MGWO
$F_1(x)$	$best_{sol}$	0.09949	0.02479	7.6E-05
	$worst_{sol}$	1.06E+00	3.76E-01	4.51E-05
	μ	6.19E-01	2.35E-01	-9.13E-06
	σ	2.66E-01	9.44E-02	3.58E-05
$F_2(x)$	$best_{sol}$	2.53E-08	7.88E-20	3.39E-23
	$worst_{sol}$	4.62E-06	9.98E-16	4.36E-19
	μ	1.94E-06	4.83E-16	2.30E-19
	σ	1.25E-06	3.19E-16	1.08E-19
$F_3(x)$	$best_{sol}$	6.59E-02	2.57E-02	1.36E-02
	$worst_{sol}$	-2.07E+01	-1.40E+01	-5.03E+00
	μ	-8.74E+00	-5.96E+00	-2.04E+00
	σ	5.81E+00	4.64E+00	1.99E+00
$F_4(x)$	$best_{sol}$	9.13E-03	6.41E-03	8.91E-04
	$worst_{sol}$	1.15E-01	6.86E-02	5.56E-03
	μ	6.18E-02	3.56E-02	2.90E-02
	σ	3.00E-02	1.87E-02	1.70E-03
$F_5(x)$	$best_{sol}$	6.14E-02	3.15E-02	9.98E-04
	$worst_{sol}$	1.06E+00	7.77E-01	6.52E-02
	μ	5.28E-01	4.37E-01	3.19E-02
	σ	3.05E-01	1.69E-01	2.11E-02
$F_6(x)$	$best_{sol}$	-6.01E+03	-7.39E+03	-8.83E+03
	$worst_{sol}$	-4.53E+03	-6.87E+03	-9.50E+03
	μ	-5.23E+03	-7.22E+03	-8.79E+03
	σ	4.34E+02	2.64E+02	1.01E+02
$F_7(x)$	$best_{sol}$	1.34E-01	7.83E-03	1.97E-11
	$worst_{sol}$	4.87E+00	2.46E+00	8.83E-09
	μ	1.74E+00	3.44E-02	4.35E-09
	σ	9.53E-01	1.31E-02	2.67E-09
$F_8(x)$	$best_{sol}$	-3.73E+00	-3.78E+00	-3.78E+00
	$worst_{sol}$	-3.58E+00	-3.68E+00	-3.81E+00
	μ	-3.66E+00	-3.73E+00	-3.80E+00
	σ	3.36E-02	3.37E-02	1.59E-02
$F_9(x)$	$best_{sol}$	-1.84E+02	-1.87E+02	-1.87E+02
	$worst_{sol}$	-1.81E+02	-1.90E+02	-1.86E+02
	μ	-1.83E+02	1.88E+02	-1.86E+02
	σ	5.32E-01	5.88E-01	2.53E-01

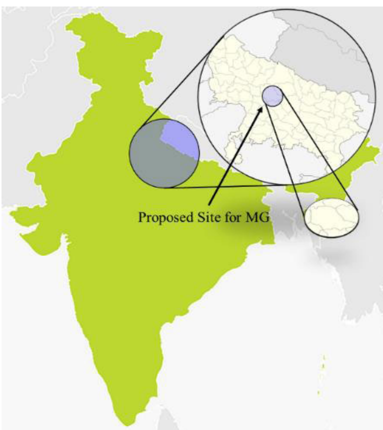

FIGURE 7. Geographical location of the proposed site.

in India as shown in Fig. 7. The test site is a retail outlet located at 26°51′ N 80°57′ E coordinates. MG is simulated in MATLAB-Simulink Environment and its performance is gauged under two different conditions with different techniques. The results of the proposed approach have been compared with Mixed Integer Linear Programming

TABLE 3. Time and cost of electricity.

TIME (HOURS)	REGION	ELECTRICITY COST ($/KWH)
04:00 – 07:00	Medium (I)	[0.09,0.16]
16:00 – 22:30	High (II)	[0.09,0.31]
22:30 – 04:00	Normal (III)	0.09 (fixed)
07:00 – 16:00	Normal (III)	0.09 (fixed)

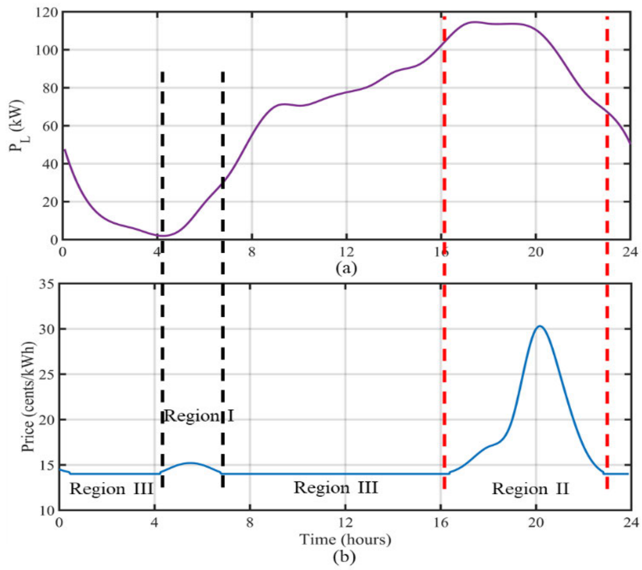

FIGURE 8. (a) Cost of electricity (b) Load profile.

based optimization technique (MILP). The two different conditions considered in the work are classified by the day type ratio (R_{dt}) i.e., the ratio of the measured and theoretical clear sky insolation [32], [33]. The different ranges of R_{dt} has been decided to identify the clear i.e., sunny condition ($R_{dt} > 70\%$) and cloudy condition ($70 > R_{dt} > 30\%$).

The uncertainties and variations in the weather conditions are considered for an effective analysis of the performance of the designed MG. The performance of the proposed energy management system for the MG is compared with the MILP based EMS based on cost and grid interactions. The cost of electricity (cents/kWh) from the utility grid is displayed in Fig. 8(a). This variation in the cost is done according to ToU and following the local electricity commission. The cost of electricity is varying from a minimum \$0.09/kWh to \$0.31/kWh and is elaborated in different regions in Table 3. The cost is varying in the region I from \$0.09/kWh to \$0.16/kWh when the load applied is medium from 04:00 – 07:00 hours. For region II, when the load is maximum and the demand is at its peak from 16:00 – 22:30 hours the cost is between \$0.09/kWh to \$0.31/kWh. The load demand graph is given in Fig. 8(b). The classification of the regions was done based on the cost of electricity supplied by the utility grid.

The load profile for the site is further elaborated in Fig. 9 with power curves of the three variable loads. These variable

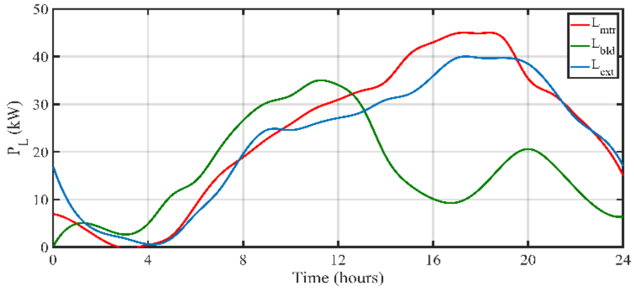

FIGURE 9. Load profile of variable loads present at the site.

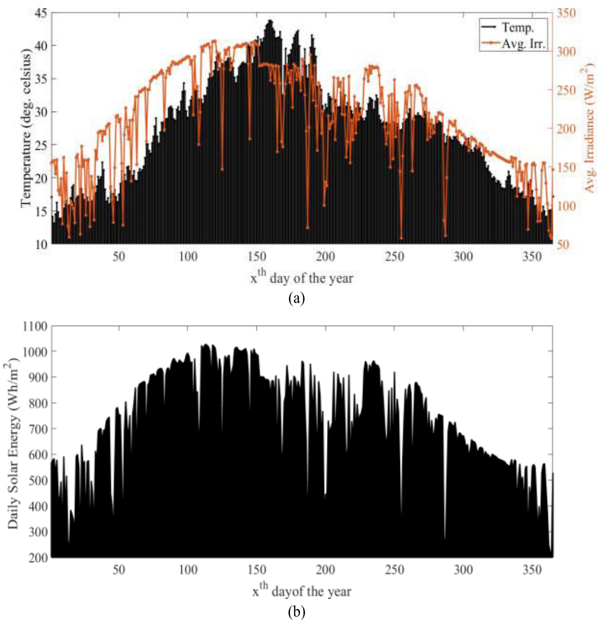

FIGURE 10. (a) Daily average of irradiance and temperature (b) Estimated solar energy generation of a year.

loads are motor load (L_{mtr}), building load (L_{bld}), and external lighting load (L_{exl}). Each of these loads are associated to specific applications at the MG site. Each type of load has different peak ratings and different operating times further elaborated in Table 4. L_{mtr} is the highest rated load and is controllable for 16 hours followed by L_{exl} for 12 hours and L_{bld} for 8 hours. L_{cnst} is the constant load that is active for the complete 24 hours and they define the critical loads. The variation in the temperature (°) and irradiance (W/m^2) for the location is shown in Fig. 10(a) and the estimated solar energy for a year is presented in Fig. 10(b).

From the source sizing method designed in [30] and [34], WECS is completely neglected and the values given in Table 4 for SPV and BESS are calculated. In addition, the designed MG and MGC consider SPV as the primary sources in RE and performance is discussed below. In Table 4, the parameter description is presented for designing an SPV based grid-connected MG. The calculation of loads is done by analyzing the real-time data of the motors, lights and other appliances that has been recorded for a complete year.

TABLE 4. Parameters for designing of MG.

Components	Parameters	Value
Grid	Nominal Line-Line Volatge (V_{rms})	440 V
	Frequency	50 Hz
Load	L_{cnst} (00:00-24:00 hrs)	35 kW
	L_{exl} (12:00-24:00 hrs)	40 kW
	L_{bld} (08:00-16:00 hrs)	35 kW
	L_{mtr} (08:00-24:00 hrs)	45 kW
SPV System	P_{pv}	160 kW$_p$
BESS	Initial SoC	50%
	SoC_{mx}	85%
	SoC_{mn}	18%
	η_B	0.95
	N_B	980 kWh

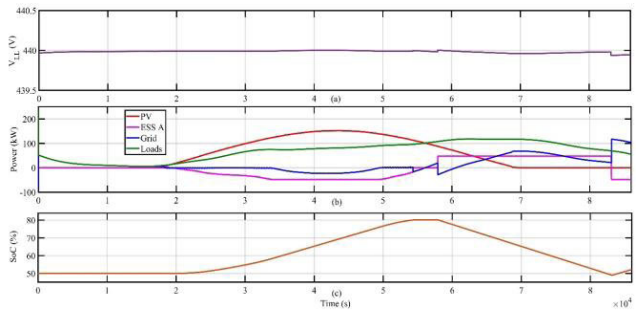

FIGURE 11. Performance of MILP based EMS on a clear day (a) Line to line voltage (magnitude) (b) Power exchange among different sources (c) SoC of the battery.

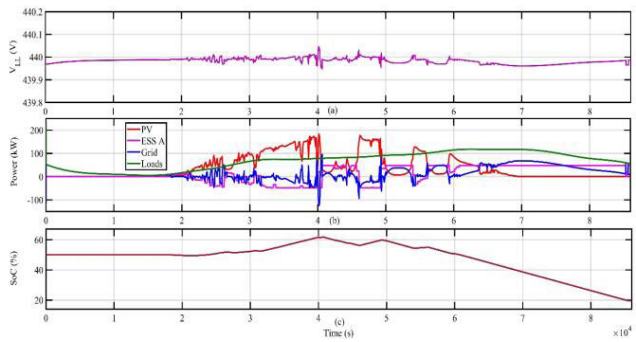

FIGURE 12. Performance of MILP based EMS on a cloudy day (a) Line to line voltage (magnitude) (b) Power exchange among different sources (c) SoC of the battery.

A. PERFORMANCE OF MILP BASED EMS

The performance of the proposed MG is discussed using linear programming-based optimization for energy management of different sources on a clear day. The results are shown in the Fig. 11 for better understanding. The line-to-line voltage is maintained at 440 V shown in Fig. 11(a). From Fig. 11(b) it is observed that when P_{pv} is zero P_L is met by the utility grid and batteries are in idle stage. Furthermore, when $P_{pv} > 0$, there is a drop in power met by the grid and is eventually zero and the surplus supply of power is in turn given to the BESS for charging. The negative power shows charging of the batteries and from Fig. 11(c) it is clear as there is an increase in SoC of the batteries. During the high demand

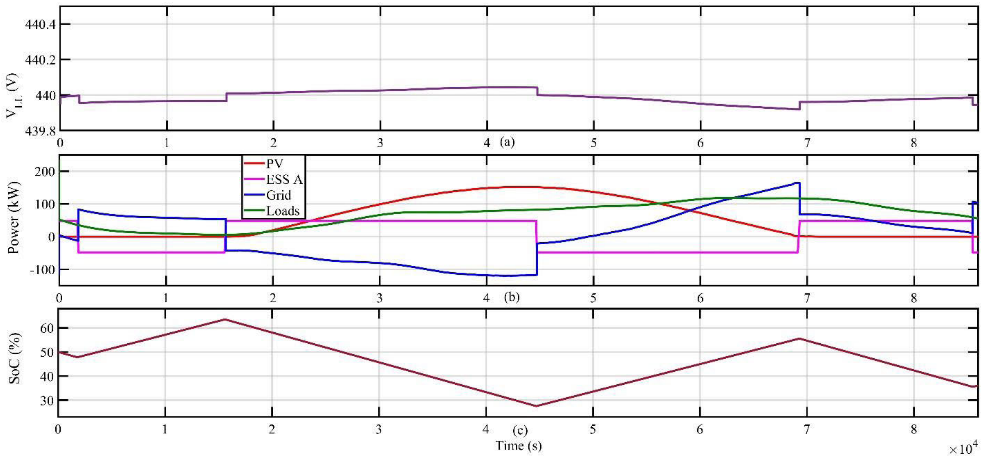

FIGURE 13. Performance of MGWO based EMS on a clear day (a) Line to line voltage (magnitude) (b) Power exchange among different sources (c) SoC of the battery.

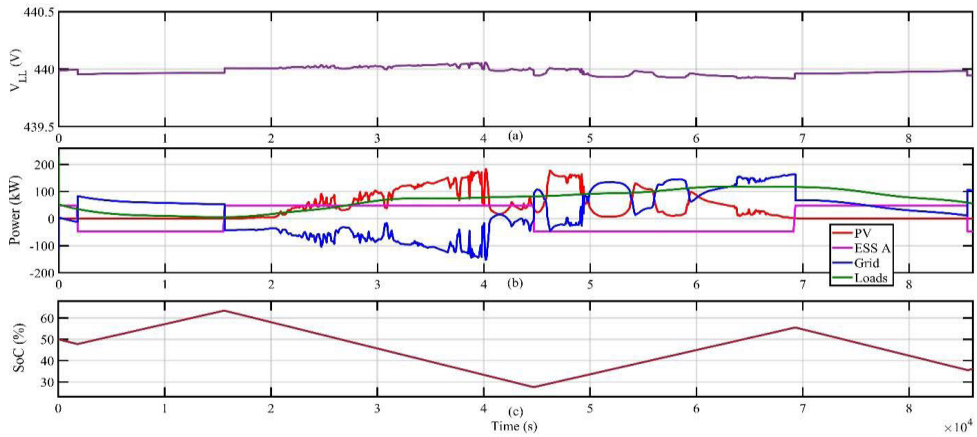

FIGURE 14. Performance of MGWO based EMS on a cloudy day (a) Line to line voltage (magnitude) (b) Power exchange among different sources (c) SoC of the battery.

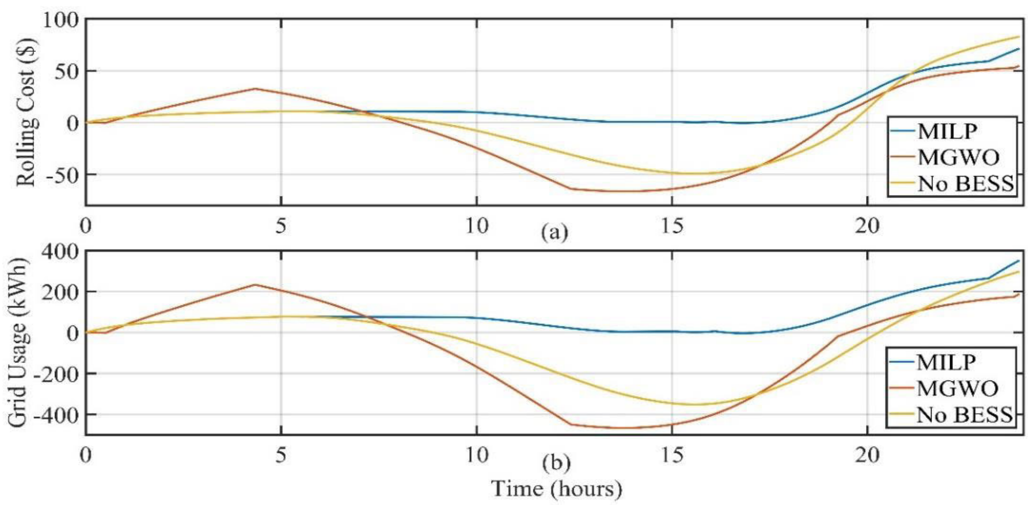

FIGURE 15. Clear day performance (a) Rolling cost (b) Grid usage.

period i.e., Region II, P_{pv} decreases, during this high-cost period the grid and power from batteries (P_B), comes into play to meet P_L.

The real-time performance of MILP based EMS for a practical situation is discussed in Fig. 12. The practical condition is obtained by predicting the power of the sources

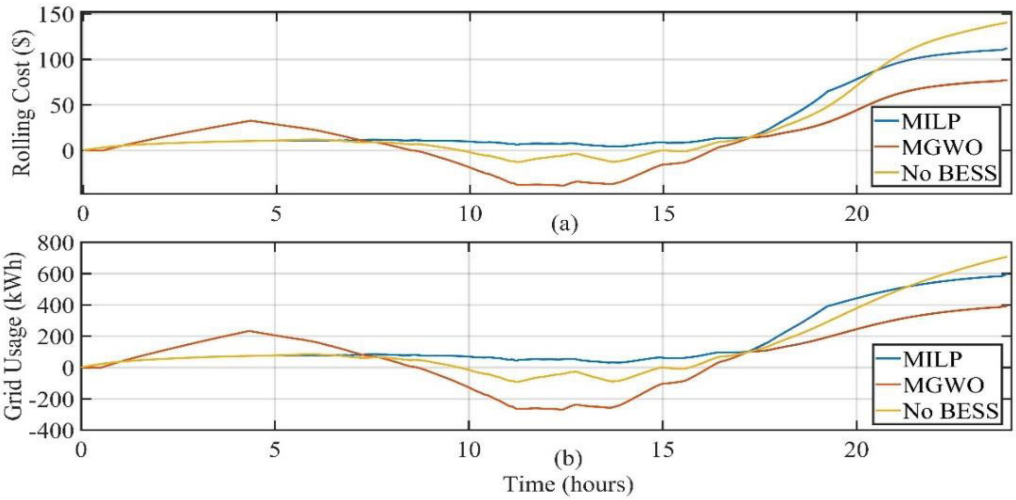

FIGURE 16. Cloudy day performance (a) Rolling cost (b) Grid usage.

of MG on a cloudy day. Moreover, the performance of SPV system is varying with many fluctuations as shown in Fig. 12(b). The performance of the BESS is different from the previous condition as, the battery charges till 62% and then is required to supply power to meet the load demand as elaborated in Fig. 12(c).

B. PERFORMANCE OF PROPOSED MGWO BASED EMS

The performance of the proposed hybrid optimization technique i.e., MGWO based MGC for energy management on a clear, sunny day is depicted in Fig. 13. The performance difference is evident because the BESS is charging when the load is least and the cost of electricity is minimum i.e. during some parts of Region I and III. From Fig. 13(b), it can be observed that extraction of grid power is comparatively more when $P_{pv} = 0$. During $P_{pv} > 0$, P_B is also >0 as the surplus power from the SPV system is exchanged with the grid for maximum gain. During peak hours i.e. Region II, BESS, and grid work in tandem to cater P_L. Thus, the SoC of the batteries is decreasing as shown in Fig. 13(c).

The real-time performance of MGWO based EMS for a practical situation is discussed in Fig. 14. Moreover, the performance of SPV system is varying with many fluctuations as shown in Fig. 14(b). The performance of the BESS is different from the previous condition as, the battery charges till 63% and then following the similar characteristics of the previous conditions as shown in Fig. 14(c). The P_{pv} being inadequate to completely meet the load profile, so the power from grid is used for compensating the deficient power.

The comparative study for the two-energy management strategy based on MILP and MGWO is presented in Table 5. The parameters used for analysis are rolling cost i.e., the cost of running the proposed MG for 24 hours and grid usage. The rolling cost is the net cost after the selling and purchase of the energy units. From Table 5, it is seen that the performance of the MGWO-EMS is better and economically viable for both clear and cloudy conditions. The rolling cost is much higher for the cloudy day when compared to the clear day, due to variability in the weather conditions. Whereas, the savings on a clear day for the proposed MG using the MGWO-EMS is 23.34% than the MILP based EMS, in addition to this, the savings increase to 45.55% on a cloudy day. For better understanding, Fig. 15 and Fig. 16 are shown for comparative study of clear and cloudy day respectively. These figures also show the effect of using BESS in designing an MG, as the rolling is highest when no BESS is considered in the different weather conditions.

TABLE 5. Comparative analysis of the proposed EMS for MG.

Condition	Parameters	MILP	MGWO
Clear	Rolling Cost ($)	71.34	54.68
	Grid Usage (kWh)	327.81	188.23
Cloudy	Rolling Cost ($)	112.43	77.24
	Grid Usage (kWh)	591.34	396.71

V. CONCLUSION

The recent development of eco-friendly technologies, promoting sustainable development, such as RE resources and hybrid MG can find increased acceptance socially and economically. The optimal energy management strategy of such a system requires consideration of design state, geophysical conditions, load demand management, and parametric constraints. In this paper, a novel MGWO based approach for optimal energy dispatch in a hybrid MG in the modern power system, integrating the variability in loads and working conditions is proposed. The computational speed and convergence of the proposed optimization technique are found to be better. A case study presented in the paper for a test location helps in effectively and efficiently designing the proposed MG and its EMS. The proposed MGC aims at reducing the operational cost and reducing the burden on the utility grid. The performance of the MGWO-EMS is tested at varying weather conditions and compared with MILP-EMS. Furthermore, the performance of MGWO-EMS is comparatively better. The savings in operational/rolling cost is 23.34% than the MILP based EMS on a clear day, in addition to this, the savings increase to 45.55% on a cloudy day. Moreover, the burden on the grid is reduced by 42.56% and 32.91% for clear and cloudy days respectively. This approach takes benefit from the price gaps between high and low-price hours of electricity from the utility grid. Also, transmission losses are reduced as energy is utilized from the RE sources and BESS has recharged accordingly. The proposed approach can be implemented on EV charging stations with varying tariffs according to the ToU, where there is a vehicle to grid and grid to vehicle topology.

APPENDIX

TABLE 6. Nomenclature and abbreviations.

$G(t)$	Irradiance at time t
$G(t)_{stc}$	Irradiance at standard condition
$G(t)_{NOCT}$	Irradiance at NOCT (0.85kW/m^2)
$T_c(t)$	Cell temperature of panel at time t
$T_{c,stc}(t)$	Cell Temperature of panel at standard condition
$T_a(t)$	Ambient temperature
$T_{c,NOCT}$	Nominal operating cell temperature
$T_{a,NOCT}$	Ambient temperature at NOCT (20°C)
d_{pv}	Derating factor of PV (%)
P_{pv}	PV array power output (kW)
α_{pv}	Temperature coefficient (%/°C)
η_{pv}	Efficiency of PV array
$f_b(g)$	Beta distribution function of g
α, β	parameters for beta distribution
μ	Mean
σ	standard deviation
E^{bt}	Energy stored in the battery (kWh)
E^{bt}_{tcf}	Total capacity fade of battery (kWh)
$P_C(t)$	Battery charged power at t (kW)
$P_D(t)$	Battery discharged power at t (kW)
ε^{op}_{bt}	Operation cost factor of battery
Z_B	Degradation factor of the considered BESS
$\eta_D(t)$	Discharging efficiency of the battery
N_B	Installed BESS capacity (kWh)
$C_s(t)$	Cost of selling electricity to grid (\$/kWh)
$C_p(t)$	Cost of purchasing electricity from grid (\$/kWh)
B_{rep}	Replacement cost of ESS
$P^{ac}_{PG}(t)$	Purchased grid power for the loads at t (kW)
$P^{dc}_{PG}(t)$	Purchased grid power for ESS at t (kW)
BESS	Battery Energy Management Systems
EMS	Energy Management System
MG	Microgrid
MGC	Microgrid Control
MGWO	Modified Grey Wolf Optimizer
MILP	Mixed Integer Linear Programming
SPV	Solar Photovoltaic
WECS	Wind Energy Conversion System

REFERENCES

[1] D. Schnitzer, D. L. Shinde, J. P. Carvallo, R. Deshmukh, J. Apt, and D. Kammen, "Microgrids for rural electrification: A critical review of best practices based on seven case studies," United Nations Found., Washington, DC, USA, Tech. Rep. 1, 2014.

[2] A. A. Khan, M. Naeem, M. Iqbal, S. Qaisar, and A. Anpalagan, "A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1664–1683, May 2016.

[3] J. Raya-Armenta, N. Bazmohammadi, J. Avina-Cervantes, D. Saez, J. Vasquez, and J. Guerrero, "Energy management system optimization in islanded microgrids: An overview and future trends," *Renew. Sustain. Energy Rev.*, vol. 149, pp. 1–20, Dec. 2021.

[4] K. Zhou, S. Yang, Z. Chen, and S. Ding, "Optimal load distribution model of microgrid in the smart grid environment," *Renew. Sustain. Energy Rev.*, vol. 35, pp. 304–310, Jul. 2014.

[5] V. V. S. N. M. Vallem and A. Kumar, "Retracted: Optimal energy dispatch in microgrids with renewable energy sources and demand response," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 5, pp. 1–27, May 2020.

[6] M. Marzband, N. Parhizi, and J. Adabi, "Optimal energy management for stand-alone microgrids based on multi-period imperialist competition algorithm considering uncertainties: Experimental validation," *Int. Trans. Elect. Energy Syst.*, vol. 26, no. 6, pp. 1358–1372, Jun. 2016.

[7] S. A. Arefifar, Y. A.-R. I. Mohamed, and T. H. M. EL-Fouly, "Optimum microgrid design for enhancing reliability and supply-security," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1567–1575, Sep. 2013.

[8] J. Sachs and O. Sawodny, "A two-stage model predictive control strategy for economic diesel-PV-battery island microgrid operation in rural areas," *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 903–913, Jul. 2016.

[9] M. Combe, A. Mahmoudi, M. H. Haque, and R. Khezri, "Cost-effective sizing of an AC mini-grid hybrid power system for a remote area in South Australia," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 2, pp. 277–287, Jan. 2019.

[10] S. Ferahtia, A. Djeroui, H. Rezk, A. Houari, S. Zeghlache, and M. Machoum, "Optimal control and implementation of energy management strategy for a DC microgrid," *Energy*, vol. 238, Jan. 2021, Art. no. 121777.

[11] A. Maulik and D. Das, "Optimal power dispatch considering load and renewable generation uncertainties in an AC–DC hybrid microgrid," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 7, pp. 1164–1176, Apr. 2019.

[12] M. Kaur, S. Dhundhara, Y. P. Verma, and S. Chauhan, "Techno-economic analysis of photovoltaic-biomass-based microgrid system for reliable rural electrification," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 5, pp. 1–20, May 2020.

[13] W. Hu, P. Wang, and H. B. Gooi, "Toward optimal energy management of microgrids via robust two-stage optimization," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1161–1174, Mar. 2018.

[14] L. Wang, Q. Li, D. Ran, M. Sun, and G. Wang, "Integrated scheduling of energy supply and demand in microgrids under uncertainty: A robust multi-objective optimization approach," *Energy*, vol. 130, pp. 1–14, Jul. 2017.

[15] D. Arcos-Aviles, J. Pascual, L. Marroyo, P. Sanchis, and F. Guinjoan, "Fuzzy logic-based energy management system design for residential grid-connected microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 530–543, Mar. 2018.

[16] J. Sarshar, S. S. Moosapour, and M. Joorabian, "Multi-objective energy management of a micro-grid considering uncertainty in wind power forecasting," *Energy*, vol. 139, pp. 680–693, Nov. 2017.

[17] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "A stochastic multi-objective framework for optimal scheduling of energy storage systems in microgrids," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 117–127, Jan. 2017.

[18] Y. Z. Li, P. Wang, H. B. Gooi, J. Ye, and L. Wu, "Multi-objective optimal dispatch of microgrid under uncertainties via interval optimization," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2046–2058, Mar. 2019.

[19] H. Abniki, S. Taghvaei, S. Mohsen, and M. Hosseininejad, "Optimal energy management of community microgrids: A risk-based multi-criteria approach," *Int. Trans. Electr. Energy Syst.*, vol. 28, pp. 1–16, Dec. 2018.

[20] H. Shuai, J. Fang, X. Ai, Y. Tang, J. Wen, and H. He, "Stochastic optimization of economic dispatch for microgrid based on approximate dynamic programming," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2440–2452, May 2019.

[21] P. Anand, M. Rizwan, and S. K. Bath, "Sizing of renewable energy based hybrid system for rural electrification using grey wolf optimisation approach," *IET Energy Syst. Integr.*, vol. 1, no. 3, pp. 158–172, Sep. 2019.

[22] A. Zakariazadeh, S. Jadid, and P. Siano, "Smart microgrid energy and reserve scheduling with demand response using stochastic optimization," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 523–533, Dec. 2014.

[23] V. Bui, A. Hussain, and H.-M. Kim, "A multiagent-based hierarchical energy management strategy for multi-microgrids considering adjustable power and demand response," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1323–1333, Mar. 2018.
[24] R. Atia and N. Yamada, "Sizing and analysis of renewable energy and battery systems in residential microgrids," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1204–1213, May 2016.
[25] P. Kou, D. Liang, and L. Gao, "Stochastic energy scheduling in microgrids considering the uncertainties in both supply and demand," *IEEE Syst. J.*, vol. 12, no. 3, pp. 2589–2600, Sep. 2018.
[26] Y. Li, L. Fu, K. Meng, Z. Y. Dong, K. Muttaqi, and W. Du, "Autonomous control strategy for microgrid operating modes smooth transition," *IEEE Access*, vol. 8, pp. 142159–142172, 2020.
[27] V. Suresh, P. Janik, J. M. Guerrero, Z. Leonowicz, and T. Sikorski, "Microgrid energy management system with embedded deep learning forecaster and combined optimizer," *IEEE Access*, vol. 8, pp. 202225–202239, 2020.
[28] Y. Lv, L. Guan, Z. Tang, and Q. Zhao, "A probability model of PV for the middle-term to long-term power system analysis and its application," *Energy Proc.*, vol. 103, pp. 28–33, Dec. 2016.
[29] U. Akram, M. Khalid, and S. Shafiq, "Optimal sizing of a wind/solar/battery hybrid grid-connected microgrid system," *IET Renew. Power Gener.*, vol. 12, no. 1, pp. 72–80, Aug. 2018.
[30] A. Kumar, M. Rizwan, and U. Nangia, "A new approach to design and optimize sizing of hybrid microgrid in deregulated electricity environment," *CSEE J. Power Energy Syst.*, early access, Dec. 21, 2020, doi: 10.17775/CSEEJPES.2020.03200.
[31] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014.
[32] P. Chaudhary and M. Rizwan, "Energy management supporting high penetration of solar photovoltaic generation for smart grid using solar forecasts and pumped hydro storage system," *Renew. Energy*, vol. 118, pp. 928–946, Apr. 2018.
[33] S. Ghosh, S. Rahman, and M. Pipattanasomporn, "Distribution voltage regulation through active power curtailment with PV inverters and solar generation forecasts," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 13–22, Jan. 2017.
[34] A. Kumar, M. Rizwan, and U. Nangia, "Optimal sizing of renewable energy resources in a microgrid for a distributed generation system," in *Proc. Int. Symp. Adv. Electr. Commun. Technol. (ISAECT)*, Rome, Italy, Nov. 2019, pp. 1–6.

ASTITVA KUMAR (Member, IEEE) received the B.Tech. degree from Uttar Pradesh Technical University, Uttar Pradesh, India, in 2013, and the M.Tech. degree in control and instrumentation from Delhi Technological University, Delhi, India, in 2015, where he is currently pursuing the Ph.D. degree with the Department of Electrical Engineering. He has published more than ten papers in reputed international journals and conference proceedings. His research interests include renewable energy integration, optimization techniques, PV power forecasting, energy management systems, and intelligent controllers for hybrid energy systems.

MUHANNAD ALARAJ (Member, IEEE) received the B.Sc. degree from Qassim University, in 2008, and the M.Sc. and Ph.D. degrees from the University of Colorado Denver, in 2013 and 2018, respectively, all in electrical engineering. He is currently a Faculty Member of the Department of Electrical Engineering, College of Engineering, Qassim University. Recently, he has been awarded sponsored research project from the Ministry of Education, Saudi Arabia. His research interests include modeling and simulation of power electronics converters, energy harvesting from renewable energy resources, integration of renewable energy resources into the power grid, and power system operation.

MOHAMMAD RIZWAN (Senior Member, IEEE) has done the postdoctoral research at Virginia Polytechnic Institute and State University, USA. He has almost 19 years of teaching and research experience. He has successfully completed three research projects in the area of renewable energy systems and published and presented more than 150 research papers in reputed international/national journals, including IEEE TRANSACTIONS and conference proceedings. His research interests include soft computing applications in power engineering, renewable energy systems, building energy management, and smart grid. He is a Life Member of ISTE and SSI, a member of the International Association of Engineers (IAENG), and many other reputed societies. He was a recipient of Raman Fellowships for Postdoctoral Research for Indian Scholars in USA, DST Start Up Grants (Young Scientists), and many more.

UMA NANGIA (Member, IEEE) received the B.E., M.E., and Ph.D. degrees in electrical engineering from the Delhi College of Engineering, University of Delhi, Delhi, in 1983, 1985, and 1999, respectively. She has done the Ph.D. under the guidance of late Prof. C. L. Wadhwa and Prof. N. K. Jain. She is currently a Professor with the Department of Electrical Engineering, Delhi Technological University, Delhi. She has published numerous research papers in national and international journals of repute. Her research interests include multiobjective optimal power flows, multiobjective economic load dispatch, optimization, and soft computing techniques and their application to the power system problems.