Research Article

Hybrid RSA-ROA Scheduling Algorithm for Minimization of Power Loss and Improving the Renewable with Sustainable Energy Harvesting in Power System

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Recently, it has been very common for wireless sensor networks (WSNs) to be used in several applications (surveillance, home automation, and vehicle tracking), as well as in environmental monitoring and wildlife tracking. A typical sensor node has a limited amount of battery life. To overcome this, one method is to use an energy harvesting device to recharge the batteries of sensor nodes. Energy reaping WSNs still lack intelligent strategies for intelligently using both energy organization and harvesting systems, though. To maximize the harvesting of renewable energy sources (RES) and minimize power scheme losses, this study provides an optimal generation scheduling strategy for a power scheme combined with distributed generation (DG) and sustainable energy storage systems (ESSs). The major goal of this work is to make it possible to use RES in a power system while still maintaining a profit. By using ESS management, we are able to get the most out of our renewable energy resources and maximize our harvesting potential. It is also possible to reduce operating losses in the power system by scheduling ESS and controlled generation at the optimal times. Near global optimal solutions are sought using a hybrid algorithm combining Reptile Search Algorithm and Remora Optimization Algorithm (RSA-ROA). The power system operational restrictions are taken into account when formulating and evaluating the optimization issue. It has been tested in a variety of circumstances to see if the proposed strategy is effective. The proposed model has 0.260 J of remaining energy, when the number of rounds is 5000, but the existing techniques have only 0.110 J and 0.045 J for the same number of rounds.

1. Introduction

WSNs are made up of a limited sum of low-cost and low-power sensors. Multiple tasks such as data sensing and simple computing can be performed by the network, as well as short-distance transmission and storage for temporary data [1, 2]. In addition to health monitoring, transportation tracking, environmental monitoring, and border surveillance, it is employed in various uses of Internet of Things [3]. Energy consumption in sensor networks is closely connected
to their longevity because of the battery’s major role in supplying power. Sensor nodes in traditional sensor networks have been batteries with a finite capacity. Although the sensor nodes have a partial battery life, the normal application will have a limited battery life as well. It takes a long time to replace the batteries of sensor nodes and making the network sustainable is often a challenging task, because they are often located in remote locations. As a result, prolonging the life of a network is a difficult task when faced with energy restrictions [4].

Researchers have found a way around the restrictions of energy harvesting technologies by adopting this method. An energy collecting technology can be used to power nodes indefinitely. The network’s energy consumption can be optimized for maximum efficiency. Increasing the sampling frequency or duty cycle of a sensor node, for example, or increasing the transmission power to reduce the energy harvesting device is more favourable. Renewable energy resources include the energy gathering system [5]. A resource’s ability to be replenished over time by natural processes is what is meant by the term “ambient energy resources.” Sensor nodes are powered by a variety of sources, including photovoltaics, wind turbines, heat pumps, and other mechanically driven devices such as batteries [6–8]. Photoelectric cells transform the solar radiation into electrical energy, which is then used in an outdoor system during the daytime rather than at night or in overcast conditions [9]. Wind energy is rehabilitated into power energy by turbines in the wind energy-based system. There are two ways to shift the turbines: horizontally and vertically. It also uses piezoelectric or electrostatic devices to turn heat into electricity, as well as TEGs to convert mechanical electricity. As a result of the unpredictable nature of energy collecting, managing energy supplies is a difficult endeavour. Wind and solar energy harvesting systems [10–13] use prediction as a well-known approach of managing renewable resources. In contrast, several contemporary WSNs that harvest energy lack a smart approach for judiciously utilizing the management and harvesting systems. Energy harvesting and battery replacement will be discussed in detail in the following paragraphs.

Battery Replacement. An efficient and successful operating system requires regular battery replacement. The central remote station constantly monitors the battery’s condition. Maintenance personnel or a team may be dispatched to the remote location to replace a low-battery device. To avoid this problem, an additional battery or energy source should be added to the sensor node. This solution is either practical, cost-efficient, or flexible for effective and sustainable WSNs because of the high energy consumption of sensor nodes in dynamic operations.

Energy Harvesting in Sustainable Manner. Wind, solar, water, and other natural energy bases can all be used to generate electricity, as well as pressure, heat, and vibration. Low-power sensor nodes can now last an indefinite amount of time thanks to energy harvesting, which has to be done in a sustainable manner. Single-source energy harvesting is a superior option for long-term WSN sustainability. When adopting single-source energy harvesting, however, irregular and insufficient battery charging might have a negative impact on the system’s stability [14–16].

With the hybrid technique of energy harvesting, it is possible to build and execute an enhanced WSN that can increase the lifespan data collection, actuation, and processing, and transmission is another option for a WSN that is effective, long-lasting, and sustainable. We therefore need clever solutions. Optimal generation scheduling is the focus of this research, which examines the best way to maximize renewable energy gathering while minimizing power losses. It is possible to identify the most important variables in RES-based electricity generation with DG and ESS using the proposed method. In practice, however, DG accommodations and dimensions cannot be modified due to producer capacity restrictions and economic benefit. DGs, in particular, are always situated in a certain location that cannot be controlled. Producers expect maximum DG outputs, while the power system’s loss may rise because of this. The output power of DGs is therefore adjusted in a way that maximizes the gathering of renewable energy. Thus, enough power can be given to the loads, and extra power can be stored in ESS (Excessive Power Storage).

1.1. Organization of This Paper. The related study of the existing technique, which is related to our research study is mentioned in Section 2. The brief explanation of the proposed model is depicted in Section 3, and the validation analysis is presented in Section 4. Finally, the conclusion of the research work is given in Section 5.

2. Related Works

WSN generation depends on duty cycle, deployment type, and battery state-run of charge (SoC), according to Sharma [17]. Using ambient energy reaping to charge WSN node batteries, we provide a novel solution to the design challenge of low energy availability (LEA). Nevertheless, solar energy harvesting is fraught with difficulties, such as the inconsistency of the power supply and the inability to accurately estimate the sun’s output, as well as problems related to temperature and the efficiency of the solar panels. The goal of this research is to extend the lifespan of WSNs by gathering solar energy. As shown by our simulations, the sensor network lifetime can be extended to an indefinite level, with an optimum duty cycle of 100%, up to 115.75 days. SEH-WSNs also saw an increase in network speed from 100 to 160 kilobits per second.

Liu [18] suggests a two-stage strategy for dealing with the dynamics of renewable energy. As part of the network preparation phase, we apply the primal cut approach to resolve an RO (two-stage) problem and build an efficient data gathering tree. With minimum overhead, we offer an algorithm that may maximize the sample rates of nodes based on the observed recharge rates. Network performance is maximized under renewable energy uncertainty by not having to reconfigure routing structure during operational
phase. The proposed strategy is shown to be successful and robust in coping with the fluctuation of renewable energy through numerical findings.

According to Gupta [19], there is an adaptive. Multi-sensing solutions based on network and node-level partnerships are proposed to boost energy efficiency. Instead of relying on cross-correlation among the recorded strictures at each node, the latter relies on nodes with active sensors (as determined by MS). MS-sensing SP’s quality can be improved by using a retraining logic. Multisensor data fusion is presented to estimate all parameters across field nodes utilizing undersampled signals from the MS-CC active sensors.

A new protocol was proposed by Sah [20] for energy harvesting clusters (NEHCP). An algorithm called hierarchical clustering routing is used to implement the NEHCP, which employs solar EH. It is the cluster head’s job to convey data collected from the sensor nodes back to the central station. The beginning phase, setup phase, and data transmission phase are all parts of the NEHCP algorithm. The EH-WSN feature gives better results in terms of network longevity because it is unique. The EH-WSNs’ energy consumption is balanced and network efficiency is increased by the simulation element of this technology.

Two-port hybrid diodes and an adaptive supercapacitor buffer energy management technique are presented by Qi [21] to accomplish combined optimization. In the hybrid diode semiactive topology, the bidirectional DC/DC converter is replaced by a unidirectional DC/DC converter and two diodes instead of the current two. As a result, 15.5 percent less energy is lost, and the control system’s cost, size, and complexity are all reduced. Adaptive supercapacitor buffer energy organization is also being developed using the novel architecture to reduce battery degradation. There is a minimum threefold increase in battery life compared to the current hybrid energy storage devices in simulations and experiments. Sensor nodes powered by sunlight for the first time have been made possible.

A wearable medical sensor device was designed by Mohsen for long-term medical use [22]. The acceleration of a human body can all be monitored in real time using this method. There are two sensors in this system: one for temperature and one for pulse oximetry. There is also a microprocessor and a Bluetooth low energy module in there. Batteries are required to power this sensor system, but they only last so long. An energy harvester that can power an array of wearable medical sensors is therefore being developed. The sensor system’s lifespan can be extended thanks to this harvester, which generates enough energy to run the scheme. The suggested hybrid energy harvester is made up of two supercapacitors, a DC-DC boost converter and two flexible solar panels. For a total of 46 hours of operation, the sensor system was put to the test in active-sleep mode, where it consumed an average of 2.13 mW over a single hour. Finally, the findings of the experiments show that the medical sensor system may be monitored for an extended period of time.

A multihop data forwarding algorithm and decision-making model for the selection of data forwarding nodes were developed by Wu [23] for WSN powered by solar cells and batteries. The Pareto optimal collection of solutions can be found using the particle swarm optimization method. Energy supply models are developed after an investigation of solar energy acquisition aspects. An algorithm for forwarding information in response to changes in network energy consumption and delay has been demonstrated in simulated results.

3. Proposed System

In this section, first mathematical models for sustainable ESS and RES are explained.

3.1. Mathematical Ideal. Equations (1) and (2) describe the optimal generation preparation problem for maximizing energy gathering and reducing losses.

Maximize \( f_1 = \max \left(P_{\text{DG dispatch}}\right) \),

\( \text{Maximize } f_2 = \min \left(P_{\text{Loss line}}\right) \).

There are two sets of proposed goal functions: \( f_1 \) and \( f_2 \). The power system’s \( P \) (DG dispatch) harvests renewable energy. In a transmission line, \( P \) (Loss line) represents the amount of power lost (MW).

3.1.1. Renewable Energy Harvesting Model. It is a fact of life that DGs are continuously run at their supreme rated power production. This could lead to unfavourable conditions for the power system, such as increased power losses. On the other hand, DG power cannot be directly controlled by the utilities. Renewable energy harvesting includes two components: DG dispatch of power and storage of power, which is the amount of power that can be stored between \( P \) (DG dispatch) and the maximum power that can be generated. ESS will store the extra power. The following is the function for gathering renewable energy sources:

\[ P_{\text{DG dispatch}} = P_{\text{DG dispatch}} - P_{\text{storage}} \]  \( \text{(3)} \)

Excess power is stored in ESS, where it is closely linked to power loss. These losses can be broken down into battery and converter losses, respectively [24], for the electric energy storage system (ESS). The following formula can be used to compute the ESS’s loss:

\[ P_{\text{LossESS}} = P_{\text{Lossbatter}} + P_{\text{Lossconverter}} \]

\[ P_{\text{Lossbatter}} = I_{\text{batter}}^2 \times R_{\text{batter}} \]

\[ P_{\text{Lossconverter}} = P_{\text{sb}} + \left(k\% \times P_{\text{storage}}\right) \]

where the battery and converter losses are denoted by \( P_{\text{Lossbatter}} \) and \( P_{\text{Lossconverter}} \), respectively. The internal resistance of the battery is \( R_{\text{batter}} \). Power storage \( P_{\text{storage}} \) determines \( I_{\text{batter}} \) charging current. Standby power loss due to components is known as \( P_{\text{sb}} \) (continuous standby loss). Losses in semiconductors and filters account for \( k \) percent of the total.
This research, on the other hand, examines the direct link of the highest amount of renewable energy gathering. As a result, ESS loss is treated as if it were a property of \( P_{\text{storage}} \) rather than \( P_{\text{battery}} \). As shown in (3), \( P_{\text{storage}} \) has a considerable impact on ESS’s power loss. Therefore, the ESS losses can be expected to be stowed power and ESS as follows:

\[
P_{\text{storage}} = P_{DG\text{output}} - P_{DG\text{dispatch}},
\]
\[
P_{\text{LossESS}} = (1 - \eta)P_{\text{storage}}.
\]  

### 3.1.2. Power Loss in Line Ideal

The generalised power flow is used in this study to determine the power losses in the power system’s line. When analyzing the steady state of a real, the power flow equation can be expressed as follows [25]:

\[
S_i = P_i + jQ_i,
\]
\[
P_i = \sum_{k=1}^{n} \left[ |V_i||V_k|Y_{ik} \cos (\theta_i - \theta_k - \alpha_k) \right], \quad i = 1, 2, \ldots, n,
\]
\[
Q_i = \sum_{k=1}^{n} \left[ |V_i||V_k|Y_{ik} \sin (\theta_i - \theta_k - \alpha_k) \right], \quad i = 1, 2, \ldots, n.
\]

Net apparent power injections to bus \( i \) are represented by \( S_i \). \( P_i \) and \( Q_i \), respectively. Number of buses in the system is \( n \). The magnitudes of the voltages on buses \( i \) and \( k \) are \( V_i \) and \( V_k \), respectively. Both \( l \) and \( k \) refer to the voltage angles at the two buses in question. The difference in admission between buses \( j \) and \( k \) is measured by \( Y_{ik} \). When two buses are in phase with one another, they are called “\( ik \)” and “\( jk \).”

This work only covers the active component power losses in lines due to a branch conductance \( (g_{ik}) \) among buses \( l \) and \( k \), which can be expressed as follows:

\[
P_{\text{LossLine}_{ik}} = g_{ik} \left[ V_i^2 + V_k^2 - 2V_iV_k \cos (\theta_i - \theta_k) \right].
\]

### 3.2. Objective Function Formulation

Achieving maximum energy means maximizing the DG’s power output or decreasing the amount of excess energy that can represent the least amount of power loss in the ESS, as discussed in Sections 3.1.1 and 3.1.2. The proposed method’s objective function is the product of (1) and (2). As a result, the following may be said about it:

\[
\text{Min } P_{\text{TotalLoss}} = \sum_{i=1}^{N_l} P_{\text{LossLine}_{i,j}} + \sum_{j=1}^{N_{st}} P_{\text{LossESS}_{j}}.
\]

Loss line \( i \) is defined as the power loss, and loss line \( j \) as the ESS loss. To put it another way, \( N_l \) and \( N_{st} \) represent the total sum of energy transmission lines and storage facilities.

### 3.3. Operational Constraints

#### 3.3.1. Power Flow Constraint

When power is transmitted between any two buses \( i \) and \( j \), where each bus is represented by a row and a column in Tables 1 and 2. An illustration of a power flow restriction is the following:

\[
I_{i,j} \leq \theta_{i,j}^\text{max},
\]

\[\text{Table 1: Details of IEEE 14-bus standard test scheme.}\]

| Type                | Cap. (MW) | Bus |
|---------------------|-----------|-----|
| Renewable DG unit 1 | 100       | 12  |
| Conventional gen. 2 | 600       | 2   |
| Renewable DG unit 2 | 100       | 10  |
| Conventional gen. 1 | 750       | 1   |
| Conventional gen. 3 | 400       | 3   |
| ESS unit 1          | 12        |     |
| ESS unit 2          | 10        |     |
| ESS unit 3          | 9         |     |

\[\text{Table 2: Details of IEEE 30-bus test system.}\]

| Type                | Cap. (MW) | Bus |
|---------------------|-----------|-----|
| Conventional gen. 1 | 200       | 1   |
| Conventional gen. 2 | 150       | 2   |
| Conventional gen. 3 | 150       | 5   |
| Renewable DG 1      | 50        | 5   |
| Renewable DG 5      | 50        | 11  |
| Renewable DG 6      | 50        | 13  |
| Renewable DG 3      | 50        | 9   |
| ESS unit 1          | 5         |     |
| ESS unit 2          | 3         |     |
| ESS unit 3          | 9         |     |

where \( I_{i,j} \) is the present line among buses \( i \) and \( j \), as shown in the figure. The line between buses \( i \) and \( j \) has a maximum current capacity of \( I_{i,j}^\text{max} \).

#### 3.3.2. Generator Constraints

The system’s generators must be run within the bus voltage’s rated active and reactive power restrictions. The voltage must also fall within the acceptable ranges of maximum and minimum. The following are possible generator constraints:

\[
P_N^{\text{min}} \leq P_N \leq P_N^{\text{max}}, \quad Q_N^{\text{min}} \leq Q_N \leq Q_N^{\text{max}}, \quad V_N^{\text{min}} \leq V_N \leq V_N^{\text{max}}.
\]

Generator bus \( N \) injects power \( (PN) \) both actively and reactively. Generator \( N \)’s maximum active and reactive powers are referred to as \( P_N \) \& \( Q_N \) max. \( P_N \) \& \( Q_N \) min are generator \( N \)’s minimal active and reactive powers. The voltage on the bus at which a generator is attached (bus \( N \)) is known as \( V_N \). Voltages \( V_N \) \& \( V_N \) min are the generator bus’s maximum and minimum operational voltages, respectively.

#### 3.3.3. Renewable Distributed Generation Restraint

Only the maximum power output from the renewable DG source is taken into account. Here are some examples of how you can set a restriction:

\[
0 \leq P_{DG,N} \leq P_{DG,N}^{\text{max}}.
\]

The active power transfer from DG to bus \( N \) is denoted by \( P_{DG,N} \). DGs at bus \( N \) have a maximum active power of \( P_{DG,N}^{\text{max}} \).
3.3.4. Load Constraints. Distribute general load across system while maintaining voltage limitations as seen in (12). A voltage deviation (VD) limit must also be adhered to when operating the load. Difference in voltage between the maximum and minimum voltage limitations is referred to as VD. We can write VD down as follows:

\[ V_{N}^{\text{min}} \leq V_{N} \leq V_{N}^{\text{max}}, \quad N = 1, \ldots, n \text{ bus no}, \]
\[ V_{i} = V_{i}^{\text{max}} - V_{i}^{\text{min}}, \quad i = 1, \ldots, m \text{ scenarios no.} \]  

Maximum and minimum bus voltage limitations are \( V_{N}^{\text{max}} \) and \( V_{N}^{\text{min}} \), respectively. Maximum and lowest system voltages for scenario \( I \) are \( V_{i}^{\text{max}} \) and \( V_{i}^{\text{min}} \), respectively.

3.4. Proposed Model: Background. For minimizing the power loss and maximizing the renewable energy harvesting as presented in Sections 3.1 to 3.3, the optimal solutions are explored by applying the hybrid RSA-ROA. With regard to this hybrid algorithm, an entirely new transition mechanism has been proposed, and its primary technique has been described.

\[
x_{(i,j)}(t + 1) = \begin{cases} 
\text{Best}_{j}(t) \times \eta_{(i,j)}(t) \times \beta - R_{(i,j)}(t) \times \text{rand}, & t \leq \frac{T}{4} \\
\text{Best}_{j}(t) \times x_{(r_{i,j})} \times ES(t) \times \text{rand}, & t > \frac{3T}{4} \end{cases}
\]  

Equation (14) yields the hunting parameter \( \eta_{(i,j)} \). No matter what, \( b \) will always be equal to 0.01. Equation (15) determines the reduction function \( R_{(i,j)} \). There are four random numbers in this problem: \( r_{1}, r_{2}, x(i, j), \) and \( N \). The sense of evolution equation (16) gives us the probability parameter \( ES(t) \).

\[
\eta_{(i,j)} = \text{Best}_{j}(t) \times P_{(i,j)}, 
\]
\[
R_{(i,j)} = \frac{\text{Best}_{j}(t) - x_{(r_{i,j})}}{\text{Best}_{j}(t) + \epsilon},
\]
\[
ES(t) = 2 \times r_{3} \times (1 - \frac{1}{T}).
\]

It is an integer with the value. The following equation determines the difference parameter \( P_{(i,j)} \):

3.4.1. Reptile Search Algorithm (RSA). Here, we will discuss the Reptile Search Algorithm (RSA). Reptile Search Algorithm (RSA) is based on the natural behaviour of crocodiles in the wild, including their encircling mechanics, hunting tactics, and social interactions [26].

**Encircling Phase.** This section introduces the RSA’s exploratory activity (encircling). Crocodiles have two distinct ways of encircling prey: high-walking and belly-walking.

Iteration number is divided into four equal parts, and the total sum of iterations is also divided into four equal parts. Based on these scenarios, RSA alternates between exploration and exploitation search stages. Two key search algorithms are used to uncover better answers in the RSA exploration mechanisms, which examine search regions and approaches.

During this step of the search, only one criterion must be met. High-walking and belly-walking search methods are carried out according to \( tT/4 \) and \( 2T/4 \) and \( t > T/4 \), respectively. The following equation shows how the position is updated:

\[
P_{(i,j)} = \alpha + \frac{x_{(i,j)} - M(x_{i})}{\text{Best}_{j}(t) \times (UB_{(i,j)} - LB_{(i,j)}) + \epsilon}.
\]

In (18), \( M(x_{i}) \) indicates the average position. These are the highest and lower limits, respectively, where it has a value of 0.1.

\[
M(x_{i}) = \frac{1}{n} \sum_{j=1}^{n} x_{(i,j)}.
\]

**Hunting Phase.** This section discusses RSA’s predatory tendencies. Crocodiles hunt in two ways, depending on their hunting habits: coordination and teamwork.

When \( t \leq T \) and \( t > 3T/4 \) are used for hunting coordination in this phase; if \( t > T/4 \) and \( t > 3T/4 \) are used, then the hunting cooperation is accomplished. Equation (19) depicts the position-updating procedures:
where the best solution is found, and the hunting parameter $\eta_{(i,j)}$ is defined by equation (14). According to equation (17), $P_{(i,j)}$ is the difference parameter. Equation (15) defines reduction function $R_{(i,j)}$.

### 3.4.2. Remora Optimization Algorithm (ROA).

The detailed explanation of ROA [27] is given in the upcoming section.

**Free Travel.** SFO Strategy (20) provided the procedure’s elite idea, which was used to model this algorithm’s location update.

$$R_{i,t}^{t+1} = R_{best} - \left( rand \times \left( \frac{(R_{best}^t - R_{rand}^t)}{2} \right) - R_{rand}^t \right), \quad (20)$$

where $R_{rand}^t$ is a random location.

**Experience Attack**

The tuyu must take little steps around the host on a regular basis in order to regulate whether or not it is essential to replace the host. The following is the formula for simulating the aforementioned principles:

$$R_{att} = R_{i,t}^t - \left( R_{i,t}^t - R_{pre} \right) \times \text{rand}. \quad (21)$$

In this example, $R_{pre}$ is where the previous iteration left off, and $R_{att}$ represents a tentative stride in that direction.

Because of this step’s fitness evaluation, the current solution $f(R_{i,t}^t)$ and the attempted solution $f(R_{att})$ are described. If, for example, the proposed solution’s fitness function value is lower than the fitness function value, then the proposed solution should be rejected.

$$f(R_{i,t}^t) > f(R_{att}). \quad (22)$$

This section shows how Remora uses a different technique for local optima than does the rest of Remora.

$$f(R_{i,t}^t) < f(R_{att}). \quad (23)$$

**Eat Thoughtfully**

**WOA Strategy**

As shown in the equations below, the location update formulation of Remora attached to the whale was reconstructed using the original WOA method:

$$x_{(i,j)}(t + 1) = \begin{cases} 
Best_j(t) \times P_{(i,j)}(t) \times \text{rand}, & t \leq 3 \frac{T}{4} \text{ and } t > 2 \frac{T}{4}, \\
Best_j(t) - \eta_{(i,j)}(t) \times e - R_{(i,j)}(t) \times \text{rand}, & t \leq T \text{ and } t > 3 \frac{T}{4}, 
\end{cases} \quad (19)$$

$$R_{i,t} = \frac{D \times e^a \times \cos (2\pi a) + R_i}{2} \quad (24)$$

$$\alpha = \text{rand} \times (a - 1) + 1,$$

$$a = \left(1 + \frac{t}{T}\right),$$

$$D = |R_{best} - R_i|.$$
improve the efficiency of search. As a result, new ideas from other places can effectively broaden the search space. More robust approaches to achieving better results are inspired by these proposals for the proposed model.

Initialization Phase. Starting with a collection of candidates \(X\) generated stochastically, the optimization process in RSA commences. Nearly optimum solutions are found in each iteration.

\[
X = \begin{bmatrix}
  x_{1,1} & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\
  x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,n} \\
  \vdots & \vdots & \vdots & \vdots & \vdots \\
  x_{N-1,1} & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\
  x_{N,1} & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n}
\end{bmatrix},
\]

where \(x(i,j)\) is the \(j\)th location of the \(i\)th solution and \(N\) is the total sum of solutions and \(n\) is the size of the dimension derived from the following equation:

\[
x_{ij} = \text{rand} \times (UB - LB) + LB, \quad j = 1, 2, \ldots, n,
\]

where \(\text{rand}\) is a random and \(LB\) and \(UB\) signify the bound, correspondingly. The flow chart of the proposed model is given in Figure 1.

The Projected Mean Transition Mechanism (MTM). At the beginning of this section, Algorithm 1 provides an explanation of the mean transition mechanism (MTM). Controlling the search and switching between the RSA and the MT are both possible with this method. It takes a lot of skill to move from one search method to the next. It calls for an efficient method of changing the update operations across multiple techniques. When the fitness does not improve after five iterations, the basic idea behind the MTM is to regulate the search approaches (I). The number of repetitions decreases if there are no benefits to be had through testing.

While the fitness function value and \(C\) serve as a counter in Algorithm 1, the TM variable can be switched from 0 to 1 to alter the search process between RSA and MT. There are a maximum number of repeats \(I\) that should be altered if no improvements are seen.

4. Simulation Results and Discussion

4.1. Test Systems Description. The proposed technique is put to test using IEEE 14-bus and 30-bus test schemes, side by side. According to the test systems, the generation units include generation and renewable DG units. Each renewable DG unit has an ESS installed to collect any extra power generated. In each site, the DG power output is a combination of the electricity energy available from the DG dispatch and the extra power stored in the ESS unit, which has different standards. Tables 1 and 2 present the component data for the 14-bus and 30-bus test systems, respectively. The efficiency of ESS is assumed to be 90% in all deployed locations for the purpose of calculating ESS losses.

The proposed WSN is being tested using MATLAB 2014 software. Table 3 shows the results of two distinct simulations. Table 4 has further information. During the simulations, we measure efficiency, the sum of active nodes, the network’s average energy consumption, the First Node Dies (FND), the loss of 10% and 20% of nodes, and the number of packages transferred.

Depending on their level of sophistication, energy collecting nodes can be classified as basic or sophisticated. During different simulations, the percentages of normal and advanced nodes in the network are 80 percent and 20 percent, respectively. Nodes in the advanced stage have three times the energy of those in the standard stage. We ran a number of simulations, and the mean results are shown here. Table 3 shows the simulations scenario of the proposed model; here we used 100 and 200 nodes for simulation, as well as the areas of 500 \(\times\) 500 m\(^2\) and 300 \(\times\) 300 m\(^2\), respectively.

Table 4 shows the different parameters used in simulation, which are used in the proposed model.

In the FND analysis, when the time is 44.4 s, the hybrid RSA-ROA method has 40439 packets for 100 node. But the single algorithm such as RSA and ROA has only 2410 packets and 3986 packets for the same number of nodes (100). When the number of nodes is 80, the hybrid model has 125268 packets, where the single models have only 5213 and 6535 packets for the analysis of PND. Next, Table 5 presents the summary for FND and PND for network 2.

From the comparative analysis in Table 6, it is shown that different types of PND, 200, 180 and 160, are used. In the FND analysis on 200 nodes, when the time is 361.2 s, the hybrid RSA-ROA method has 72239 packets. But the RSA and ROA have only 3840 packets and it reaches around 19.2 s and 4140 packets in 20.7 s for the same node 100. When the number of nodes is 160, the hybrid model has 229453.5 packets in 1202 s, where the single models have only 17357.4 in 93.3 s and 14928.9 packets in 78.1 s for the analysis of PND. Table 7 and Figure 2 show the experimental analysis of total number of live nodes for network 1.

When the initial rounds start, all the techniques have 100 nodes, but when the rounds are high, all techniques have different number of nodes. For instance, when the number of rounds is 1500, the RSA has 28 nodes and ROA has 30 nodes, but the proposed model has 90 nodes. This is due to the integration of RSA model and ROA model. When the number of rounds is 3500, the RSA has only 30 live nodes, ROA has 35 live nodes, and the proposed model has 91 live nodes. Finally, when the number of rounds is 5000, the proposed model has 82 live nodes, ROA has 35 live nodes, and RSA has 30 live nodes. Figure 3 presents the number of live nodes for proposed network 2.

In this second network, the initial nodes are 200 for zero rounds. When the number of rounds is increased, the live nodes for existing technique are less, when compared with the proposed model. When the number of rounds is 4500, the RSA has 125 nodes, ROA has 130 live nodes, and the proposed model has 187 live nodes. When the number of rounds is 2000, the proposed model has 183 live nodes, the RSA model has 130 nodes, and ROA has 138 live nodes. This
analysis shows that the number of lives nodes is higher for the proposed model compared to the existing techniques. Table 8 and Figure 4 show the remaining energy for network 1.

Initially, all models have 0.600 J, but when the number of nodes increases, the energy is also reduced. When the number of rounds is 500, the remaining energy of RSA is 0.111 J, that of ROA is 0.065 J, and that of the proposed model is 0.410 J. When the number of rounds is 2000, the remaining energy of RSA is 0.111 J, that of ROA is 0.055 J, and that of the proposed model is 0.340 J. When the number of rounds is 3500, the remaining energy of RSA is 0.111 J, that of ROA is 0.045 J, and that of the proposed model is 0.290 J. For the second network, the experimental values are shown in Table 9 and Figure 5.

When the number of rounds is 500, the proposed model has 0.360 J, ROA has 0.180 J, and RSA has 0.020 J. For all

(i) Initialize the TM parameter value (TM = 0).
(ii) sumFF = 0;
(iii) for (t = 1 to T) do
  (iv) sumFF = sumFF + currentFF
  (v) C = (C + 1);
  (vi) if (currentFF ≥ sumFF) then
  (vii) if (C > I) then
  (viii) TM = flip(TM);
  (ix) sumFF = 0;
  (x) C = 0;
  (xi) end if
  (xii) end if
  (xiii) end for

Algorithm 1: The projected mean transition mechanism (MTM).

Table 3: Simulations scenario.

| Network       | Sink     | Number of nodes | Area (m²)   |
|---------------|----------|-----------------|-------------|
| Proposed network 1 | (0,0)   | 100             | 300 × 300   |
| Proposed network 2 | (250,250) | 200             | 500 × 500   |
different rounds, the existing RSA has stable remaining energy (i.e., 0.020 J). When the number of rounds is 1500, the proposed model has 0.200 J and ROA has 0.180 J. But, at one particular round, all techniques including the proposed model have stable remaining energy (i.e., 0.180 J). Table 10 shows the performance analysis of proposed model in terms of throughput.

The throughput of the proposed hybrid model is increased, when the number of nodes is also increased. In the throughput experiments for network 1, the RSA achieved 109 kbps, ROA achieved 114 kbps, and the proposed hybrid model achieved 157 kbps when the number of nodes reached 2000. These same techniques achieved 149 kbps, 170 kbps,

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**Table 4: Parameters used in simulation.**

| Parameter           | Value                     |
|---------------------|---------------------------|
| \( P_{DG\_dispatch} \) | 5 nJ/bit/message           |
| \( P_{storage} \)    | 50 nJ/bit                 |
| \( P_{ESS} \)        | 10 pJ/bit/m2              |
| \( P_{DG\_output} \) | 0.0013 pJ/bit/m4          |
| Packets size        | 8192 bits                 |
| Message size        | 100 bits                  |
| Energy of threshold down | 0.01 J          |
| Energy of threshold up          | 0.1 J                    |

**Table 5: Summary of FND and partial node death (PND) for proposed network 1.**

| Protocol          | FND (100 nodes) | PND (90 nodes) | PND (80 nodes) |
|-------------------|-----------------|----------------|----------------|
|                   | Time (s)        | Packets        | Time (s)       | Packets        | Time (s)       | Packets        |
| RSA               | 24.1            | 2410           | 53.2           | 5213.5         | 72.7           | 6901.2         |
| ROA               | 40.1            | 3986.7         | 69.8           | 6535.6         | 95.5           | 8354.8         |
| Hybrid RSA-ROA    | 44.4            | 40439          | 1288.6         | 125268.5       | 1150.8         | 12459          |

**Table 6: Summary of FND and PND for proposed network 2.**

| Protocol          | FND (200 nodes) | PND (180 nodes) | PND (160 nodes) |
|-------------------|-----------------|-----------------|-----------------|
|                   | Time            | Packets         | Time            | Packets         | Time            | Packets         |
| RSA               | 19.2            | 3840            | 59.6            | 11584.3         | 93.3            | 17357.4         |
| ROA               | 20.7            | 4140            | 50.4            | 9865.7          | 78.1            | 14928.9         |
| Hybrid RSA-ROA    | 361.2           | 72239           | 868.5           | 170170          | 1202            | 229453.5        |

**Table 7: Number of live nodes for proposed network 1.**

| Total no. of rounds | 0   | 500  | 1000 | 1500 | 2000 | 2500 | 3000 | 3500 | 4000 | 4500 | 5000 |
|---------------------|-----|------|------|------|------|------|------|------|------|------|------|
| RSA                 | 100 | 20   | 25   | 28   | 30   | 28   | 25   | 30   | 28   | 25   | 30   |
| ROA                 | 100 | 35   | 38   | 32   | 38   | 32   | 30   | 35   | 38   | 30   | 35   |
| Hybrid RSA-ROA      | 100 | 90   | 88   | 90   | 83   | 87   | 90   | 91   | 90   | 87   | 82   |

**Figure 2: Graphical representation for network 1.**

**Figure 3: Graphical representation of the proposed model for energy.**
and 220 kbps when the number of nodes reached 4000. Finally, when the number of nodes reached 5000, the RSA achieved 182 kbps, ROA achieved 200 kbps, and the proposed hybrid model achieved 255 kbps throughput. Figures 5 and 6 show the graphical analysis of the proposed hybrid model for both networks.

Table 11, Figure 7, and Figure 8 show the experimental analysis of the proposed method for routing overhead for networks 1 and 2.

For proposed network 1, the routing overheads of RSA, ROA, and the hybrid model are 0.8, 0.7, and 0.5, respectively when the number of nodes is 2000. The RSA has 0.98, ROA has 0.9, and the proposed hybrid model consumed only 0.82 routing overhead when the number of nodes reached 4000. From this analysis, it is clearly proven that
the number of nodes influences the performance of routing overhead of each model. The hybrid model achieved 0.49 to 0.82 of routing overhead when the numbers of nodes were 1000 to 5000, while the single models, RSA and ROA, achieved 0.63 to 1.26 and 0.51 to 1.07 of routing overhead when numbers of nodes were 1000 to 5000. Figure 8 shows the graphical analysis of proposed network 2 in terms of routing overhead.

![Graphical representation of the proposed method in terms of throughput for network 2.](image)

**Figure 6**: Graphical representation of the proposed method in terms of throughput for network 2.

**Table 10**: Validated analysis of the proposed method for throughput (kbps).

| No. of nodes | Proposed network 1 | Proposed network 2 |
|--------------|---------------------|--------------------|
|              | RSA | ROA | Hybrid RSA-ROA | RSA | ROA | Hybrid RSA-ROA |
| 1000         | 100 | 98  | 126           | 104 | 119 | 136           |
| 2000         | 109 | 114 | 157           | 120 | 128 | 166           |
| 3000         | 128 | 115 | 176           | 148 | 159 | 189           |
| 4000         | 149 | 170 | 220           | 159 | 190 | 234           |
| 5000         | 182 | 200 | 255           | 192 | 220 | 263           |

![Graphical representation of the proposed method in terms of routing overhead for network 2.](image)

**Figure 7**: Graphical representation of the proposed method in terms of routing overhead for network 1.

**Table 11**: Performance analysis of the proposed method for routing overhead.

| No. of nodes | Proposed network 1 | Proposed network 2 |
|--------------|---------------------|--------------------|
|              | RSA | ROA | Hybrid RSA-ROA | RSA | ROA | Hybrid RSA-ROA |
| 1000         | 0.7 | 0.6 | 0.4           | 0.63 | 0.51 | 0.49           |
| 2000         | 0.8 | 0.7 | 0.5           | 0.70 | 0.58 | 0.46           |
| 3000         | 0.9 | 0.7 | 0.62          | 0.69 | 0.63 | 0.57           |
| 4000         | 0.98 | 0.9 | 0.82          | 0.71 | 0.69 | 0.74           |
| 5000         | 1.23 | 1.18 | 0.96         | 1.26 | 1.07 | 0.82           |

![Graphical representation of the proposed method in terms of routing overhead for network 2.](image)

**Figure 8**: Graphical representation of the proposed method in terms of routing overhead for network 2.
5. Conclusion

In this paper, the optimum generation programming was studied using the hybrid model in the power system. The proposed method was implemented keeping in mind maximum renewable energy harvest and minimization of energy losses. The optimal solutions for the proposed method were identified and obtained by integrating RSA and ROA algorithms. The comparative cases of single technique with hybrid model were made to exploit the potential and effectiveness of the proposed method in two different networks, where the single models, RSA and ROA, achieved 0.63 to 1.26 and 0.51 to 1.07 of routing overhead, respectively, when the numbers of nodes were 1000 to 5000. The simulation results showed the effectiveness and good performance of the proposed method for obtaining optimal solutions for generation programming, especially with maximum harvesting of renewable energy and minimizing energy losses. Energy losses were clearly low depending on the optimum storage power of the ESS and minimizing line losses with maximum renewable energy harvest. In addition, the maximum renewable energy harvest is greatly affected by the reduction of conventional generations and reduced ESS losses.

Data Availability

No data were used to support the findings of this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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