Efficient energy management system using Internet of things with FORDF technique for distribution system

Usha Rani Vinjamuri1,2 | Dr. B. Loveswara Rao3

1 Department of EEE, Gokaraju Rangaraju Institute of Engg. & Tech, Kukatpally, Hyderabad, Telangana 500090, India
2 Research Scholar, Koneru Lakshmaiah Education Foundation/ Asst. Professor, Department of EEE, Gokaraju Rangaraju Institute of Engg. & Tech, Bachupally, Hyderabad, Telangana, India
3 Department of EEE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh 522502, India

Correspondence
Usha Rani Vinjamuri, Research Scholar, Koneru Lakshmaiah Education Foundation/ Asst. Professor, Department of EEE, Gokaraju Rangaraju Institute of Engg. & Tech, Bachupally, Hyderabad, Telangana, India.
Email: ushakiran295@gmail.com

Abstract
Energy management system for the distribution system using Internet of things with hybrid technique. The proposed hybrid technique is the joined execution of both the fruitfly optimisation algorithm and random decision forest and named as FORDF strategy. The main objective of the proposed system is to optimally manage the power and resources of distribution system by persistently screen the data from the Internet of things-based communication system. In the proposed system, each home device is interfaced with data acquisition module with IP address bringing about a huge work wireless network of devices. So as to encourage the improvement of demand response for distribution system to deal with the energy, the Internet of things-based communication system is utilised. So as to ideally deal with the energy, the optimal load demand prediction and the energy control PROCESSES are handled by the FORDF system. Besides, the optimum utilisation of the accessible resources and the flexibility of such networks are given and expanded by the Internet of things based distribution system. Furthermore the proposed technique is qualified to satisfy the general SUPPLY and energy demand. At long last, the proposed model is implemented in MATLAB/simulink platform and the exhibition is contrasted and different systems

1 | INTRODUCTION

The world-wide increasing demand for power, combined with the need for security of energy supply has led to an ongoing effort to shift from the traditional power generation grid to a flexible smart and multi-source power network that includes Renewable Energy Sources (RES) [1]. As both demand and supply dynamically varies through time, a highly complex environment has emerged that can be approached as a networked system of interconnecting processes with numerous variables where real time data collected from devices, systems and processes need to be handled and frequently evaluated [2]. Therefore, the design and operation of a multi-source energy network involves numerous decisions across several levels [3–5]. A special category of power networks with unique challenges and needs is the autonomous off-grid networks where RES (mainly, photovoltaic panels (PV) or wind generators) are the main source of power. The intermittent nature of RES can be securely managed with the utilisation of intermediate storage systems, such as, accumulators (battery stacks) [6–8].

Alternatively, hydrogen production, storage and usage through fuel cells can serve the need for continuous availability of power. These types of networks can be applied to off grid locations where the transportation of fuel is difficult, involving small communities where autonomy is important [9].

Using energy efficiently in distribution system saves money, enhances sustainability and reduces carbon footprint at large. The energy management scheme of fuzzy logic-based controller [10,11], hierarchical control scheme [12], sliding mode control and neuro-fuzzy control [13,14] have been executed to overcome the above confinement. In any case, the above techniques may not occur in a better force and less determined state after the miscalculation [15]. Consequently, the need for smart energy management is on the rise for distribution system and for smart cities (SCs) in general. However, the lack of low cost, easy to deploy and low maintenance technology has somewhat limited a large-scale deployment of such systems. The sheer quantity of data collected throughout different cities of a country presents multiple challenges in data storage, organisation and analysis [16]. The interrelation of several technologies,
systems with diverse design constraints, operation requirements and communication solutions that exists is grid networks, can be realised by a novel synergetic paradigm which is the enabling concept of the Internet of things (IoT) [15-18]. The IoT is a convergence of three main visions, the network, things and semantics that are oriented to middleware, systems (from sensors to systems) and knowledge.

IoT technology is natural candidates to address these challenges. IoT technologies can provide a ubiquitous computing platform to sense, monitor and control the household appliances energy consumption on a large scale [19]. This data is collected using many different wireless sensors installed in residential units [10,12,20,21]. The variety of energy management systems (EMSs), integrated energy systems and customer equipment can generate many different data formats, resulting in a lack of interconnectivity and interoperability in industrial EMSs. The main goal in the integration of EMSs is to allow the communicating entities to interact with each other using a common information model. This results in the need to be able to understand and map the meaning and context of information that resides in different domains [13,14]. In view of this requirement, a common information model is needed to support the ability to semantically align the information for inter-domain communication for the EMSs in distribution system [22].

This paper presented the hybrid FORDF technique for optimal energy management in the IoT based distribution system. The RDF technique is used to load demand prediction and the fruitfly optimisation algorithm (FOA) is used for optimal energy management [23]. The remainder of this paper is organised as follows: In Section 2, we provide a review of the recent research works of the optimal energy management in distribution system. In Section 3, the EMS using IOT at the distribution system is presented. Section 4 describes the problem formulation of the proposed work. Section 5 presents the structure of the proposed work. Section 6 includes the simulation results of the user to optimally operate the proposed distribution system. Finally, Section 7 draws the conclusions.

### 2 RECENT RESEARCH WORK: A BRIEF REVIEW

Because of the high electricity consumption in smart home applications, it is imperative to establish a distribution system-centric energy management, as well as, to make sure that this system is utilised in a proper way. In the past decade, efforts in academia have shifted towards increasing energy efficiency in manufacturing. Some of them are reviewed here.

Faheem et al. [24] have illustrated an innovative ways to handle the power quality and reliability issues for both service provider and consumers. The key aims of the smart grid (SG) in SGs were to preserve a certain level of residents’ life quality and support the entire spectrum of their economic activities. A novel energy efficient and reliable data gathering routing protocol for wireless sensor networks-based SG applications was presented. Liu et al. [25] have focused on designing an IoT-based EMS based on edge computing infrastructure with deep reinforcement learning. First, an overview of IoT-based energy management in SCs was described. Then the framework and software model of an IoT-based system with edge computing are proposed. After that, an efficient energy scheduling scheme with deep reinforcement learning for the proposed framework was presented Yassine et al. [26] have elucidated a new platform that enables innovative analytics on IoT captured data from smart homes. The use of fog nodes and cloud system to allow data-driven services and address the challenges of complexities and resource demands for online and offline data processing, storage and classification analysis was also addressed.

Li et al. [27] have proclaimed an energy detection system called smart energy theft system based on machine learning and statistical models. Three stages of decision-making modules were the first stage was the prediction model which uses multi-model forecasting system. The system integrates various machine learning models into a single forecast system for predicting the power consumption. The second stage was the primary decision making model uses simple moving average for filtering abnormally. The third stage was the secondary decision making model makes the final stage of the decision on energy theft. The usage behaviour of consumers from their historical data and predicts the demand for energy every hour for the individual consumer for the next 72 h using time series analysis was noticed by Jackson Tom et al. [28]. Also, the work statistically studies the usage pattern of appliances in every home thereby finding which appliances play a significant role during the peak hour usage. This work will help utilities understand how their consumers use electricity and can encourage consumers to shift usage of peak hour appliances to non-peak hours. Also, consumers can grant control of individual appliances to utilities, to curtail the load during peak hours to reduce the demand.

#### 2.1 The motivation for the research work

The literature review indicates that various communication protocols have been utilised in EMS for distribution system. However, for a seamless integration of all residential devices, an open-source light weight communication protocol is required. This will foster interoperability leading to scalable systems. Installation of home EMS can help home owners to understand contribution of each device towards the overall electricity bill they receive. In addition, most previous work has primarily focused on individual distribution system and lacks the energy management provisions for regional utility providers or national level utility centres. The technology to collect huge volumes of data from home sensor networks is available, however, managing the collected data efficiently and extracting deeper insights from it remains a challenge. The existing paradigms on EMS and cost saving models are implemented on discrete units. Although numerous analytical algorithms are available, which can process huge volume of data, but many of these are not capable to complete task sufficiently. A few research procedures have been accounted for on investigating streaming data, but still needs a lot of work to be done in making these commercially reasonable.
3 | ENERGY MANAGEMENT STRATEGY USING INTERNET OF THINGS AT THE DISTRIBUTION SYSTEM

For the present movement in the distribution system, every one of the measures which are incorporated into energy management those are arranged and executed to guarantee minimum energy consumption. So as to decrease the total operational energy consumption, to utilise essential and extra materials financially and to ceaselessly improve the vitality effectiveness in the organisation, the authoritative and specialised techniques were impacted by energy management. For interests in improving energy efficiency, the energy flux and serves are deliberately recorded by an EMS. For making energy policy, and characterising and accomplishing strategic objectives, every one of the elements of an organisation is essential which are envelops by the EMS. For actualising energy management with resources, the organisational and informational structures are incorporated into EMS. It figures and actualises the energy policy, with the planning, presentation, operation, monitoring and measurement, control and correction and internal audits, just as a normal management survey.

3.1 | The need of Internet of things for the renewable energy sources

IoT is without further ado alluded as IoT which is the innovation created by the gathering of internet, micro-electromechanical systems, wireless technologies and micro services [3–6]. IoT is just a blend of one of kind identifiers, objects, machine tools, computer devices and digital machines. These days, part of issues identified with present-day science and engineering systems would be looked at by this IoT technology.

Considering the renewable resources, for example, the PV system, wind turbine (WT) power system for power generation, these include various types of equipment with different sorts of operational practices. In any case, the persistent and steady power generation is beyond the realm of imagination by the PV and WT system because of the time-varying solar intensity and bad weather conditions [18]. This condition in a roundabout way influences the functioning of other system components like power converter voltage levels, battery state of charge, energy demands by loads and so forth. Now and then these issues cause disappointment in framework till it is persistent. Checking and controlling these kinds of failures are troublesome by the human, so they have to visit the plant site much of the time and keep up the record of operational data. It is very dreary employment when the plant is situated in faraway spots. So part of times are taken by the human to anticipate these sorts of disappointment, regardless of whether once in a while the disappointment forecast and tending to is inconceivable by human because of the terrible showing of the system. Thus, a ceaseless monitoring system is furnished alongside renewable sources. This monitoring system stores the data about the system and its parameters in the cloud platform. The performance of the system and the purpose behind terrible showing are analysed by this stored data. At the point when the performance is poor because of certain faults, this permits making investigating and maintenance operation. Along these lines, the performance monitoring and optimising the system parameters with a remote-control option required the IoT technology.

3.2 | Proposed system model for Internet of things based energy management system

For monitoring, controlling and sparing energy, a significant number of the associations to locate shrewd approaches to controls the expanding cost and demand for energy. The brilliant EMS can lessen the cost of the resources while still satisfy the necessary energy demand. In the huge private, business and modern segments, better energy management consumption is performed through the rising advancements of IoT and huge information.

This paper displays an EMS for distribution system using IoT framework with hybrid technique for smart homes. In this introduced system, a data acquisition module that is interfaced with each home device that is an IoT object with a unique IP address bringing about an enormous mesh wireless network of devices. For further handling and investigation, the energy consumption data gathered by the data acquisition module from every device of each smart home transmitted to the centralised server. This information from every single local location gathers into big data on the utility server. So as to deal with the energy consumption in a superior manner, the proposed EMS displayed the hybrid FORDF technique to minimise the power cost by maximising the profit. The architecture of the proposed system for IoT based EMS is illustrated in Figure 1. This section describes the architecture of the proposed system in detail. As shown in Figure 1, there are multiple home appliances in a residential area which receive the utility tariff. We propose an EMS to schedule...
the smart appliances of a home in order to minimise the electricity cost and user comfort maximisation (i.e. profit). A smart home is equipped with smart appliances, proposed controller, Cloud IoT, sources and storages and data acquisition module. Cloud IoT acts as a bridge between utility and consumer. Appliances send their energy consumption pattern to proposed controller which schedules them according to the price signal sent by the utility. Cloud IoT receives price signals from utility and sends it to proposed controller. Simultaneously, it takes energy consumption data from proposed controller and sends it to utility. Utility and Cloud IoT communicate with each other through wireless networks such as Z-wave, ZigBee or a wired protocol.

Zigbee is a wireless protocol which operates in a mesh network. That is, it uses a device to relay a signal to other devices, strengthening and expanding the network. Zigbee can be built in dimmers, door locks, thermostats and more. Similar to Zigbee, Z-Wave is an open source mesh network protocol. Technically speaking, the main difference between the two is the data throughput—Z-wave is roughly 6 times slower than Zigbee. It does, however, require less energy to cover the same range as Zigbee. Smart Things and Lowes Iris use Z-Wave appliances, Cloud IoT and proposed controller exchange information through home area network. In this research work, we consider smart home, each home equipped with number of appliances. In our scenario a decision can be made in 24 h, 1 week and 1 year. Dividing a day into 24 time intervals would allot 1 h to the device which requires only few minutes to operate and rest of the time would be wasted as the scheduler will not turn ON appliances other than the selected appliances for that specific time interval. Hence, selected time interval would reduce the electricity cost and make system more robust. For scheduling, smart appliances are classified into different classes according to the nature of their power consumption pattern.

3.2.1 Integration of renewable energy sources

Photovoltaic power system model

For the power generation in smart homes, the PV system is interfaced with the roof of the home (Figure 2). The smart home does not meet its electricity needs entirely with the PV source, but only when the utility delivers electricity at the highest cost. The power generated by the PV system is expressed in the following equation,

\[ E_{PV}(t) \quad \forall t \in \{1, 2, \ldots, 24\} \]  

(1)

The energy generated for each timeslot \( t_\alpha - t_\beta \) by the PV sources, so the total energy generated by the PV source for each day is computed using the following equation [29–34],

\[ E_{PV} = \sum_{t=0}^{T} E_{PV}(t) \]  

(2)

When the PV meeting a minimum capacity then only it is integrated expressed in the following equation,

\[ E_{PV} \geq E_{PV}^{min} \]  

(3)

The expected PV is installed on the generation of smart home forecasting device, according to which the planner plans the application. Mostly, the power generated from PV source is mostly affected by some conditions such as solar irradiance \( I_r \), area of the PV \( A_{PV} \), the outdoor temperature at that time \( T_o(t) \) and inverter efficiency \( \eta \). The general output power generated by the PV is expressed as follows [35],

\[ E_{PV} = \eta_{PV} \times A_{PV} \times I_r \left( 1 - 0.005(T_o(t) - 25) \right) \]  

(4)

Wind power system model

In the wind power system model, the power generation is determined according to the wind speed and the bearings. Here, the speed of the wind is varied due to the geographic position, meteorological elements etc. The kinetic energy generated from the wind is captured by the WT and transmitted it into usable energy. The structure of the WT system is shown in Figure 3. The following equations are used to express the WT’s output power subject to the function of the rated wind speed \( \bar{S} \), the
cut-in wind speed \((S_{ci})\) and the cut-out wind speed \((S_{co})\).

\[
P_{WT} = \begin{cases} 
0 & \text{if } S < S_{ci} \text{ or } S > S_{co} \\
S^3 \left( \frac{P_r}{S^3 - S_{ci}^3} \right) - P_r \left( \frac{S_{ci}^3}{S^3 - S_{ci}^3} \right) & S_{ci} \leq S \leq S_r \\
P_r & S_r \leq S \leq S_{co}
\end{cases}
\]

(5)

where the output power generated by the WT is denoted as \(P_{WT}\), the rated wind power is represented as \(P_r\) and the speed of the wind is denoted as \(S\).

**Micro turbine model**

A small high-speed gas turbine is known as the MT which produces electrical power inside the 20–500 kW range. The principle four parts required by the MT are compressor, combustor, turbine and generators. The MT is commonly arranged into two kinds named as single and split-shaft. The turbine and generator are interfaced on a similar shaft are known as the single-shaft MT. The yield frequency of the MT is from around 400 Hz as much as a few kilohertz. The power electronic converters are utilised to change over the frequency into 60 Hz. In this paper, the split-shaft MT is utilised.

**Battery energy storage system model**

In the hybrid energy system, might be the vulnerability of wind speed and the irregular sunlight-based radiation conditions influence the power generation, around there, the lead-acid and lithium-based batteries are utilised as a backup energy storage device which is illustrated in Figure 4. Figure 5 represents battery energy storage system.

Commonly, due to the ease, long life expectancy and strength, notwithstanding the business accessibility of these batteries which is employed in most large-scale energy storage projects. During a lack of interference of sustainable power source, battery storage is measured to accomplish load demand, typically alluded to as autonomous days \(AD\). Subject to the load and \(AD\), the capacity of the battery is designed which formulated by the following equation [36],

\[
C_B = \frac{(D_L \times AD)}{(DOD \times \eta_{bat} \times \eta_{inv})}.
\]

(6)

where the capacity of the battery is denoted as \(C_B\), the load demand is represented as \(D_L\), the depth of discharge is signified as DOD, the battery efficiency and the inverter efficiency are expressed as \(\eta_{bat}\) and \(\eta_{inv}\) respectively. When the hybrid PV/WT system is unfit to supply the required energy, the formulation of the BESS is utilised. In order to improve the techno-economic performance simultaneously, the hybrid PV/WT and battery system are formulated.

### 3.2.2 Energy consumption model

In each hour of a day, the total energy consumption of all the appliances are computed using the following expressed equation,

\[
P_T(t) = W(t) + V(t) + U(t).
\]

(7)

\[
P_T(t) = \sum_{f \in F_{ap}} \left( \sum_{t=1}^{24} \chi_f \times \delta_f(t) \right) + \sum_{s \in S_{ap}} \left( \sum_{t=1}^{24} \chi_s \times \delta_s(t) \right) + \sum_{z \in Z_{ap}} \left( \sum_{t=1}^{24} \chi_z \times \delta_z(t) \right).
\]

(8)

In the above equation, \(W\) is the energy consumed by uninterruptible appliances, \(V\) is the energy consumed by flexible appliances, \(U\) is the energy consumed by fixed appliances, \(t\) is the time intervals, \(\chi\) power ratings of appliances, \(F_{ap}\) set of fixed appliances, \(S_{ap}\) set of shiftable appliances, \(Z_{ap}\) set of uninterruptible appliances and \(\delta\) ON/OFF status of appliances. The per-hour energy consumption is evaluated and added to
compute the total energy consumed (demand of consumer) in a day.

### 3.2.3 Energy cost model

In order to evaluate the electricity cost of each appliance, the pricing signal is multiplied with energy consumed by appliances which are expressed in the following equation,

\[
EC_T = \sum_{t=1}^{T} (P(t) \times \lambda(t)).
\] \hfill (9)

In the above equation, the pricing signal is represented as \( \lambda \), \( P(t) \) is the total power consumption of shiftable, fixed and uninterruptible appliances, \( C(t) \) is the total electricity bill.

### 4 PROBLEM FORMULATION

In an optimisation problem, the objective function formulation is a key advance. The primary objective of this paper is limiting the electricity cost by augmenting shopper comfort. Here, the smart home is interfaced with the IoT cloud which sends the demand response (DR) and preferences to the cloud object. The IoT cloud object in like manner offers DR signal which contains important load scheduling and optimisation. This IoT cloud object is legitimately spoken with the energy management monitor and control centre. In this centre, so as to deal with the energy, the optimal load demand is anticipated by the optimisation approach. Home machines are classified dependent on operating time and energy utilisation necessity for effective management of energy. In the proposed work, the total electricity cost is must be not exactly the most extreme limit characterised which is communicated in the accompanying equation,

\[
\max \sum_{i=1}^{n} p_i \times x_i. \hfill (10)
\]

\[
\sum_{i=1}^{n} \omega_i \times x_i \leq C. \hfill (11)
\]

where \( p_i \) is the profit of each item, \( x_i \) represents the binary number 1 and 0 means ON/OFF state of each appliance, the weight of each item is denoted as \( \omega_i \). The operating cost of a device is taken as its profit. The main goal is to reduce electricity costs by maximising profit. The operational cost of an appliance is taken as its profit. The main goal of the present work is to minimise the electricity cost which is expressed as follows,

\[
\min \sum_{t=1}^{T} \sum_{i=1}^{m} P_i \times \gamma_i(t). \hfill (12)
\]

Subject to,

\[
\sum_{t=1}^{T} \sum_{i=1}^{m} P_i \times \gamma_i(t) \times \lambda(t) < C. \hfill (13)
\]

\[
\tau_{sch} = \tau_{otr}. \hfill (14)
\]

At the time slot \( t \), the ON/OFF state of the appliance is denoted as \( \gamma_i(t) \), operation start and end times of the appliance is denoted as \( \tau_{sch}, \tau_{otr} \) and maximum allowable power to be consumed is represented as \( C \). Peak creation and system stability issues are leads when overcoming this barrier. So, in the proposed work, the energy monitoring and control centre utilised the optimisation algorithm (FORDF) to overcome these issues. The detailed description of the proposed FORDF approach is delineated in the section underneath.

### 5 PROPOSED FORDF SCHEME FOR INTERNET OF THINGS BASED ENERGY MANAGEMENT

For optimal energy management, the proposed work displayed an effective hybrid methodology in the IoT based distribution system. The proposed hybrid methodology is named is FORDF procedure because of hybridisation of both the FOA and the random decision forest (RDF) strategy. FOA is the swarm intelligence optimisation algorithm that is motivated by the conduct of fruit flies [37]. RDF is an ensemble classifier that uses numerous decision tree models to predict the result [38]. The main aim of the proposed system is to optimally manage the power and resources of distribution system by decreasing the cost function by maximising the profit. The target of the proposed work is pointed as pursues: (1) to propose an EMS for distribution system utilising IoT framework with hybrid FORDF procedure; (2) to deal with the power and resources of distribution system by constantly monitor the data from the IoT-based communication framework; (3) to encourage the advancement of DR EMS for distribution system; (4) to expand the adaptability of the networks and give optimum utilisation of the accessible resources.

The point by point depiction of the proposed FORDF method is portrayed in the area underneath. The flowchart of proposed framework is given in figure 7.

#### 5.1 Load demand prediction using random decision forest

The RDF algorithm is otherwise known as the ensemble CLASSIFIER because it combines the number of decision trees for
the prediction process. In RDF, the bagging is one of the main principles; were randomly selected sample data \( n \) from the training set \( S_n \) is fitted to a regression tree [39]. This randomly selected sample is known as the bootstrap sample. Here, the numbers of bootstrap samples (\( S_n^1, \ldots, S_n^q \)) are selected using the bagging algorithm. Likewise, the \( q \) predicting trees (\( \tilde{h}(X, S_n^1), \ldots, \tilde{h}(X, S_n^q) \)) are collected by the CART algorithm after that all the predictor’s outputs are aggregated. Also in the bagging algorithm, \( m_t \) predefined numbers are selected from the \( p \) features (total number of DR) in order to split a node after that among the \( m_t \) selected features, the best cutting (optimum DR) is defined by the RDF algorithm [40]. The selected features from each node are uniform which has the probability \( p = 1 \). In all trees the value of \( m_t \) is same and it is recommended to be the square root of the features number \( p \).

\[
m_{\text{try}} = \left[ \sqrt{p} \right].
\] (15)

The RDF is characterised into two features named as out-of-bag error (OOBE) and variable importance (VI) measuring. The internal cross-validation is considered as the OOBE which is the mean prediction error of first-seen observations [41]. The generalisation ability of the constructed model is defined by the OOBE function which is estimated using the following equation,

\[
\text{OOBE} = \frac{1}{n} \sum_{i=1}^{n} \left( Y_i - \tilde{Y}_i \right)^2.
\] (16)

In the above equation, each observation \( S_n \) is represented as \( (X_i, Y_i) \) defined by the OOBE. The average difference of the OOBE and the permuted features are used to defined the VI measure which is computed by the difference between the mean errors of disturbed and original OOBE which is expressed as follows,

\[
\text{VI}(X_j) = \frac{1}{q} \sum_{i=1}^{q} (\text{OOBE} - \text{OOBE}).
\] (17)

In the above equation, \( \text{VI}(X_j) \) is the importance of the \( j \)th feature. The feature is important when the random permutations of the \( j \)th feature generate an increase of error [42]. The greater is the score \( \text{VI}(X_j) \), the more important is feature \( X_j \).

5.2 Internet of things based energy management using fruitfly optimisation algorithm

In this area, for the optimal EMS in the distribution system, the FOA approach is utilised. The ideal vitality the board is accomplished depends upon the target capacities, for example, least-cost by augmenting the benefit. The FOA was initially designed by Pan (2011, 2012) which is dependent upon the food foraging conduct of organic product fly which is a little red eye flies. The aged nourishment in kitchen draws in the organic product flies. The nourishment away from 40 km is smelled by these flies. The exceptionally wide scope of nourishment sources is found by the extraordinary qualities of the red-eye (i.e., compound eye) of these flies [43–47] (Figure 6).

There are not many procedures are trailed by these flies so as to decide the position of the nourishments. At first, the apheresis organ is utilised to smells the food source and flies towards that location; at that point it flies close to the location of food and the food is found by the sensitive vision; other fruit flies’ rushing location; at last, it flies towards that heading. In the proposed technique, the bit by bit procedure of the natural product flies for ideal vitality the board is depicted in the area underneath.

5.2.1 Step by step process of fruitfly optimisation algorithm

**Step 1: Initialisation process**

In the initialisation process, the output DR generated by the RDF; power generated by the sources, cost functions and the related generation limits are act as the input of the FOA and which is randomly generated using the following matrix equation,

\[
D = \begin{bmatrix}
R_{11} & R_{12} & \cdots & R_{1n} \\
R_{21} & R_{22} & \cdots & R_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
R_{n1} & R_{n2} & \cdots & R_{nn}
\end{bmatrix}.
\] (18)
where the randomly generated DR is $D$ and $R_{ij}$ is the random solutions, that is, $i, j \in S$.

**Step 2: Fitness function calculation process**

The fitness function (optimum energy) is determined based on the electricity cost and profit of each item which is defined in Section 4. The objective function for obtained the optimal solution is expressed in the following equation,

$$\max \sum p_i \times x_i = \beta.$$  \hspace{1cm} (19)

where $p_i$ is the profit of each item, $x_i$ represents the binary number 1 and 0 means ON/OFF state of each appliance. The operating cost of a device is taken as its profit. The main goal is to reduce electricity costs by maximising profit.

$$\min \sum EC_T = \alpha.$$  \hspace{1cm} (20)

where $EC$ is the electricity cost of each item in the distribution system.

**Step 3: Movement process**

In this process, the solution is updated subject to the step 2 of the algorithm which is expressed in the following equation,

$$\beta_{\text{best}} = \beta_{\text{best}}.$$ \hspace{1cm} (21)

$$\alpha_{\text{best}} = \alpha_{\text{best}}.$$ \hspace{1cm} (22)

$$X - \text{axis} = X_{(\text{best index})}.$$ \hspace{1cm} (23)

$$Y - \text{axis} = Y_{(\text{best index})}.$$ \hspace{1cm} (24)

**Step 4: Termination**

Once the process is completed, the optimum solution is achieved. Otherwise, continue the process until the termination criteria is met. Finally, post process and visualise results.

6 | SIMULATION RESULTS AND DISCUSSIONS

This section analyses the performance of the proposed technique which is implemented in MATLAB/Simulink 7.10.0 (R2012a) platform, 4 GB RAM and Intel(R) Core(TM) i5. The proposed energy management scheme is the combination of renewable sources such as PV, WT, MT and the BESS. In order to meet the load demand, the proposed system used to minimise the cost by maximising the profit. In the proposed system, the DR of each device of each smart home collected by the framework is transmitted to a centralised server. In order to optimally manage the energy, the optimal load demand prediction and the energy control processes are processed by the FORDF technique. In the hybridisation of the proposed approach, the RDF technique is used to predict the optimal load demand to manage the energy while the FOA is used to the optimal energy management. In order to analyse the effectiveness of the proposed method this is compared with the existing techniques such as FOA [42], particle swarm optimisation (PSO)–aided artificial neural network (ANN) and grasshopper optimisation algorithm (GOAPSNN) [48], squirrel optimisation with gravitational search–aided neural network (SOGSNN) [49] and improved artificial bee colony (IABC) [50,51]. The load demand evaluated by the proposed method for one day, one week and for one year is illustrated in Figure 8. In the subplot 8(a), the 24 h time period evaluation of the load demand is illustrated. In this plot, the power is normally greater than 5 kW at the beginning of the time period after that it can be increased to 25 kW between the time intervals of 10–20 h after that it can be suddenly reduced to below 10 kW after the time period of 20 h. In the subplot 8(b), the load demand is evaluated for 1 week. In the initial day, the load demand rate is 2600 kW, on Monday it can be increased to greater than 2800 kW which is suddenly reduced to 2000 kW on Wednesday. These increasing and decreasing processes are repeated for 1 week. The yearly load demand evaluation using the proposed method is illustrated in the subplot 8(c). In this plot, the load is calculated per month wise.

6.1 | Performance analysis

This section analyses the performance of the PV, WT, MT and BESS for 24 h, 1 week and for 1 year using the proposed FORDF technique. Figure 9 illustrates the power generated by the sources and power stored in battery for every hour of the day. The power generated by the PV using the proposed FORDF technique is shown in the subplot 9(a) which illustrates the generated power of PV is varied according to the timeslots. The maximum power generated by the PV using the FORDF technique is shown in the subplot 9(a) which illustrates the generated power of PV is varied according to the timeslots. The maximum power generated by the PV using the FORDF technique is 6 kW which is generated between the time intervals of 15–20 h. The power generated by the WT using proposed FORDF...
Figure 9 shows the power generated by the sources using FORDF scheme for 24 h. (a) Photovoltaic power, (b) wind turbine power, (c) MT power and (d) power stored in battery energy storage system.

Figure 10 illustrates the power generated by the sources using FORDF scheme for 1 week. (a) Photovoltaic power, (b) wind turbine power, (c) MT power and (d) power stored in battery energy storage system.

The maximum power generated by the WT using the FORDF is greater than 7 kW which is generated between the time intervals of 10–20 h. The power generated by the MT using proposed FORDF technique is shown in subplot 9(c). The maximum power generated by the MT using the FORDF is greater than 12 kW which is generated between the time intervals of 5–20 h. The power stored in BESS using proposed FORDF technique is shown in the subplot 9(d). The maximum power stored in BESS using the FORDF is greater than 3 kW which is generated between the time intervals of 10–15 h.

Figure 10 illustrates the power generated by the sources and power stored in the battery for every day of the 1 week. The power generated by the PV using proposed FORDF technique is shown in subplot 10(a) which delineates the generated power of PV is varied according to every day in a week. The maximum power generated by the PV using the FORDF is 850 kW which is generated on day 7. The power generated by the WT using proposed FORDF technique is shown in the subplot 10(b). The maximum power generated by the WT using the FORDF is greater than 800 kW which is generated on day 5. The power generated by the MT using proposed FORDF technique is shown in the subplot 10(c). The maximum power generated by the MT using the FORDF is 600 kW which is generated in a day 2 and 6. The maximum power stored in BESS using proposed FORDF technique is shown in the subplot 10(d). The maximum power stored in BESS using the FORDF is 1000 kW in a day 2 and 6.

Figure 11 illustrates the power generated by the sources and power stored in the battery for every month of 1 year. The power generated by the PV using proposed FORDF technique is illustrated in the subplot 11(a) which delineates the generated power of PV is varied according to every month in a year. The maximum power generated by the PV using the FORDF is 1600 kW which is generated in-between the month 4 and 6. The power generated by the WT using proposed FORDF technique is shown in subplot 11(b). The maximum power generated in-between the month 10 to 12. The power generated by the MT using proposed FORDF technique is shown in subplot 11(c). The maximum power generated by the MT using the FORDF is greater than 1800 kW which is generated in a month 8. The maximum power stored in BESS using proposed FORDF technique is shown in the subplot 11(d). The maximum power stored in BESS using the FORDF is greater than 2000 kW which is generated in-between the month 4 and 12.

6.2 Comparison analysis

This section delineates the comparison analysis of the power generated by the sources for 24 h. Here, the power generated by the proposed FORDF is compared with the existing techniques such as FFO, PSO–aided ANN and GOAPSNN [48], SOGSNN and IABC. The comparison analysis of power generated by the sources for 24 h of time period is illustrated in Figure 12. In this plot, the generated power of PV, WT, MT
and the power stored in BESS is varied according to every hour in a day. The subplot 12(a) shows the PV power generation using the proposed and the existing approaches. In this plot, the FORDF technique generated the maximum power (6 kW) between the time intervals of 15–18 h. The subplot 12(b) shows the WT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is greater than 7 kW which is generated between the time intervals of 15–20 h. The subplot 12(c) shows the MT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is greater than 15 kW which is generated between the time intervals of 17–20 h. The subplot 12(d) shows the power stored in BESS using the proposed and the existing approaches. In this plot, the maximum power stored by the FORDF is greater than 4 kW in between the time intervals of 18–20 h.

The comparison analysis of power generated by the sources for every day in a week is illustrated in Figure 13. In this plot, the generated power of PV, WT, MT and the power stored in BESS is varied according to every day in a week. The subplot 13(a) shows the PV power generation using the proposed and the existing approaches. In this plot, the FORDF technique generated the maximum power (greater than 800 kW) on day 7. The subplot 13(b) shows the WT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is 800 kW which is generated in a day 5 of a week. The subplot 13(c) shows the MT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is greater than 600 kW which is generated in a day 2 and 6 of a week. The subplot 13(d) shows the power stored in BESS using the proposed and the existing approaches. In this plot, the maximum power stored by the FORDF is 1000 kW in a day 2 and 6 of a week.

The comparison analysis of power generated by the sources for every month in a year is illustrated in Figure 14. In this plot, the generated power of PV, WT, MT and the power stored in BESS is varied according to the month of a year. The subplot 14(a) shows the PV power generation using the proposed and the existing approaches. In this plot, the FORDF technique generated the maximum power (greater than 1500 kW) in a month 5, 8 and 10 of a year. The subplot 14(b) shows the WT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is 2500 kW which is generated in a month 11 of a year. The subplot 14(c) shows the MT power generation using the proposed and the existing approaches. In this plot, the maximum power generated by the FORDF is 2000 kW which is generated in a month 8 of a year. The subplot 14(d) shows the power stored in BESS using the proposed and the existing approaches. In this plot, the maximum power stored by the FORDF is greater than 2000 kW in a month’s 5, 9 and 12 of the year.
6.3 Cost comparison analysis

This section delineates the comparison analysis of the electricity cost of each source for 24 h. Here, the electricity cost of each source found by the proposed FORDF is compared with the existing techniques such as FFO, GOAPSNN, SOGSNN and IABC. The comparison analysis of electricity cost of each source for 24 h of time period is illustrated in Figure 15.

In this plot, the electricity cost of PV, WT, MT and BESS is varied according to every hour in a day. The subplot 15(a) shows the PV electricity cost defined using the proposed method is compared with the existing FFO technique. In this plot, the FORDF technique has a minimum electricity cost (1 $). The subplot 15(b) shows the electricity cost of WT defined using the FORDF which is compared with the existing GOAPSNN technique. The subplot 15(c) shows the electricity cost of MT defined using the FORDF which is compared with the existing IABC technique. The subplot 15(d) shows the electricity cost of BESS defined using the FORDF which is compared with the existing SOGSNN technique. In this comparison results, the proposed FORDF has less cost for all the sources.

The electricity cost analysis of all sources using the proposed and the existing methods are shown in Figure 16. In this plot, the electricity cost of PV, WT, MT and BESS is varied according to every day of a week. The subplot 16(a) shows the PV’s electricity cost defined using the proposed method is compared with the existing FFO technique. The subplot 16(b) shows the electricity cost of WT defined using the FORDF which is compared with the existing GOAPSNN technique. The subplot 16(c) shows the electricity cost of MT defined using the FORDF which is compared with the existing IABC technique. The subplot 16(d) shows the electricity cost of BESS defined using the FORDF which is compared with the existing SOGSNN technique. In this comparison results, the proposed FORDF has less cost for all the sources.

Figure 17 illustrates the electricity cost of PV, WT, MT and BESS which is varied according to every month of a year. The subplot 17(a)-17(d) shows the minimum electricity cost of PV, WT, MT and BESS is achieved using the FORDF is compared with the existing techniques such as FFO, GOAPSNN, IABC and SOGSNN. The results obtained from this comparison shows; the proposed FORDF technique has less cost when compared with the existing method. The power generation of each source is varied in a month by month according to the
weather conditions. Based on this varied power generation the electricity cost is also varied which is clearly illustrated in those comparison plots.

7 | CONCLUSIONS

In this paper, an EMS for distribution system using IoT framework with a hybrid technique is presented. The hybrid technique presented in this paper is the combination of both the efficient FFO algorithm and RDF technique. In order to predict the DR and optimum energy management, this hybrid approach presented in this paper. The main goal of the present work is to reduce electricity costs by maximising profit. For analysing the performance of the proposed method which is compared with the other existing techniques named FFO, GOAPSNN, SOGSNN and IABC. The result obtained from the simulation shows that, by utilising the proposed hybrid technique, continuous monitoring the data from the IoT-based communication framework is managed with effective results. Also, the proposed technique is effective for finding optimal solutions with less computation and reduces the complexity of the algorithm. The future scope for the proposed study is pointed in the following:

In the energy sector, the application of block chain can accelerate the IoT effectiveness by providing a decentralised platform for distributed power generation and storage systems enhancing energy security and efficiency. In addition, radio optimisation techniques, such as, modulation optimisation or communication can be applied to reduce the power consumption of the nodes. More advanced metaheuristic algorithms can be used for the optimal solutions for the problems facing in EMS-IoT field. In future, we propose a scalable and self-configuring peer-to-peer-based architecture for large scale IoT networks, aiming at providing automated service and resource discovery mechanisms, which require no human intervention for their configuration. In particular, we can be focussed on both local and global service discovery (SD), showing how the proposed architecture allows the local and global mechanisms to successfully interact, while keeping their mutual independence.

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