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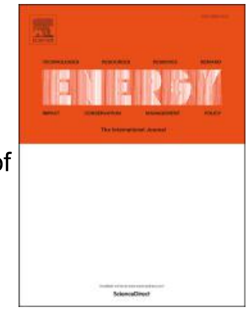

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PII: S0360-5442(18)32150-9

DOI: https://doi.org/10.1016/j.energy.2018.10.153

Reference: EGY 14050

To appear in: *Energy*

Received Date: 30 May 2018

Revised Date: 23 October 2018

Accepted Date: 26 October 2018

Please cite this article as: Roy K, Mandal KK, Mandal AC, Ant-Lion Optimizer algorithm and recurrent neural network for energy management of micro grid connected system, *Energy* (2018), doi: https://doi.org/10.1016/j.energy.2018.10.153.

Ant-Lion Optimizer algorithm and Recurrent Neural Network for Energy Management of Micro Grid Connected System

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Abstract: In this paper, an intelligent technique for EMS based on Recurrent Neural Network (RNN) with aid of Ant-Lion Optimizer (ALO) algorithm is presented to find energy scheduling in MG. The optimal operation programming of electrical systems through the minimization of production cost as well as better utilization of renewable energy resources, such as the PV system, WT, and storage system. The objective of the proposed method is utilized to the optimum operation of micro-sources for decreasing the electricity production cost by hourly day-ahead and real-time scheduling. The proposed method is able to analyze the technical and economic time-dependent constraints. The proposed method attempts to meet the required load demand with minimum energy cost. To accomplish this aim, demand response (DR) is evaluated by utilizing the RNN and additional indices for evaluating customer response, such as consumers information based on the offered priority, DR magnitude, duration, and minimum cost of energy

(COE). Finally, the ALO algorithm is developed to solve the economic dispatch issues for determining the generation, storage, and responsive load offers. The proposed method is implemented in MATLAB/Simulink working platform and their performances are tested with the existing methods such as GA, ABC, and BFA respectively.

Keywords: Energy management system, Micro grid, PV, WT, ALO and RNN

1. Introduction

This century is relied upon to witness extraordinary development and difficulties in force era, conveyance, and utilization. Ecologically cordial (renewable and clean choices) power era innovations will assume a critical part in future force supply because of expanded worldwide open consciousness of the requirement for natural security and yearning for less reliance on fossil powers for vitality creation [3]. These advancements incorporate force era from renewable energy (RE) assets, for example, wind, photovoltaic (PV), micro hydro (MH), biomass, geothermal, sea wave and tides, and clean alternative energy (AE) power era innovations, for example , fuel cells (FCs) and micro turbines (MTs) [1]. The advantages of renewable vitality infiltration incorporate an abatement in outer vitality reliance, diminish in transmission and change misfortunes and further enhance the framework dependability, and so forth [4] [16]. To build the vitality unwavering quality, wind and sun based vitality are utilized as double vitality sources. In any case, occasional climatic conditions and geographic conditions influence the wind-sun powered vitality yield [8]. Consequently, a third vitality framework is expected to enhance the vitality supply unwavering quality. Therefore, the PEM energy unit in a perfect world satisfies the requirement for any start up force. At this point, when the wind-close planetary system vitality yield is inadequate, the energy unit reinforcements supply framework

[9]. A general force framework utilizes battery vitality stockpiling to dodge a force blackout or force surges brought on by common natural components.

The late pattern of renewable vitality advancement is a mix of circulated force sources and vitality stockpiling subsystems to frame a little smaller scale network that can decrease loss of vitality from force transmission lines over long separations [7]. A renewable-based smaller scale network can be comprehended as a specific instance of a more broad idea called a 'shrewd lattice', which is an interdisciplinary term for an arrangement of innovative answers for electric force framework administration [2]. The present day idea of small scale network is profoundly encouraging as an answer for the issue because of lack of fossil fuel in future in ordinary force era. Smaller scale matrix is a stage to incorporate DERs into appropriation system. The DERs may incorporate DGs and circulated stockpiling (DS) [12]. Small scale frameworks work in matrix associated or island mode, and may involve dispersion systems with private or business end-clients, in rustic or urban ranges [14] [19]. Operation of smaller scale lattice relies on upon fruitful combination of DERs which is connected with a few variables like force quality issues. The force quality issues ought to be painstakingly managed to accomplish acceptable estimations of voltage and recurrence in matrix associated and islanded method of small scale framework in relentless state and, amid element state i.e. move from framework associated mode to islanded mode and the other way around [6] [20].

The vitality acquired from the RES is spotless and makes no contamination, however then again it is stochastic and subsequently hard to control. Because of this disadvantage, a high infiltration of the RES can make dependability, unwavering quality and force quality issues in the principle electrical lattice. Consequently, an ideal method for incorporating the vitality acquired from the RES must be outlined [10] [17]. In this regard, the crossover framework, shaped by interconnecting little, particular era and capacity gadgets has ended up being the best method for taking care of the vitality demand with high unwavering quality, adaptability and cost adequacy [5] [11]. Vitality administration of cross breed vitality frameworks is vital for guaranteeing ideal vitality usage and vitality maintainability to the greatest degree. What's more, the expansion in infiltration of renewable vitality in force frameworks, especially at the conveyance level, presents new difficulties for recurrence and voltage control since they can change the era/request parity of the system quickly when contrasted with routine alternators whose progression are administered by their idleness consistent [13] [18]. Dynamic connection between the heap request and the renewable vitality source can prompt basic issues of security and force quality. Along these lines, dealing with the stream of vitality all through the mixture framework is crucial to expand the working existence of the layer and to guarantee the consistent vitality stream. The expanding number of renewable vitality sources and appropriated generators requires new systems for their operations with a specific end goal to keep up the vitality equalization between the renewable sources and utility framework or smaller scale network [15].

The rest of the paper is followed as below. The problem formulation and the detailed explanation of the suggested technique are offered in Section 3. Previous to that, the current research works are offered in Section 2. The simulation results and conversation are specified in Section 4. At last, the Section 5 finishes the document.

Contribution of the Research

(i) To analyze the MG operations and their cost functions.

(ii) To predict the wind speed with the lesser period.

(iii) To reduce the uncertainty and error of prediction.

(iv) To achieve the optimal scheduling with the demand response and the generation cost.

(v) To satisfy the demand side management and analyze the corresponding performances.

(vi) Test the system with two scenarios such as, normal loading conditions and load increase period.

Objectives

The objective of the paper is to minimize the EMS based utilization cost for 24 hours with the help of the proposed Ant-Lion Optimizer algorithm and Recurrent Neural Network method. Mainly it focused to analyze the MG operations and their cost functions. For evaluating the MG operations, the corresponding constraints are defined. In addition, the wind speed, PV irradiance and SOC of battery are also analyzed. The important point is to implement the algorithm is to reduce the uncertainty and prediction error while satisfying the demand response of the system. Based on the objectives, some papers are analyzed and try to get the better way of solutions. Some of the papers are reviewed in the next section.

2. Recent research works: A brief review

Various research works are as of now existed in writing which in light of micro grid energy management system. Some of them audited here.

Fatemeh Najibi *et al.* [21] have directed to one warm and electrical model for photovoltaic. Mousa Marzband *et al.* [22] have introduced a calculation for energy management system (EMS) in view of multi-layer ant colony optimization ((EMS-MACO) to discover vitality planning in MG. The primary target of the procedure was the ideal operation of smaller scale hotspots for diminishing the power generation cost by hourly day-ahead and ongoing planning. The calculation depended on subterranean ant colony optimization (ACO) technique and could investigate the specialized and monetary time subordinate requirements. That calculation endeavors to take care of the required burden demand with least vitality cost in a local energy market (LEM) structure.

Kallol Roy *et al.* [23] have presented an Improved Artificial Bee Colony (IABC) calculation for displaying and overseeing MG associated framework. IABC varies from ABC as a result of its incorporation of Gravitational search algorithm (GSA) in the scout honey bee stage. Henceforth, the scout honey bee stage was generously enhanced as the gravitational consistent of GSA increments looking precision. In the procedure, ideal MG's design was resolved taking into account load request by diminishing the fuel cost, outflow elements, working and upkeep cost. By utilizing the contribution of MG's arrangement, for example, WT, Photovoltaic cluster (PV), Fuel Cell (FC), Micro Turbine (MT), Diesel Generator (DG) and battery stockpiling and the relating cost works, the technique accomplishes the required multi-target capacity.

Asit Mohanty *et al.* [24] have proposed the utilization of fractional order PID controller (FOPID) for receptive force remuneration and solidness examination in a stand-alone small scale network. Further change of steadiness edge and streamlining of the framework parameters have been accomplished by the controller, in view of Imperialist focused calculation. Ali Deihimi *et al.* [25] have exhibited MOUWCA (multi-objective uniform water cycle algorithm) for ideal operation administration of MG considering operation expense and outflow as destinations. MG as a bunch of shoppers and DGs can work in stand-alone and lattice associated modes, and frequently needs ESS (vitality stockpiling framework) to handle era overflow/deficiency. Through an intelligent procedure, charging/releasing of ESS was adjusted over a day taking into account the wanted request of hours for releasing ESS.

Kallol Roy *et al.* [26] have proposed a half and half enhancement calculation for displaying and dealing with the miniaturized Micro grid (MG) framework. The ideal monetary model of vitality wellspring of the MG units were expected to portray the working expense of the yield power created, the target of the half breed model was to minimize the fuel expense of the MG sources, for example, FC, MT and DG. The issue detailing thinks about the ideal design of the MG at any rate fuel cost, operation and support costs and also discharges decrease. Mousa Marzband *et al.* [27] have proposed a multi-period artificial bee colony (MABC) streamlining calculation for financial dispatch considering era, stockpiling and responsive burden offers. Artificial Neutral Network(ANN) joined with Markov-chain (MC) (ANN-MC) methodology was utilized to anticipate non-dispatch able force era and burden request considering instabilities. The survey of the late research work demonstrates that, the benefit of brought together era of conveyed vitality assets, potential choices assumes a critical part in examination as of late. The administration of dispersed vitality with miniaturized scale lattice is one of the multi-target issues in vitality administration. Since, impeccable financial model of vitality wellspring of small scale framework units are expected to portray the working cost taking into report the yield power produced. In this way, the limitations of the multi-target advancement issue is change into a simpler sub issue that can then be tackled and utilized as the premise of an iterative procedure. Hereditary calculation is one of the worldwide advancement methods which used to take care of the enhancement issue. Therefore, the best arrangement is united to the worldwide arrangement as opposed to a nearby arrangement. All things considered, this difference happens to unverifiable while running with multi-target streamlining, which regularly includes an arrangement of arrangement focuses. Scientifically, a solitary worldwide answer for a multi-target advancement issue does not be available unless the ideal arrangement happens to be achievable. Likewise, the streamlining procedure is relying upon the hereditary administrators, for example, hybrid, transformation, propagation and so on. In this way, the computational intricacy and time taken to unite the arrangement of this calculation is expanded. In writing not very many works are displayed to take care of this issue and the introduced works are incapably giving the best arrangement.

3. Problem Formulation

In the section, the mathematical implementation of EMS optimization problem is described according to the following objective function:

$$B(Y): \min F(X) \tag{1}$$

$$F(X) = \sum_{\kappa}^{N} \Phi_{\kappa} \left(\Psi_1(K) + \Psi_2(K) + \Psi_3(K) + \rho_{\kappa} \right) \tag{2}$$

Where, $\Psi_1(K), \Psi_2(K), \Psi_3(K), \rho_{\kappa}$ *and* Φ_{κ} is described as the cost function of Non-dispatchable and dispatchable resources, the cost function of energy storage system in charge and discharge mode. After that, the values of are the cost function ofstate cost of energy consumed by responsive loaddemand (RLD), the penalty cost resultingfrom undelivered power (UP) during the time periodt. Here, the total production cost is minimized while satisfying generation resources constraints. The penalty cost is included in the objective function, which is considered for the MG operator to avoid undelivered power to the NRL. Each one of these costs can be calculated as follows.

$$\Psi_{\kappa}^{\alpha} = \sum_{i=1}^{N_{\alpha}} \mathrm{H}_{\kappa}^{i,\alpha} \left(\sigma_{\kappa}^{i,\alpha} \right) \tag{3}$$

$$\Psi_{\kappa}^{\beta} = \sum_{i=1}^{N_{\beta}} \mathrm{H}_{\kappa}^{i,\beta} \left(\sigma_{\kappa}^{i,\beta} \right) \tag{4}$$

$$\Psi_{\kappa}^{\lambda} = \sum_{i=1}^{N_{\lambda}} \mathrm{H}_{\kappa}^{i,\lambda}\left(\sigma_{\kappa}^{i,\lambda}\right) \tag{5}$$

By utilizing the above equation, the cost function of the energy generated by non dispatchable, diapatchable resources, load are determined. From the above equations, the $\sigma_{\kappa}^{i,\alpha}$ and $\sigma_{\kappa}^{i,\beta}$ are the i[th] non dispatchable resources, dispatchable resources, $\mathrm{H}_{\kappa}^{i,\alpha}$ and $\mathrm{H}_{\kappa}^{i,\beta}$ are the output power generated by the ith non dispatchable and dispatchable resources. Then the N_{α} and N_{β} are the number of nondispatchable and dispatchable resources in the MG system. Moreover, the cost of energy consumed by ES is evaluated by utilizing the following equation,

$$\Psi_{\kappa}^{\mu+} = \sum_{i=1}^{N_{\mu}} \mathrm{H}_{\kappa}^{i,\mu+}\left(\sigma_{\kappa}^{i,\mu+}, \gamma_{\kappa}^{\mu}\right) \tag{6}$$

$$\Psi_{\kappa}^{\mu-} = \sum_{i=1}^{N} \mathrm{H}_{\kappa}^{i,\mu-}\sigma_{\kappa}^{i,\mu-}\left(1-\gamma_{\kappa}^{\mu}\right) \tag{7}$$

$$\psi_{\kappa} = \mathrm{H}_{\kappa}^{\Gamma}.\sigma_{\kappa}^{\Gamma} \tag{8}$$

In the equation (5), (6) and (7), the σ_{κ}^{Γ} is the offer price when the system is encountered with the UP and $\mathrm{H}_{\kappa}^{\Gamma}$ is the amount of power is not supplied by MG. Here, γ_{κ}^{μ} denoted as the status of the ES operation mode. $\gamma_{\kappa}^{\mu} = 0$ When the ES is discharging mode and $\gamma_{\kappa}^{\mu} = 1$ is the charging mode [28]. For achieving the objective function, the following constraints are analyzed and determined. The power balance equation is specified as the following,

$$\mathrm{A} : \left(\aleph + \Re^{-} + \mathrm{T}\right) = B : \left(\mathrm{E} + T + \Re^{+}\right) \tag{9}$$

From the above equations illustrates that the energy generated by non dispatchable, diapatchable resources and load respectively [28]. Subsequently, the following equation is considered for evaluating the objective function.

$$0 \leq \sum_{i=1}^{N_\alpha} \mathrm{H}_\kappa^{i,\alpha} \leq \mathrm{H}_\kappa^{m,\alpha} \tag{10}$$

Where, $\mathrm{H}_\kappa^{m,\alpha}$ is the maximum power generated by non dispatchable generation units during the time period κ. The remaining constraints are considered and determined from [27]. Therefore, the summation of consumed power by these customers should be equal to the summation of EGP during a daily operation system [29]. In the paper, a hybrid technique is proposed for solving the above optimization problem. Here, the Recurrent Neural Network (RNN) and Ant-Lion Optimizer (ALO) algorithm is utilized for getting the optimal outputs. The detailed explanation of the proposed method is described in the following section.

3.1. RNN and ALOwith MG for an optimal energy management

In the paper, an intelligent control technique is proposed for energy management of micro grid with distribution system resources with micro grids. The intelligent technique is the combination of recurrent neural network (RNN) and Ant-Lion Optimizer (ALO) algorithm technique. The micro gird connected system is based on the photovoltaic (PV) system, wind turbine (WT) and storage system respectively. The proposed control strategy is used to manage the power flows between the energy sources and the grid. It is meet available renewable energy power and to maintain the grid power demand from the grid operator. The electrical power needed by the grid operator is given as a reference to the input of micro grid. The proposed strategy must be distributed the entire power reference between the system parts properly. Here, batteries are utilized as an energy source, to stabilize and permit the renewable power system units to keep running at a steady and stable output power. Based on the concepts, the block diagram for the MG with the proposed method is depicted in the Fig.1.

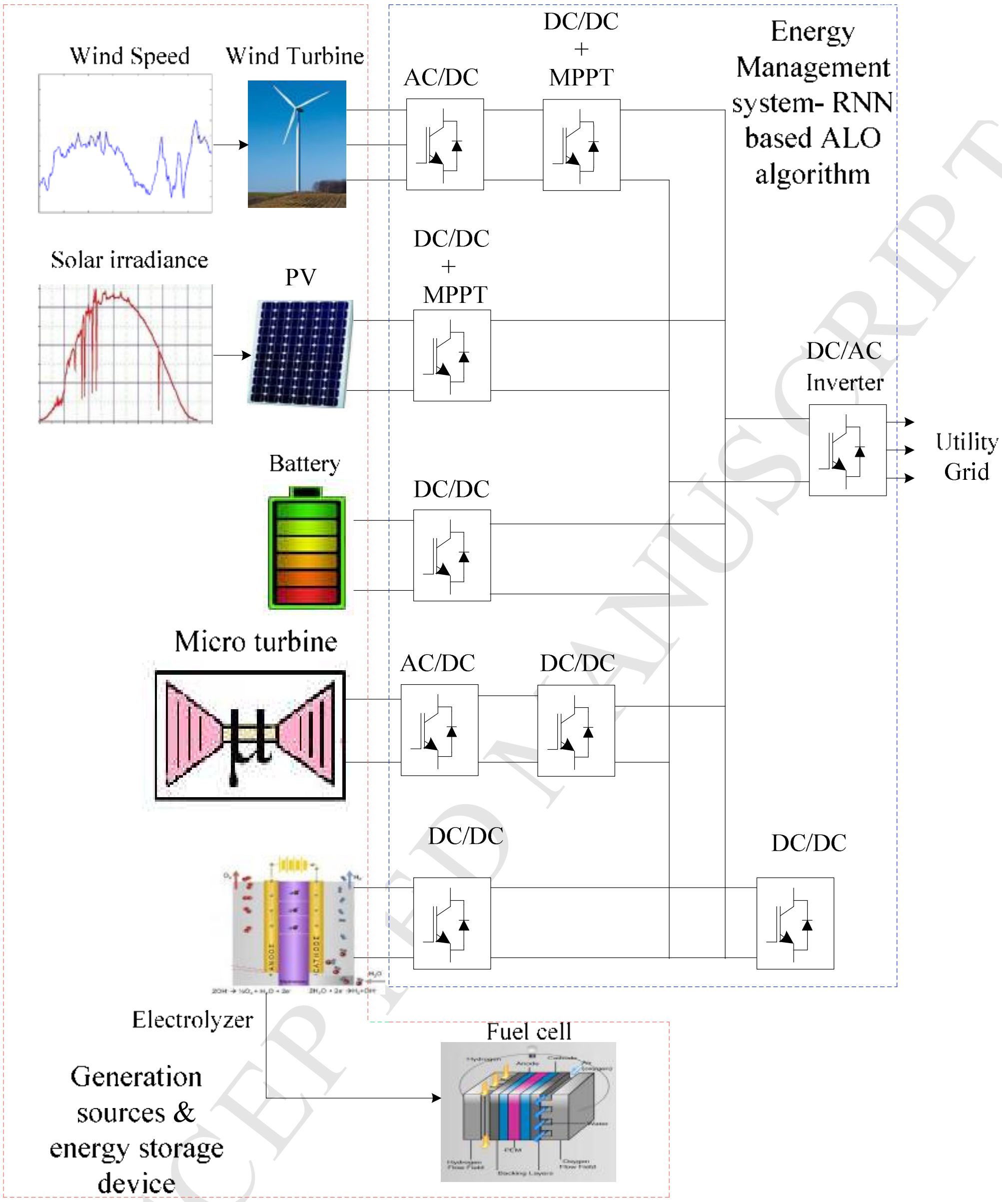

Figure 1: Block diagram with the proposed ALO-RNN method

In the Fig.1, the non-dispatchable resources, dispatchable resources and energy storage devices are mentioned. In the non-dispatchable units, the Wind/PV renewable energy resources are considered and the dispatchable unit is MT. The energy storage device is considered as the Battery, Aqua-electrolyzer and Fuel cell respectively. For the MG system, the energy management system is determined and the total generation cost functions is evaluated with the utilization of the proposed method. The detailed analysis of the proposed method is described as the below section.

Energy Management System

Here, the energy management of MG is examined in the grid-connected mode for the distinctive activity. At first, the MG can be planned with the corresponding ratings after that the control tasks are performed. Amid the task of MG, the load demand must be met all the time under the grid mode. To accomplish the ideal activity, the goal of MGs can be settled and unraveled with the use of the optimization algorithm. The objective function is to be characterized with the wind/solar generation power, MT, battery, FC and AE respectively. Shortly the resources are included as the energy storage devices and the non-dispatchable/dispatchable resources respectively. For energy saving and natural advantage, the wind and solar generation power are completely utilized. To determine the energy management tasks, the control factors incorporate dynamic power and operation state of ESS and dispatchable units, dynamic power traded with the main grid over the time horizon are characterized. The objective functions are determined as the fuel costs, operation and maintenance costs, and startup costs, the cost of the ESS, and is the revenue obtained from buying and selling power to the main grid. There are likewise fundamental power balance conditions, power limits and ramp limits of controllable units, maximum startup time of dispatchable units to be considered. At a given time step, the working state and arranged intensity of controllable units are resolved. Power controlled by the proposed technique will ease the power variances of non-dispatchable units because of any anticipating mistake of information, and enhance voltage and power stream in the meantime. The goal is to limit cost of power regulation with a penalty function.

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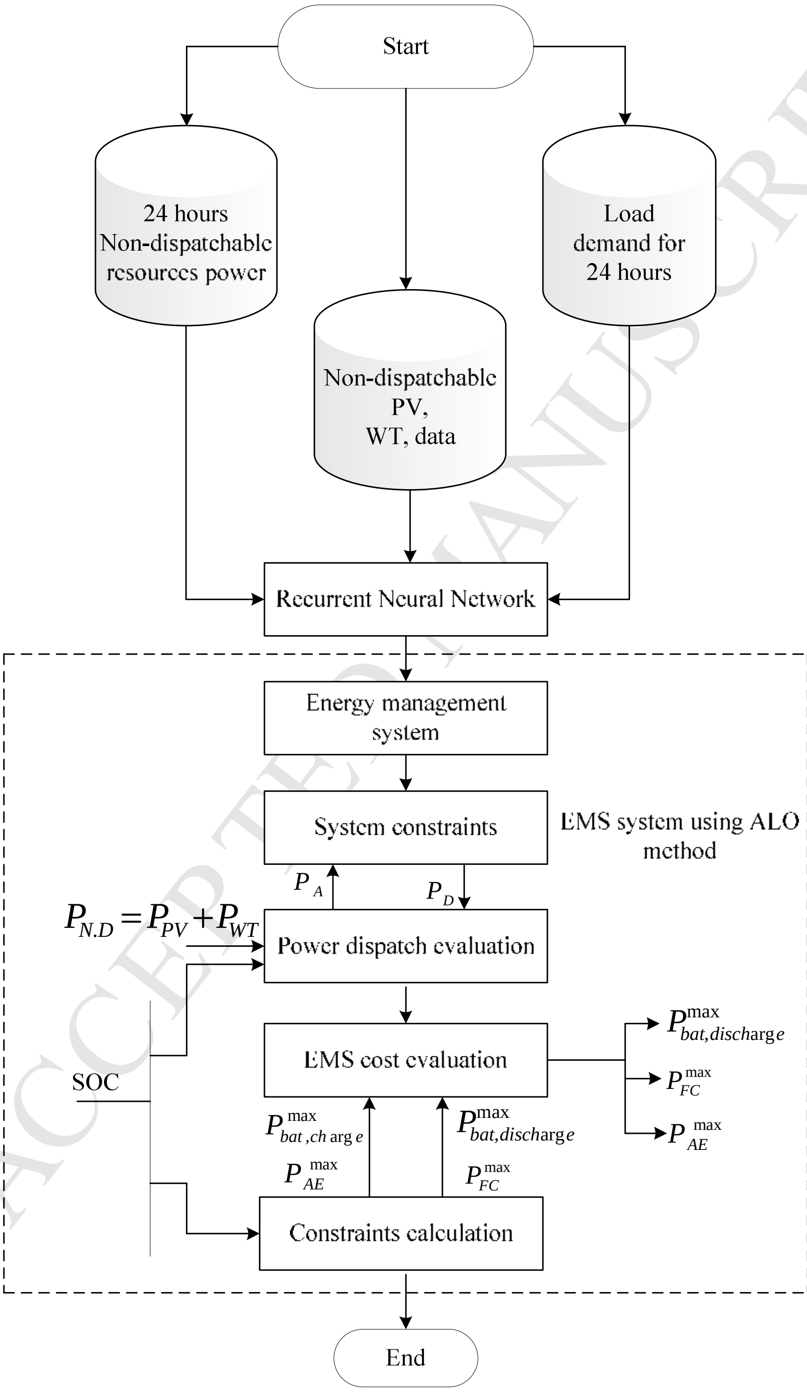


Figure 2: Energy Management system with proposed method

Therefore, the optimal operation is achieved when the objective of MGs is to be minimized and maximized revenues. This control idea is suited for MG energy management since it permits an prediction when a dispatchable source is required. By somewhat sustaining power into the ESS and discharging it after some time at the most elevated amount of demand, dispatchable units can work steadily and effectively. Then again, the control algorithm knows about the variety inclinations of the non-dispatchable source control and of when the ESS will achieve its upper/bring down energy levels. Thusly, power of the dispatachable/non-dispatchable resource units and of the ESS is managed early, adjusting the required increment/curtailment for future time steps and settling any forecasting errors at future time steps when they happen. The proposed technique is augmenting incomes over a given time horizon by finding the most ideal control grouping of controllable units, considering market prices, forecasting power of non-dispatchable units, and load level. At that point the fuel cost for the dispatachable resources are considered as the energy management issue and comprehended with the use of proposed technique. The power reserve coefficient relies upon forecasting accuracy of uncontrollable units capacity and load level, which leaves sufficient power edge of controllable units to manage continuous power fluctuation attributable to forecasting error. The working flow of the energy management system with the RNN based ALO algorithm is depicted in the Fig.2. After that, the training process of the RNN is mentioned as the below section.

3.1.1. Recurrent Neural Network for Load demand

RNNs vary from fundamental feed forward neural networks in their hidden layers. Each RNN hidden layer obtains inputs not only from its preceding layer but also from initiations of itself for preceding inputs. The humblest form of fully recurring neural network is an MLP with the preceding set of hidden unit activations feeding back into the network together with the inputs. Note that the time t has to be discretized, with the beginnings updated at each time step [33]. The time scale might resemble to the operation of real neurons, or for reproduction schemes any time step size suitable for the provided issue can be utilized. A delay unit desires to be familiarized to hold activations until they are administered at the subsequent time step. An abridged version of this feature is illustrated in Fig.4. In the actual RNN that we used, every node in the hidden layer is associated with the previous activation of every node in that layer. Though, most of these links have been left out in the figure for lucidity [34]. In the paper, RNN is utilized for the prediction of load demand. The RNN contains a number of inputs, depending on the activation functions of the RNN results in the output level of the neuron. Here, we are training the RNN using the target power demand with the corresponding input time intervals of a day, i.e., daily demand dataset based on the available WT and PV energy. The training process is explained in the following.

Training structure of RNN

The training phase and testing phase are the two phases and input layer, hidden layer, context layer & output layer are the four layers that enfolds RNN, where 'n' neurons are implemented in the hidden and context layer [35]. There is a one-step time delay in the feedback path so that previous outputs of the hidden layer, furthermore known as the states of the network, are engaged to figure new output values. The topology is same to that of a feed forward network; separately from that the outputs of the hidden layer are implemented as the feedback signals. The formulating diagram of a RNN with voltages as input and one current as output is enlightened in Fig.3

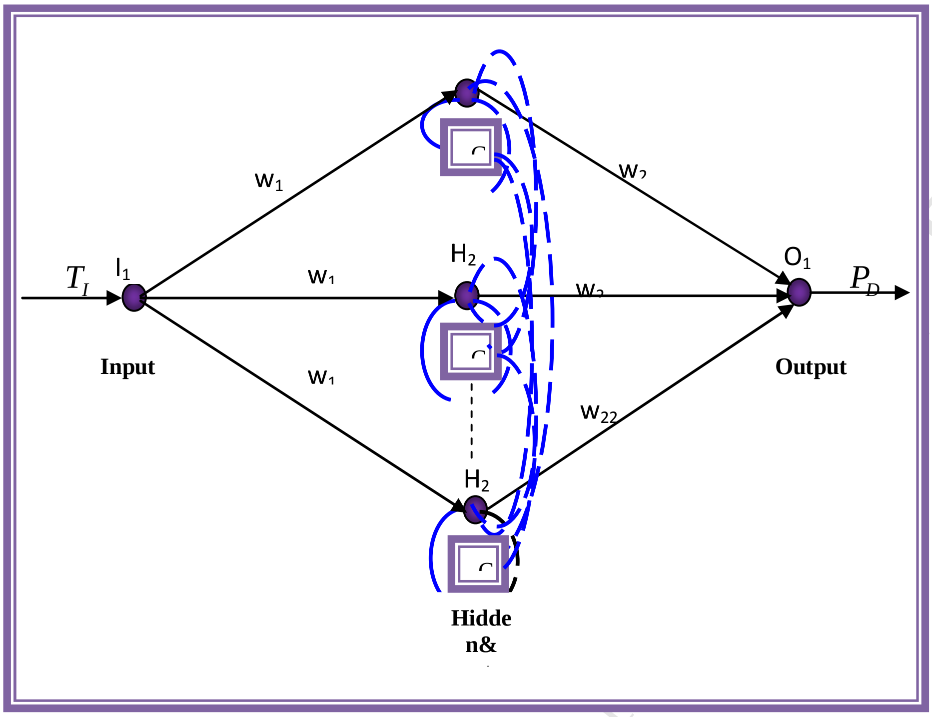


Figure 3: Training structure of proposed recurrent layer neural network

Here, the time interval T is the input of the network, power demand $P_{WT}(t)$ is the output of the network. The RNN output is provided to the inverter current controller. At this time, the input layer to hidden layer weights are quantified as ($w_{11}, w_{12}, \ldots\ldots\ldots, w_{1n}, \; and \; w_{21}, w_{22}, \ldots\ldots w_{2n}$). The random weights of recurrent layer and the output layer neuron are produced at the quantified interval $[w_{\min}, w_{\max}]$. For every neuron of the input layer weight is owed with the unity value. The RNN is trained with the help of back propagation through time delay (BPTT) algorithm along with Bayesian regulation. In the training process, the inputs and output are specified with the $\gamma_i(n) = \sum_j \delta_j(n) w_{ij}(n)$. The RNN procedure is on the basis of the forward and backward pass. The process of Bayesian instruction BPTT algorithm is specified as beneath.

Procedure for training

1) Initialize all the inputs to the input layer and assign their weights.

2) The forward pass of the RNN is described as the following equations,

$$\gamma_i(n) = \sum_j \delta_j(n) w_{ij}(n) \tag{11}$$

$$\delta_i(n) = f_i(\gamma_i(n)) \tag{12}$$

Where, δ_i and w_{ij} stipulates the activation state of neuron i at a time n and optimize weights value. The activation function f_i depends on the basis of the network inputs and the context layer inputs.

3) At this time, the hidden node functions are formulated on the basis of the activation functions. The unseen node activation function is passed via the sigmoid function to determine the decision vector,

Where, $i = 1,2$ and the RNN output is $\hat{y} = W_{2i} f_i$ for a single output system output weight matrix.

4) In the forward process of back propagation, the output of the each neuron is calculated in the backward pass using the following function,

$$\delta_i(n) = f_i(\gamma_i(n), C_i(n)) \tag{13}$$

$$\gamma_i(n) = \sum_{j \in H} \delta_j(n) w_{ij} + \sum_{j \in I} \gamma_j(n) w_{ij} + \sum_{j \in C} \delta_j(n - \tau_{ij}) wij \tag{14}$$

Where, f, H, I and C are represents the activation function of neuron, hidden layer values, input neurons values, the values of the neuron that store in data about the preceding network stage. Then γ_j is a j[th] input neuron and τ_{ij} is an integer value representing the dislocation in recurrent linking done over the times.

5) In the fifth step, the back propagation error is determined from the following equation,

$$\mu_m = \delta^t - \hat{\delta} \tag{15}$$

The errorcan be decreased with the help of the Bayesian Regularization method.

6) At this time, the neural network is trained with the Bayesian Regularization method. In this Bayesian Regulation method, the objective performance is modified by uniting the mean sum of squared network errors and weights and creates a better employed network by picking exact amalgamation. These are the procedures involved in the Bayesian Regularization method that is a function with network training and on the basis of Levenberg-Marquardt optimization, the weight and bias values are updated in this function

$$\mu_d = \frac{1}{N}\sum_{i=1}^{N}\left((\mu_m)^2\right) \tag{16}$$

7) Finally, the weights of the networks are updated. For updating the weights, this equation is expanded in the following,

$$B_r = \kappa\mu_d + \eta\mu_w \tag{17}$$

Where, μ_w is the summation of squares of the network weights. Then η and κ are the parameters to be optimized in Bayesian framework [36] [37]. Till BP error gets decreased to a least value, and then the procedure is repeated. The well trained networks are accomplished from the output of neural network technique. Then the investigation of the proposed technique is described in the subsequent segment.

3.1.2. Ant-Lion Optimizer algorithm for MG

Recently, in 2015 Mirjalili proposed nature inspired algorithm called Ant Lion Optimizer (ALO) which mimics hunting behavior of ant lions in nature. The ALO algorithm also finds superior optimal designs for the majority of classical engineering problems employed, showing that this algorithm has merits in solving constrained problems with separate search spaces. The main inspiration of the ALO algorithm comes from the foraging behavior of antlion's larvae. Larvae phase and adult phases are two important stages in the life cycle of ALO. Ant lions hunt in larvae phase and uses adult phase for reproduction. Larvae stage is the inspiration to ALO algorithm. Ant lions dig cone shaped pit in sand by moving in circular path and throwing the sand out with jaws. After digging the trap larvae wait for pray (ants). The size of the trap is depends on the hungry level of the ant-lion and moon size [30]. If hungry level or moon size is more, then trap size is more and vice versa. If pray come into the cone surface it will easily fall down into it. If ant lion find that pray in the trap, it will catch the pray. There are mainly five operations in ALO algorithm namely random movement of ants, construction of trap, trapping of ants in traps, catching preys and re-construction of traps.

Operators of the ALO algorithm

The ALO algorithm mimics interaction between antlions and ants in the trap. To model such interactions, ants are required to move over the search space, and antlions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk is chosen for modeling ants' movement as follows:

In the ALO algorithm, the antlion and ant matrices are initialized randomly using the function A. In every iteration; the function B updates the position of each ant on an antlion selected by the roulette wheel operator and the elite. The boundary of position updating is first defined proportionally to the current number of iteration. Two random walks then accomplish the updating position around the selected antlion and elite [31]. When all the ants randomly walk, they are evaluated by the fitness function. If any of the ants become fitter than any other antlions, their positions are considered as the new posts for the antlions in the next iteration. The best antlion is compared to the best antlion found during optimization (elite) and substituted if it is necessary. These steps iterative until the function C returns false. Theoretically speaking, the proposed ALO algorithm can approximate the global optimum of optimization problems due to the following reasons:

- Exploration of the search space is guaranteed by the random selection of antlions and random walks of ants around them.
- Exploitation of search space is ensured by the adaptive shrinking boundaries of antlions' traps.
- There is a high probability of resolving local optima stagnation due to the use of random walks and the roulette wheel.
- ALO is a population-based algorithm, so local optima avoidance is intrinsically high.
- The intensity of ants' movement is adaptively decreased over the course of iterations, which guarantees convergence of the ALO algorithm.
- Calculating random walks for every ant, and every dimension promotes diversity in the population.
- Antlions relocate to the position of best ants during optimization, so promising areas of search spaces are saved.
- Antlions guide ants towards promising regions of the search space. The best antlion in each iteration is stored and compared to the best antlion obtained so far (elite).
- The ALO algorithm has very few parameters to adjust.

- The ALO algorithm is a gradient-free algorithm and considers problem as a black box [32].

In the paper, ALO algorithm is utilized for providing the optimal management of MG and getting the minimum generation cost of MG. The inputs are considered as the WT power, PV power, MT power and battery power. The objective function of the proposed algorithm is the minimization of cost function. Based on the objective the optimal management process is determined. This session presents the important steps in ALO algorithm for evaluating the TCSC capacity. Initially, WT power, PV power, MT power and battery powerare utilized to initialize in the algorithm. The random positions of the ants are saved in the matrix M_{ant}

$$M_{ant} = \begin{pmatrix} A_{1,1} & A_{1,2} & \dots & A_{1,n} \\ A_{2,1} & A_{2,2} & \dots. & A_{2,d} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ A_{n,1} & A_{n,2} & \dots & A_{n,d} \end{pmatrix} \tag{18}$$

$A_{m,n}$ is the value of mth variable (dimension) of nth ant, n=number of ants (population size).

After that, evaluate the fitness function of the ants, by using the following equation,

$$F_i = \min(F(X)) \tag{19}$$

Fitness of all ants will be stored in the matrix M_{OA} in terms of objective function f.

$$M_{OA} = \begin{pmatrix} f\left(\left|A_{1,1}, A_{1,2}, \dots\dots, A_{1,d}\right|\right) \\ f\left(\left|A_{2,1}, A_{2,2}, \dots\dots, A_{21,d}\right|\right) \\ . \\ . \\ . \\ f\left(\left|A_{n,1}, A_{n,2}, \dots\dots, A_{n,d}\right|\right) \end{pmatrix} \tag{20}$$

After that, assigned the position and fitness of ant lion are represented by the matrices $M_{Antlion}$, M_{OAL} respectively.

$$M_{antlion} = \begin{pmatrix} AL_{1,1} & AL_{1,2} & \dots & AL_{1,n} \\ AL_{2,1} & AL_{2,2} & \dots. & AL_{2,d} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ AL_{n,1} & AL_{n,2} & \dots & AL_{n,d} \end{pmatrix} \tag{21}$$

$$M_{OAL} = \begin{pmatrix} f\left(\left|AL_{1,1}, AL_{1,2}, \dots.., AL_{1,d}\right|\right) \\ f\left(\left|AL_{2,1}, AL_{2,2}, \dots.., AL_{2,d}\right|\right) \\ . \\ . \\ f\left(\left|AL_{n,1}, AL_{n,2}, \dots.., AL_{n1,d}\right|\right) \end{pmatrix} \tag{22}$$

By utilizing the fitness function, the Antlions fitness is evaluated. After that, the random movement of ants is randomly moved to search food. Random movement of ants is given by Equation.

$$X(t) = [0, cumsum(2r(t_1)-1), cumsum(2r(t_2)-1), \dots\dots., cumsum(2r(t_n)-1)] \tag{23}$$

Where, cumsum represents cumulative sum, n=maximum number of ants, t= step of random walk (iteration) and

$$r(t) = \begin{cases} 1 & if\ \ rand > 0.5 \\ 0 & if\ \ rand \le 0.5 \end{cases} \tag{24}$$

From the above equation, the rand is a random number produced with uniform distribution in [0, 1]. To restrict the random movement within the search space, normalized form is used, which is based on min–max normalization. Position of ants can be updated by Equation

$$X_m^t = \frac{\left(X_m^t - a_m\right)\left(d_m - c_m^t\right)}{\left(d_m^t - a_m\right)} + c_t \tag{25}$$

Where, a_m, b_m are minimum and maximum of random walk of ants c_m^t, d_m^t represents minimum and maximum mth variable at t th iteration.

Trapping of ants

In the process, the mathematical expression of the trapping of the ants to the ant lion's pits is given by Equations.

$$c_m^t = Ant - lion_n^t + c^t \tag{26}$$

$$d_m^t = Ant - lion_n^t + d^t \tag{27}$$

Construction of trap

Here, the fittest ant-lion is selected using the roulette wheel method. Ants sliding towards ant lion Sliding of ants into pits is given by Equations.

$$c^t = \frac{c^t}{I} \tag{28}$$

$$d^t = \frac{d^t}{I} \tag{29}$$

Where, $I = 10^{w\left(\frac{t}{s}\right)}$, t is the current iteration and S is the maximum number of iteration and w is the constant whose values.

$$w = \begin{cases} 2 & if\ t > 0.1S \\ 3 & if\ t > 0.5S \\ 4 & if\ t > 0.75S \\ 5 & if\ t > 0.9S \\ 6 & if\ t > 0.95S \end{cases} \tag{30}$$

Catching the pray and reconstruction process of pit

Ant lion catches the ant when it reaches the pit bottom and consumes. After this, ant has to update the position in order to catch new prey. This process is represented by Equations

$$Antlion_n^t = Ant_m^t \qquad\qquad if \;\; f\left(Ant_m^t\right) > f\left(Antlion_j^t\right)$$

Elitism

Elitism is used to keep the best solutions in every stage. Best ant lion obtained is treated as elite, which is the fittest ant lion [31]. Elite should affect the ant lion in every stage (random movement). For this every ant is assumed to associate with an ant lion by Roulette wheel and elite which is given by Equation.

$$Ant^t = \frac{R_A^t + R_B^t}{2} \tag{31}$$

Where, R_A and R_B represents the random walk around the selected ant lion and elite at t th iteration simultaneously. From the above process is completed, the optimal results are obtained by using the objective function. The above process is repeated until the maximum iteration is reached. The flowchart for the proposed algorithm is shown in Fig.4. The pseudo code of the ALO algorithm is described as below.

Pseudo code of ALO algorithm

Initialize the first population of ants and antlions randomly

Calculate the fitness of ants and antlions

Find the best antlions and assume it as the elite (determined optimum)

While the end criterion is not satisfied

    For every ant

        Select an antlion using Roulette wheel

        Update c and d using equations

        Create a random walk and normalize it using equations and

        Update the position of ant using equations

    End for

Calculate the fitness of all ants

Replace an antlion with its corresponding and it if becomes fitter

Update elite if an antlion becomes fitter than the elite

End while

Return elite

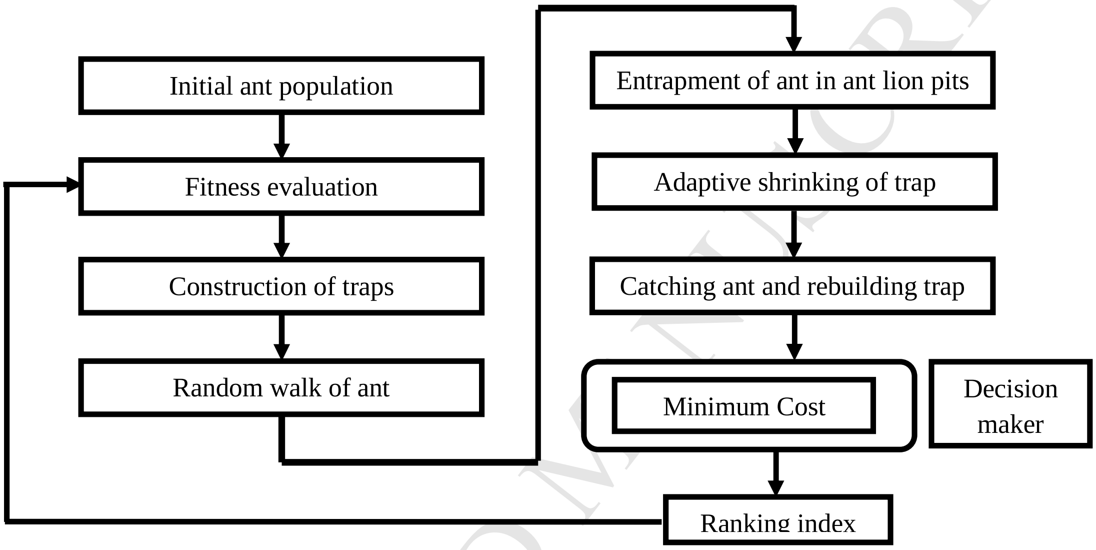


Fig 4. Flowchart of ALO algorithm

4. Results and Discussion

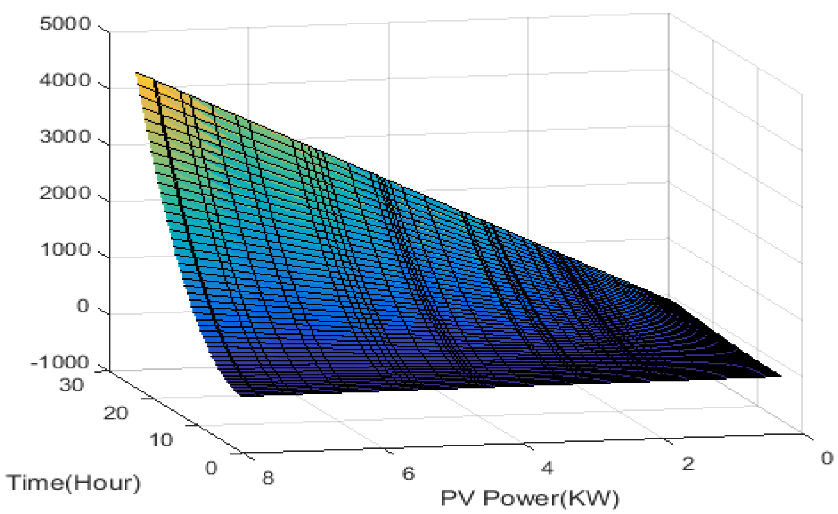
In this paper, RNN and ALO algorithm is utilized to minimize the total generation cost and to maximize the utilization power of PV and WT. The proposed technique is utilized for an optimal operation of micro grid, who's considered as the renewable energy sources and the energy storage system. From the utilization of RNN, the demand response of the micro-grid is obtained, which are the two non-dispatchable resources (PV and WT), a dispatchable resource (MT), and ES integrated with some responsive (EWH and DR). Initially, the WT, PV, MT and Battery powers are determined using RNN while achieving the DR. The rating of the MG is determined from the paper [28]. Subsequently, the generation cost of the micro grid is minimized while utilizing the ALO algorithm.The proposed technique is implemented in MATAB/Simulink R2015a platform. The performance of the proposed method is evaluated and compared with the existing technique such as, GA, ABC and BFA respectively, which is helpful for identifying the effectiveness of the proposed method. The implementation parameters of the proposed and existing methods are tabulated in table 1.

Table 1. Implementation parameters

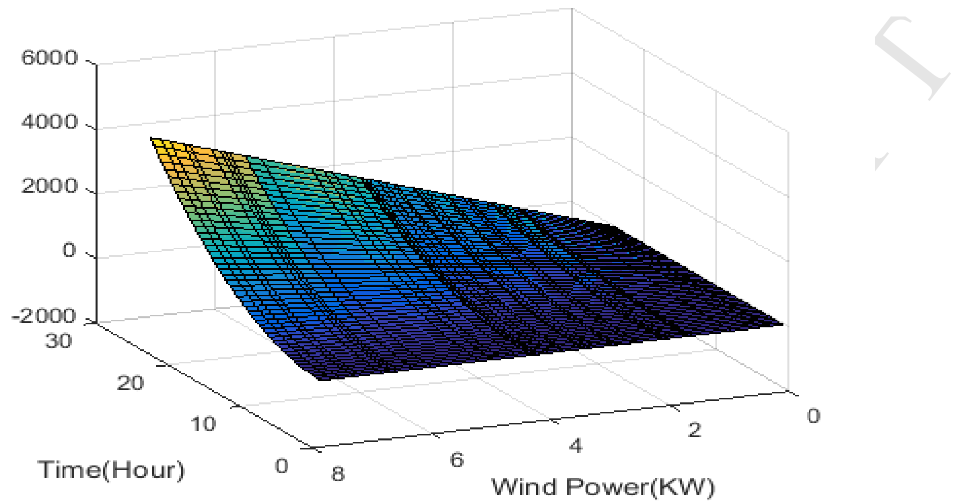
S.No	Description	Algorithm	Values
1	Maximum iteration	ALO	100
2	Population size (n)		10
3	Ratio (I)		1
4	Number of Bacteria (s)	BFA	4
5	Number of chemotactic (Nc)		4
6	Length of a swim (Ns)		4
7	Length of a swim (Nre)		2
8	Probability		0.25
9	Crossover rate	GA	0.01
10	Mutation rate		0.03
11	Maximum iteration		100

12	Bee Length	ABC	4
13	Population Size		2

Utilizing the proposed method, the total costs are analyzed in the various load demand. The proposed method based DR is optimizing the accessible sources in the 24 hours, as it is observed in the following figure. Initially, the 24 hours data for Wind/PV is depicted in the Fig.5 and given to the input of the RNN. RNN is used to analyze the data in the training process and testing period the corresponding data is evaluated. From their performances, the error value is computed, which is used to prove the effectiveness of the RNN and obtained the optimal results. The testing/ training process of the data and the error prediction is illustrated in the Fig. 6 (a), (b) and (c). It is also seen in the figure that the inputs related to proposed method are energy price, the contract related to DR and the specifications related to DER sources considered in the system. Here, various inputs are considered including the information related to forecast data for both non-dispatchable energy sources, battery, MT and loads, the specification of equipment are analyzed and their maximum capacity of the powers are determined in the 24hours time periods.

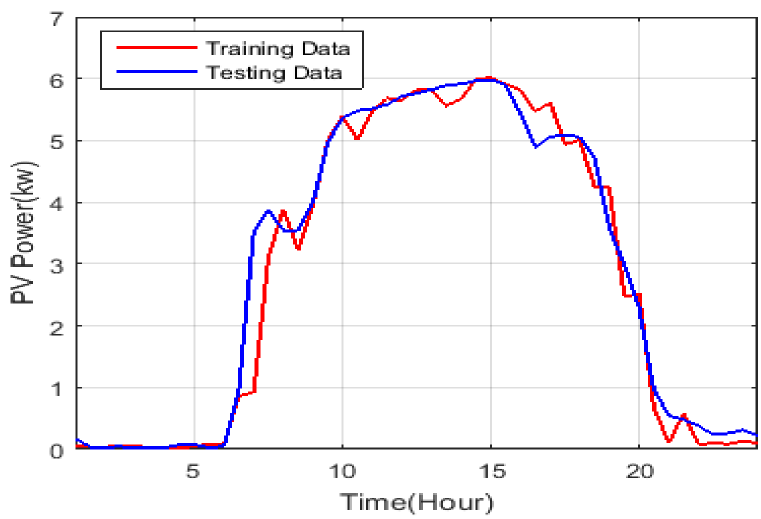


(a)

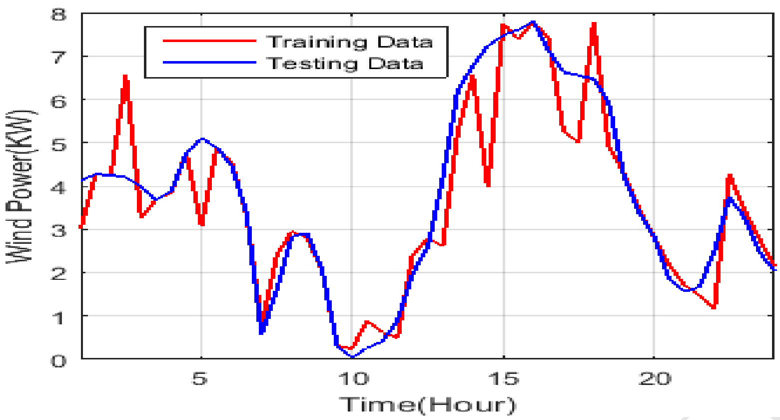


(b)

Figure 5: RNN testing performances in (a) PV and (b) WT power-3D representation



(a)



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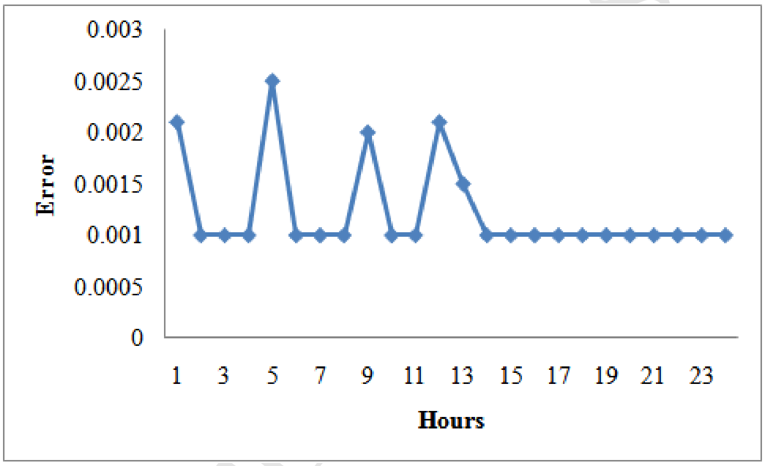
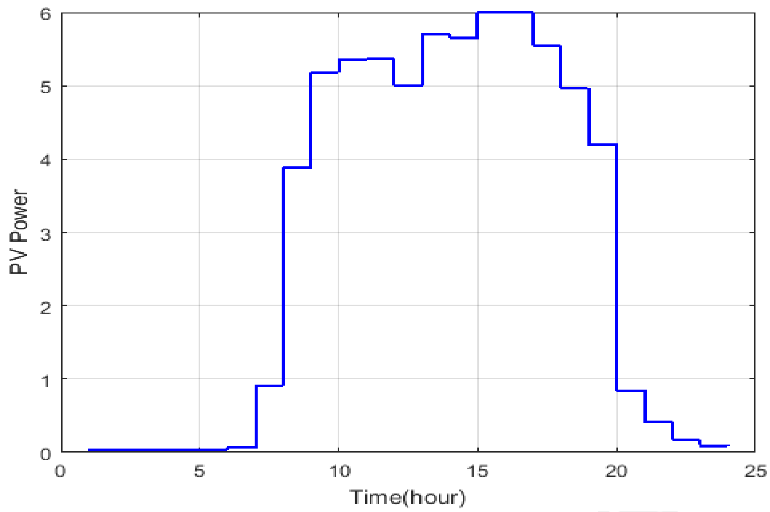
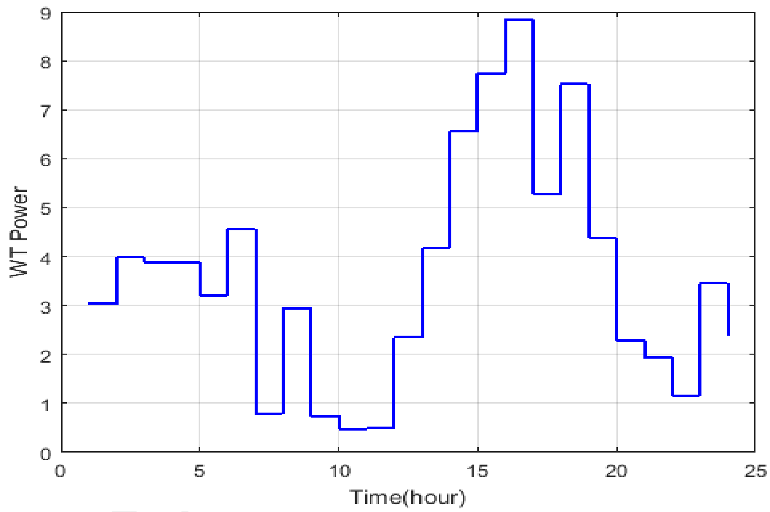


(c)

Figure 6: Analysis of RNN Training and Testing in (a) PV (b) Wind and Error



(a)



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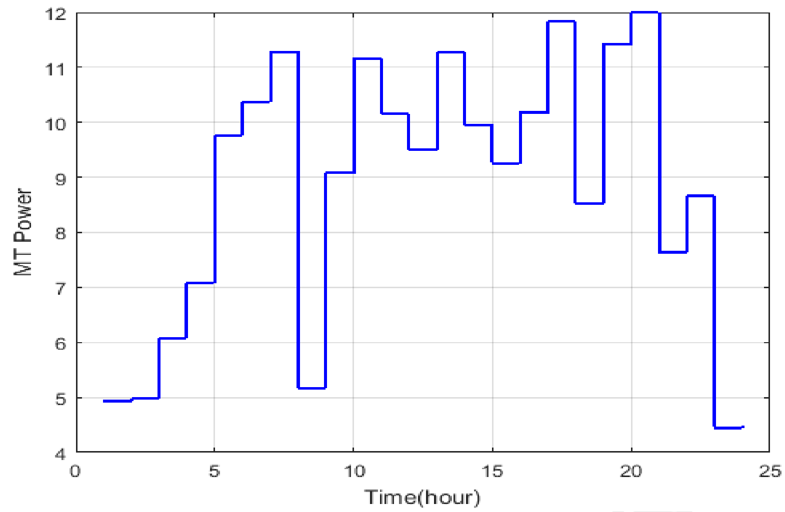

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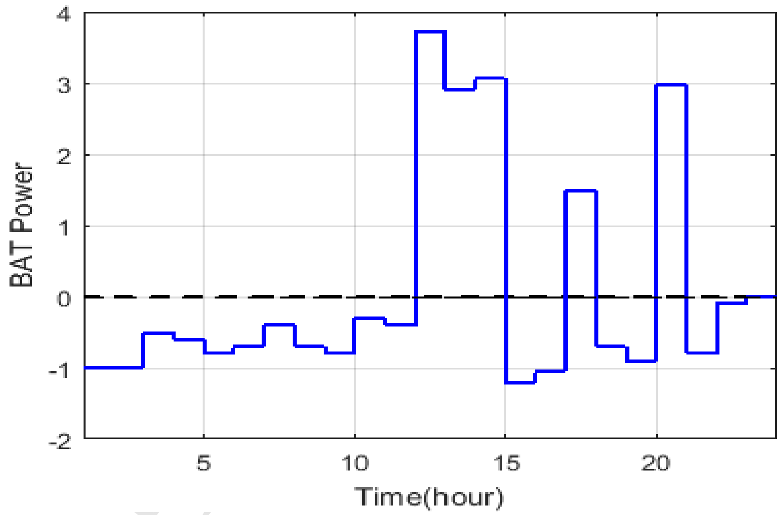


(d)

Figure 7: Analysis of (a) PV (b) WT (c) MT and (d) BatteryPower using proposed method

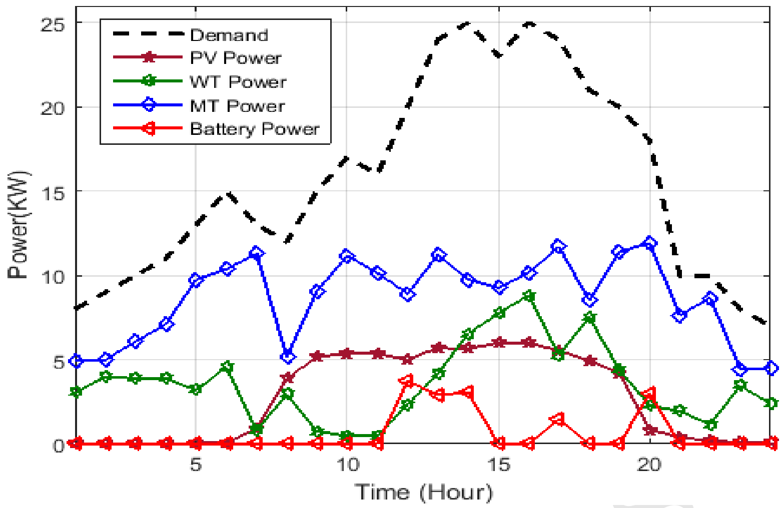
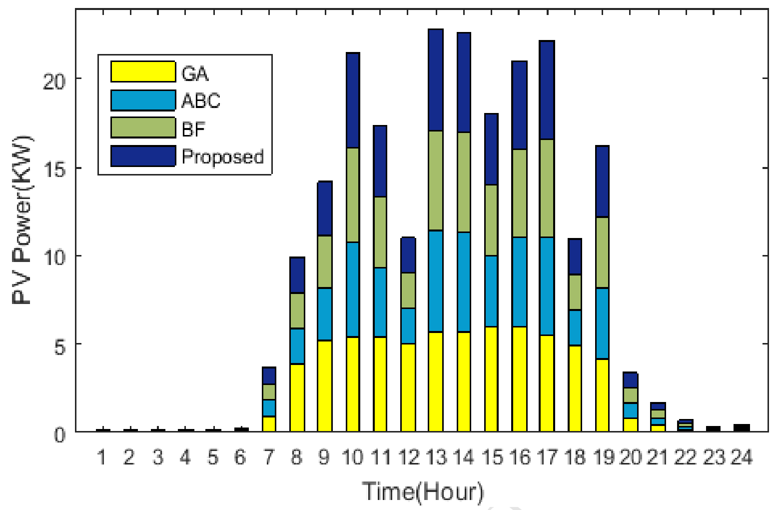


Figure 8: Analysis of Demand Vs PV, WT, MT and Battery power using proposed method

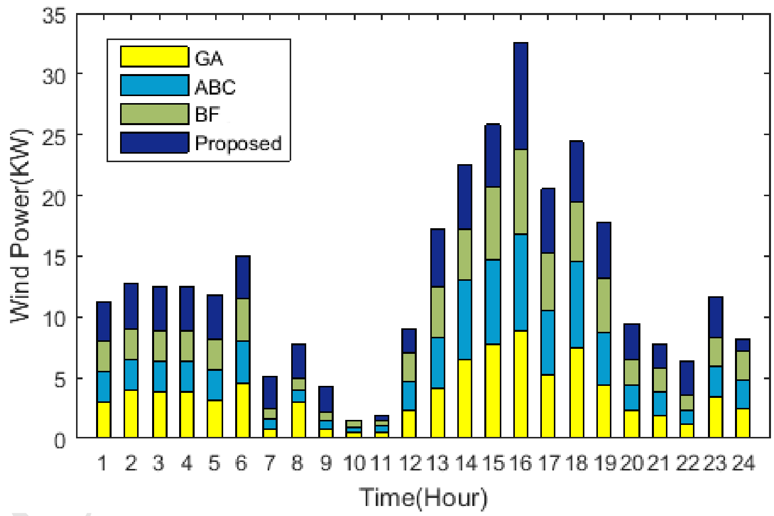
During the 24 hour periods, the WT, PV, MT and ES power values are determined using the proposed technique. As it is observed in Figures 7 and 8, the maximum utilization of MT, WT, PV and battery is analyzed based on their demand values. While using the battery, it is charged in the time period 1-12 hours. At the time instant, SOC is determined and at the end of this operation. In the discharging mode, the battery power is utilized in the time instant t=12 to 22 hours. However, the power needed for charging the ES is provided by MT. Similarly, the remaining time period, the ES is evaluated for supplying a part of power shortage, while using the proposed technique is operated in the charging mode and continuing to reach SOC. During 24 hours, the SOC power performances are determined using the proposed method. The required power for charging the energy storage device is offered from the MT. More SOC causes the expansion of the capacity for providing the loads amid whatever is left of the framework day by day task. In the specific time period, the EMS is as of now utilized battery for providing a piece of power lack, while in existing technique. The battery is worked in the charging mode and proceeding to achieve SOC. It is still cinched until the finish of this interim. In spite of proposed technique, to repay the lack of the power, the battery has been perceived and whatever is left of the power will be accustomed to charging the energy storage device. Once, the power is saved and the total generation cost is limited. The base and most extreme limit of the SOC is 80-20% and the underlying limit is half. To meet the most extreme level of the SOC is accomplished with the assistance of the proposed technique. In view of the above investigation, the SOC is kept up and the cost capacities likewise decided. From the analysis, the proposed method is reached maximum power to meet the demand power. Likewise, the existing methods GA and ABC are utilized to get the optimal outputs and compared with the proposed method.

4.1. Comparison Analysis

Here, the PV, WT, MT and battery power profiles for each of the four presented algorithmsare shown inFig. 9(a), (b), (c) and (b). From the above figure 7, the generated power of micro grid is analyzed in 24 hours. During the peak hours (t=10 to 17 hours), the maximum PV power is generated and utilized, which is shown in figure 9(a). While using WT, the maximum power is generated based on the wind speed. By utilizing the proposed method, the time instant (t=16-20 hours) maximum power is generated. In the figure 9(a), the generated power of PV is analyzed using the proposed method. In the time instant (t=1 to 7 hours), the PV is attained the maximum power 3.2042kW and in the peak hours (t=8 to 18 hours) it is increased about 8.83kW. It is increased up to 5.6258kW, again it is reduced about 2.3849kW. While analyzing the wind power, in the time instant (t=1 to 7 hours), the generated power is decreased from 3.0362 to 0.7987kW and the power is increased. Again, the power is reduced up to 4.5596kW in the particular time instant (t=18 to 24 hours). Similarly, the other dispatchable and non-dispatchable resources are analyzed.



(a)



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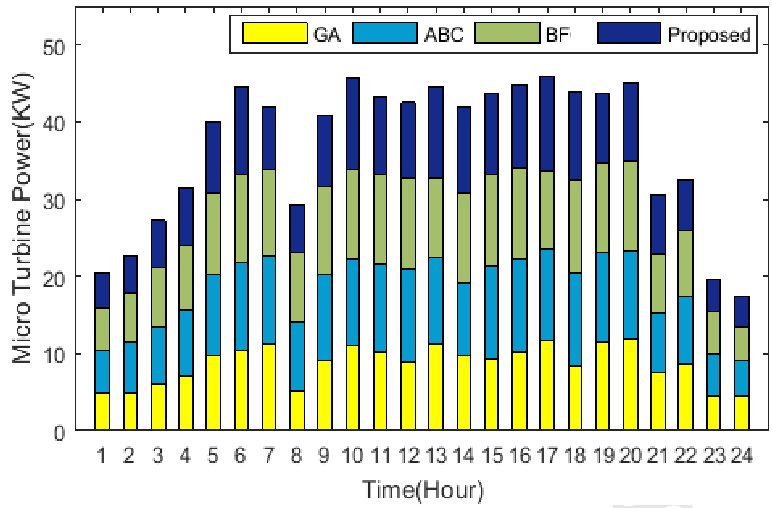

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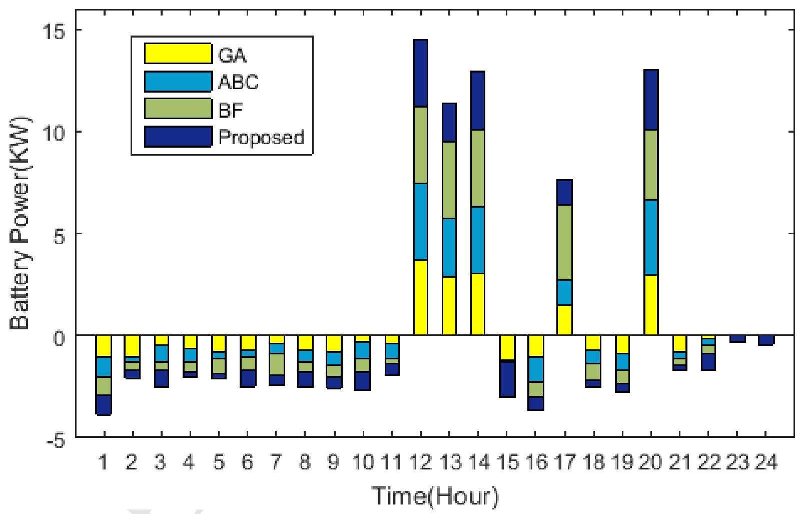
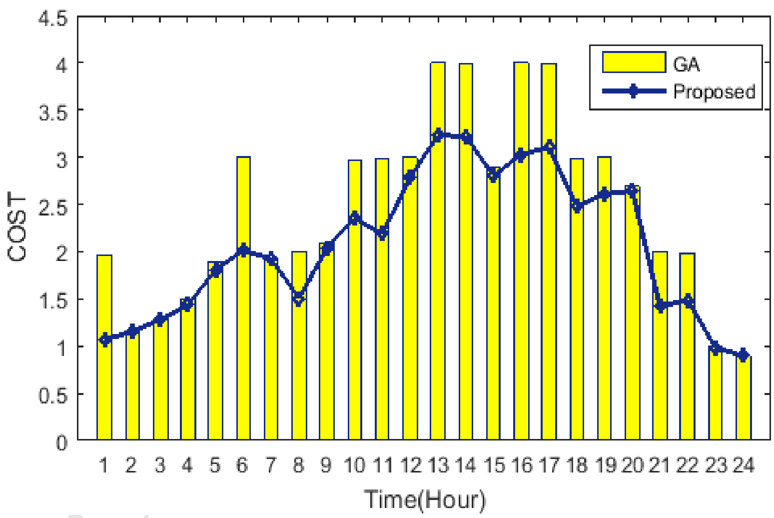


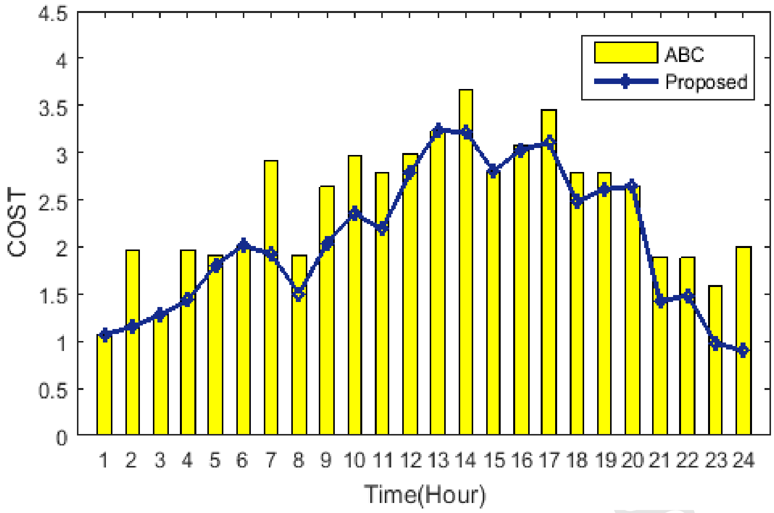
(d)

Figure 9: Comparison Analysis of (a) PV (b) WT (c) MT and (d) Battery Power

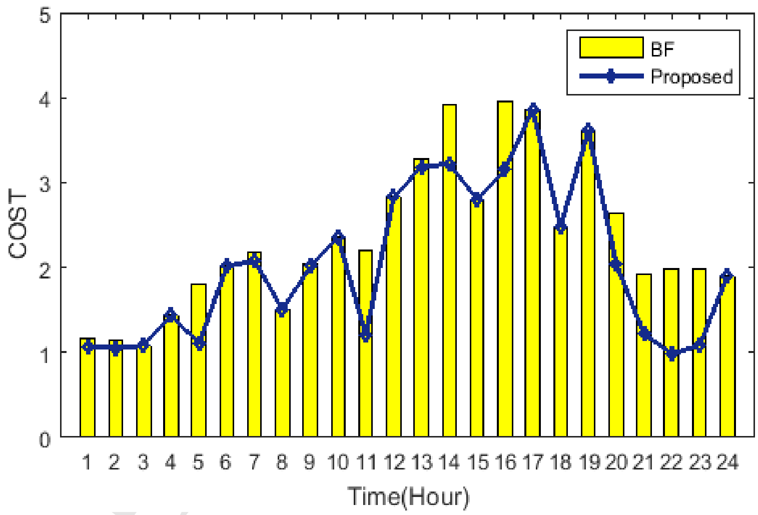
While analyzing the battery power, the battery is working in the charging mode at the time instant (t=1 to 12 hours). After that, the time instant (t=13 to 16 hours) the maximum power (3.7289kW) is evaluated from the battery, which is in discharging mode of operation. Under these conditions, a part of the required power is supplied by ES and MT systems. As it is observed in the figure, some of the power required by the load cannot be supplied. In this scenario the production of WT system reduces by PV and WT systems is at normal operation state, and the excess power is used for feeding ES, DR and/or EWH system. Similarly, the other existing methods are utilized to analyze the generated power of micro grid. Moreover, the maximum generated powers and utilized powers are analyzed in the proposed method and contrasted with the existing techniques. After that, the total generation cost is analyzed and compared with the existing methods such as, GA, ABC and BFA methods. The comparison analysis of generated power and cost of micro-grid is analyzed and depicted in the following figures 10-13.



(a)



(b)



(c)

Figure 10: Cost analysis of proposed method with (a) GA (b) ABC and (c) BFA

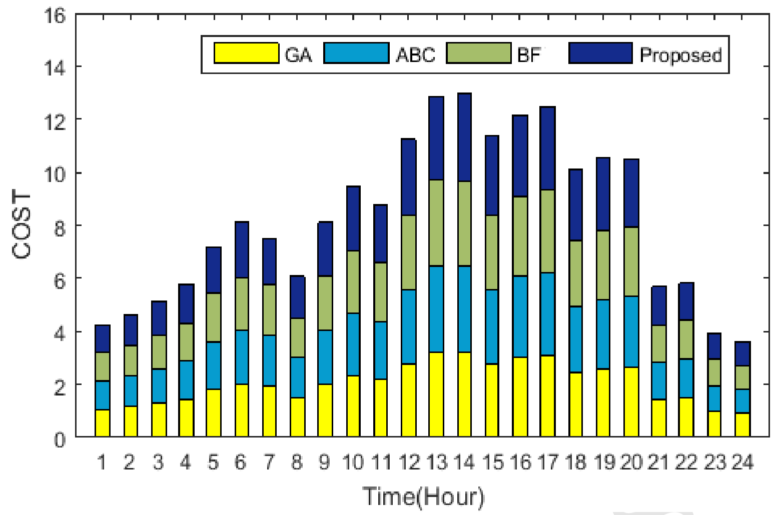


Figure 11: Comparison Analysis of Cost function

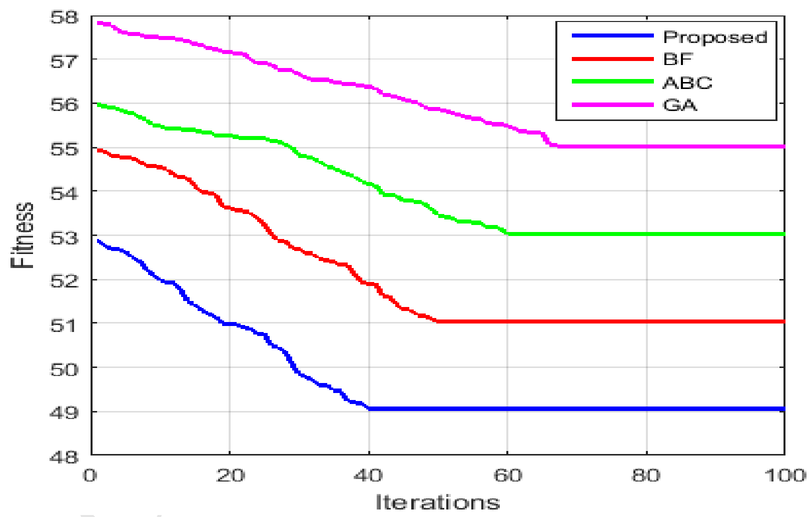


Figure 12: Convergence Analysis graph

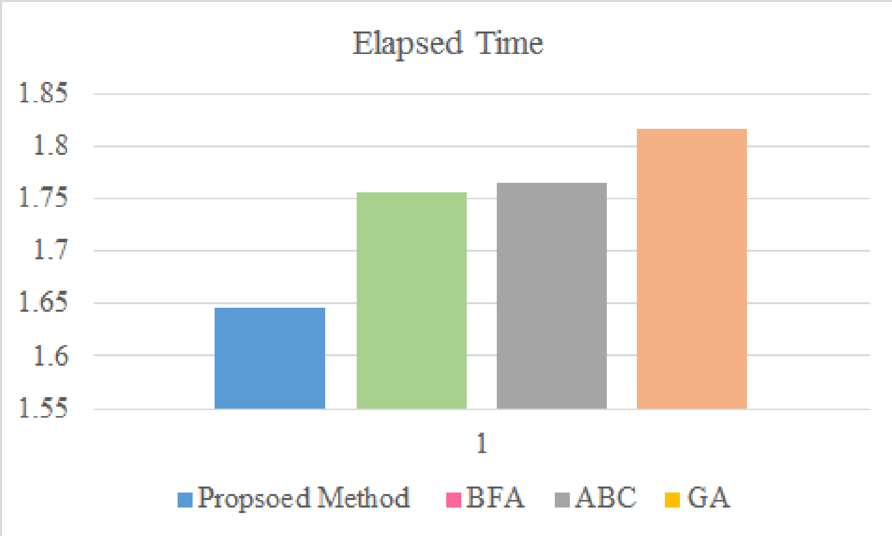


Figure 13: Comparison Analysis of Elapsed Time

During the 24 hours, the ES is observed in their corresponding power utilization, cost of the MG. With the peak hours, the maximum power utilization of MG is above 75% for 85% of the time, which stores more energy when compared to other optimization algorithms. In figure 8 the bar graphs related to the cost according to their PV, WT, MT and battery during charging and discharging are shown. As it is observed in Fig. 9(d), in most of the time, ES is operated in charging mode. This charging period is mainly concentrated in the time range of 1to 11 hours. During the rest of the period, ES is usually discharging. Finally, the average cost obtained by the proposed method is the lowest compared with GA, ABC and BFA methods. In other words, optimization techniques provide lower costs comparing to conventional EMS.

Table 2: Comparison analysis for cost and computation time using various methods

Methods	Proposed method	Existing methods					
		BFA	ABC	GA [38]	MABC [39]	PSO [40]	FA [38]
Cost ($)	49.2869	58.3447	60.8912	60.3275	61.8912	59.5296	63.4523

Execution time (Sec)	1.69	1.75	1.76	1.8	10.14	27.45	7.785
No iteration	40	50	60	67	72	85	87

From the above table, the execution time and cost functions of the proposed and existing method is determined. Here, the proposed method is achieved the less generation cost 49.2869 ($) compared with the remaining methods. In order to compare the performance of the proposed algorithm with that of the other algorithms, Fig.11 presents the execution time of the developed code and total generation cost of implementing all proposed method, GA, ABC and BFA algorithms. As seen in this figure, run time of all proposed algorithms are less than 2 min, but the proposed method has the minimum execution time. In addition, as shown in this figures, the value of the objective functions in proposed method is very close to reference values. Then the convergence analysis of the proposed method is determined and compared with the existing methods. It shows that, the proposed method achieves less cost of the MG when compared to the other methods.

5. Conclusion

In this paper, RNN and ALO algorithm is utilized for optimal operation of MG. The objective of the proposed method is minimized the production cost as well as better utilization of renewable energy resources. The micro gird connected system is based on the PV system, WT and storage system. For achieving the objective function, DR is evaluated utilizing the RNN which gives the information of customer response and duration. The DR constraints are expressed with the information of other consumers and the excess power generated has been modelled to obtain the minimum total generation cost and less market clearing price. The optimal programming for generation scheduling combined with DR has been performed to minimize the operation cost of MG linked to customer information. Since renewable resources such as WT and PV have intermittent characteristic, approaches to analyze economic dispatch in MGs would be stochastic rather than deterministic. After that, the ALO algorithm is utilized to solve the economic dispatch issues to evaluate the generation, storage and responsive load offers. The proposed method is implemented in MATLAB/Simulink working platform and their performance is tested. The performance of the proposed method is compared with the exiting methods such as, GA, ABC and BFA respectively. The obtained results show that the highly better reduction of the total generation cost with adequate and real time control of DR. The proposed method has less computation time when compared with other techniques. This paper the renewable energy storage devices are analyzed for the 24 hours. If the data of the renewable energy sources are increased or varied (i.e., one year or more than two year), the cost functions and demand response are also changed. For this case, the proposed method takes to solve the issues with the higher computation time and the training process of the RNN is also creates the complexity. This technique provides better outputs but not the accurate results because this technique is needed to the enhancement. To get the optimal operations, another enhancement is needed and determined the corresponding cost functions. The power scope of the hybrid sustainable power source units isn't the mind boggling one however minor changes would be important that is, exclusively the trademark parameters of the ESS devices ought to be refreshed by the equipment utilized in the HRES.

APPENDIX-A

Parameters	**Descriptions**	**Values**
Voltage	Energy storage System	24 V

Nominal Ah capacity at +25c		84
Fully charged voltage		26 V
Cut off discharge voltage		21 V
Max. continuous charge current		34 A
Max. continuous discharge current		160 A
Max. battery power (charging mode)		0.816 kW
Max. battery power (discharging mode)		3.84 kW
Initial SOC		50 T (%)
Max.SOC		80 %
Min. SOC		20 %
Initial stored energy in battery		1 kWh
Max. stored energy		1.6 kWh
Min. stored energy		0.403 kWh
Total capacity of ES		2 kWh
Charge efficiency factor		96 %
Max.instantaneous power	PV	6 kW
Min.instantaneous power		0
Max.instaneouss power	WECS	8 kW
Min instaneous power		0.45
Max. instantaneous power	MT system	12 kW

Min instantaneous power		3.6
Max. power	EWH system	5 kW
Min.power		0

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Highlights

- RNN with ALO algorithm is proposed for analyzing the EMS in MG
- PV, WT, MT, FC and Battery are considered as the MG
- Demand response (DR) is evaluated using RNN method
- The objective function is to minimize the cost functions and maximum profits.
- Tested with the exiting methods such as, GA, ABC and BFA