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Original Article

Derived Self Generative Roulette Wheel Memetic Optimization Based Bidding Strategy for Micro-grid Interfaced Renewable Energy Management

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Abstract *- Renewable Energy Sources (RES) are an alternative one for addressing growing energy demand to diminish climate change while promoting sustainable expansion. In the microgrids, energy management is defined as the statistical info and control system that provides the topologies needed to guarantee the distribution and generation systems' electricity at the least possible operational costs. But, a technical challenge for the operation of MGs is how to find the optimal method to manage various Distributed Renewable Energy Resources (DRERs) and loads. To deal with these issues, the Derived Self Generative Roulette Wheel Memetic Optimization based Bidding Strategy (DSGRWMOBS) Model is introduced for price takers and customers with Micro-grid interfaced RES at negligible computational expenses. In the DSGRWMOBS Model, the system data, like generator data, consumer data, aggregate load, and price, are collected. The collected data are considered the initial population. After that, the memetic process variables population size, crossover rate, and mutation rate are initialized. Then, the DSGRWMOBS Model creates the initial random population of bidding coefficient rivals. Then, market-clearing prices are evaluated using the bidding coefficients. The fitness value of each population rate is determined based on generation, demand, and a dispatch schedule that meets reliability constraints to maximize profit. After determining the fitness function, the DSGRWMOBS Model performs the selection, crossover, and mutation for Micro-grid interfaced RES to achieve the ideal solution (system data with higher profit). In this way, the DSGRWMOBS Model helps the Micro-grid interlinked RES at negligible computational expenses. The simulation result shows the performance enhancement of the DSGRWMOBS Model in terms of metrics such as operation cost, energy management precision, and solar Energy. The results authenticate that the DSGRWMOBS Model obtains healthier performance by means of reaching advanced energy management accuracies and solar Energy with negligible operation cost.*

Keywords *- Renewable energies, Energy management, Micro-Grid, Market clearing prices, Bidding coefficients.*

1. Introduction

Microgrids play a key role in today's power networks by simplifying the integration of distributed RES, energy storage technologies, and regulated loads [1, 2]. With an ever-increasing penetration of RES like solar and wind, microgrids actively participate in both the local and wholesale power market by competitively bidding for energy and related services [3, 4]. However, due to the intermittent nature of renewables, uncertainties in load, scheduling storage, network constraints, and fluctuating market prices, effective bidding within a microgrid is by no means an easy task [5, 6]. Therefore, an efficient and computationally accurate energy management and bidding strategy is necessary for ensuring economic operation and a reliable power supply [7, 8]. Approaches such as stochastic programming, robust optimization, model predictive control, game-theoretic methods, and meta-heuristic algorithms have been widely adopted for micro-grid bidding and energy management [9, 10]. In fact, their goal is to maximize profit and reduce operational costs. However, most of these techniques are of high computational Complexity with ample execution time and scalability issues, hence not appropriate for real-time and large-scale market environments [11, 12].

This may be because memetic algorithms remedy the deficiencies of pure evolutionary algorithms by incorporating some local search mechanisms, which leads to an enhanced and balanced global exploration-local exploitation capability [13]. Evolutionary operator selection, such as roulette wheel selection, enables the probabilistic fitness-based selection of individuals [14, 15]. However, in traditional selection mechanisms, certain limitations are encountered in terms of premature convergence, insufficient diversity, and slow convergence speed of converged solutions for highly uncertain and dynamic energy market data [16]. Extensive research on micro-grid energy management and bidding strategy development still leaves a significant research gap in developing a low-complexity, high-accuracy, computationally efficient bidding optimization framework that can handle renewable uncertainty, reduce operational cost, and enhance real-time decision-making capabilities [17, 18]. Most of the existing approaches based on stochastic, robust, and meta-heuristic methodologies either attain higher accuracy with a high computational burden or reduce the Complexity at the cost of optimality and reliability [14, 19].

Furthermore, the existing methods lack an effective balance in the capability for global search and local refinement, which results in suboptimal bidding solutions and increased operational expenses. In an effort to surmount the aforementioned limiters, this paper presents a Derived Self-Generative Roulette Wheel Memetic Optimization-based Bidding Strategy for micro-grid interfaced renewable energy management. The proposed model integrates the self-generative roulette wheel selection method within a memetic optimization framework in order to realize efficient exploration and exploitation of the solution space. The DSGRWMO-BS Model utilizes the system data, inclusive of generator parameters, consumer demand, aggregate load, and market price, as the initial population. The proposed approach adapts selection, crossover, and mutation operations to determine optimal bidding coefficients and market-clearing prices while satisfying system reliability constraints. Consequently, the proposed method significantly reduces computational cost, improves energy management accuracy, and enhances solar energy utilization in microgrid operations.

1.1. Novelty and Comparison with Existing Works

Most of the existing microgrid bidding and energy management strategies, including stochastic optimization, model predictive control, PSO, AIS, and robust optimization techniques, are predominantly concerned with uncertainty handling and cost minimization, but they suffer from high computational Complexity, larger execution time, premature convergence, and limited real-time adaptability. In this regard, the proposed Derived Self Generative Roulette Wheel Memetic Optimization-based Bidding Strategy (DSGRWMO-BS) proposes a novel hybrid framework that integrates self-generative roulette wheel selection with adaptive Lévy mutation in a memetic optimization environment to achieve an effective trade-off between global exploration and local exploitation that has not been considered in the existing approaches. Unlike the traditional methods, the proposed DSGRWMO-BS essentially reduces the computational overhead while preserving considerable reliability and optimality. Further, comparative simulation results depicts the projected system progresses energy management accuracy by 13% and 8%, reduces operation cost by 35% and 25%, and enhances solar energy utilization by 31% and 21% compared to the outmoded Energy Management Scheme and Stochastic Model, respectively; hence, it clearly establishes the novelty and superiority of the proposed approach towards real-time microgrid bidding and energy management applications.

2. Literature Work

Numerous research works on Bidding Strategy for Interfaced Renewable Energy Management. Some of the recent works are reviewed in this section,

A. Aldosary et.al. [20] proposed a way to reduce dependability expenses in order to obtain the lowest total cost. Stated differently, V2G is used to reduce procedures. A new stochastic system applying the unscented transform is proposed to advance with high vagueness triggered by PV, PEV charging/discharging, and wind power.

H. Shen et al. [21] have demonstrated that linking consumers with a photovoltaic system equipped with a BES unit stabilizes power through ideal arrangement and bidding in DA and RT markets, depending on the Current Electricity Price (RTP). Moreover, this piece aims to boost LA's profits. Most articles model household loads and renewable generation using deterministic approaches.

A. Nikpour et.al. [22] have introduced the most effective stochastic bidding method in the combined Energy and AS market. Weibull is used to quantify the change in speed of wind and solar ambiguities, and also the probability of calling AS is determined for each conceivable AS. As a result, the bidding approach's risk is managed using CVaR.

R. Lee et al. [23] have approached modest bidding techniques, and inventory management limitations to challenge a linear optimal solution are formulated for both profit maximization and cost minimization situations. A decision maker must either buy a portion of an asset from the marketplace or from the production unit—a local record by fixed volume, in order to meet its time-changing needs in the minimization cases. The decision authority in the maximizing cases takes a time-changing stream of the asset. It may be engaged in inventory for future sale or sold to the market.

Y. Alidrissi et al. [24] have investigated an energy administrative plan for a microgrid that consists of a main DC load, a battery, and a solar module as the primary source. To enable the PV module to function in either MPPT or LPM mode, the planned MG incorporates a DC-to-DC boost converter. Additionally, the structure interfaces the battery with the DC bus by a DC-DC bidirectional converter.

L. Luo et al. [25] have illustrated that a PV, WT, FC, MT, and BESS are among the RES that make up this energy management scheme for a grid-interconnected microgrid. A new mathematical approach is projected for the photovoltaic unit functioning in a microgrid. This model evaluates how variable irradiances on different days and seasons affect the microgrid's day-ahead scheduling.

F.Wang et.al. [26] have addressed the best course of action for a Distributed Energy Resources (DER) aggregator that operates an RTP demand response program while controlling WT, PV systems, and BES units. By placing a bid on the electrical market and scheduling its DER to satisfy its clients' load demands, the DER aggregator can obtain electricity.

Although various works have been reported on energy management in microgrids and bidding strategy, the approaches developed so far still suffer from a unified, computationally efficient methodology that can concurrently handle renewable uncertainties, market volatility, and real-time decision-making. Most of the developed stochastic and deterministic models rely on heavy probabilistic analysis or complicated mathematical formulations, resulting in limited scalability and practical applicability. Likewise, many meta-heuristic and evolutionary algorithms face problems such as premature convergence, slow optimization speed, and unbalanced global search and local refinement. These shortcomings stress the need for an improved hybrid optimization strategy with better convergence speed, higher accuracy, and lower computational cost, thus motivating the development of the proposed DSGRWMO-BS model.

2.1. Problem Statement

Increased penetration of RES and participation of electric vehicles brings significant uncertainties in microgrid energy management and market bidding strategy. Various stochastic and deterministic models are used in the existing literature, which still cannot accurately represent the high variability of PV, wind, and consumer/EV behavior. These uncertainties tend to suboptimal arrangements by increasing the operational cost, dropping the income of aggregators and producers. Current bidding and energy management schemes also lack a unified framework that can address uncertainty, cost minimization, and profit maximization simultaneously. An improved, robust optimization-based energy management strategy is thus required that can provide reliable operation and enhanced economic performance in extreme conditions of uncertainty.

3. Methodology

Micro-grids are a capable technology that increases reliability and economics of energy supply to the end consumers. Micro-grid integrated renewable generating sources in a low-voltage network. A microgrid is a local energy system for producing and distributing Energy. A microgrid is a miniature power grid system that manages the dispersed energy properties with renewable and non-renewable Energy. Micro-grids are employed in future intellectual grids to permit the widespread application of renewable energy bases in an efficient and dependable way. Many researchers carried out their energy management using different optimization techniques. However, the existing energy management practices have been unsuccessful in diminishing the process cost and increasing energy administration precision.

To improve the performance, the Derived Self Generative Roulette Wheel Memetic Optimistic Bidding approach (DSGRWMO-BS) is presented. The key role of the DSGRWMO-BS system is to diminish the computational rate for price takers and also the customers with Micro-grid interfaced RES. DSGRWMO-BS Model uses the memetic optimization for performing the micro-grid energy management. Figure 1 shows the overall architectural diagram of the Derived Self Generative Roulette Wheel Memetic Optimization-based Bidding Strategy Model.

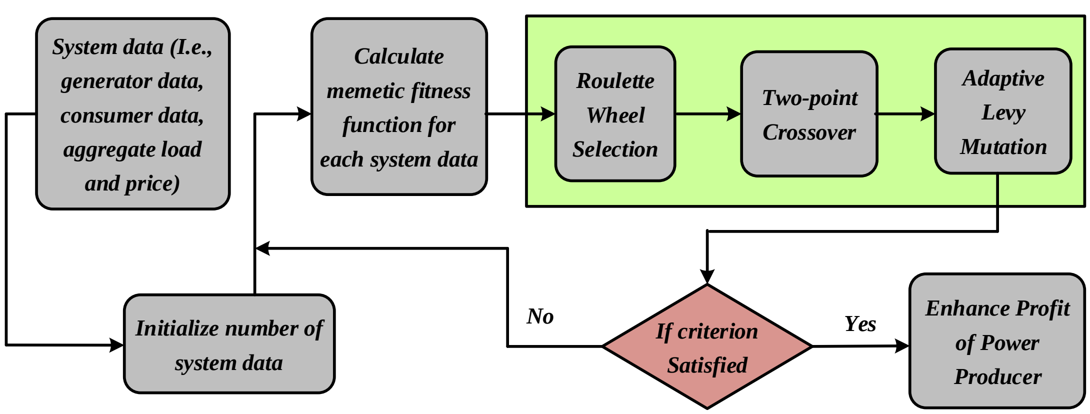

Fig. 1 Architecture diagram of DSGRWMO-BS model

Figure 1 explains the architecture diagram of the DSGRWMO-BS Model to identify an optimum solution with a Microgrid interconnected structure for increasing the revenue of power makers.

Initially, system data is considered as an input. After that, the memetic fitness function is determined for every system's data. Then, the DSGRWMO-BS system accomplishes the bio-inspired variables such as roulette selection, the two-point crossover process, and the adaptive lévy mutation process.

After that, it checks whether the conditions are fulfilled. The procedure is repeated until it reaches the correct state and finds the optimal system data. A brief explanation of the DSGRWMO-BS Model is provided in the upcoming sections.

3.1. Memetic Optimization Algorithm

In the DSGRWMO-BS Model, the Memetic Optimization Algorithm (MOA) is a stochastic global empirical search that combines the problem-specific identifier with evolutionary procedures. MA emulates the evolution process as a search heuristic.

The heuristic approach attains improved resolutions by solving the optimization issues. A memetic algorithm achieves solutions to optimization problems through a natural evolutionary process, such as inheritance, mutation, selection, and crossover.

Initially, the system data is arbitrarily created and considered as the initial population of n−bit chromosomes in the DSGRWMO-BS Model. Subsequently, the memetic fitness, selection, crossover, and mutation procedure is maintained to enhance the revenue of producers.

3.2. Initialization of Population

In the population loading stage, the population is arbitrarily generated with system data. In the DSGRWMO-BS Model, the generated system data are dispersed in a proper sequence between the lower and its upper limits. After that, appropriateness is computed for every system data point.

3.3. Memetic Fitness Calculation

The Memetic Fitness function is employed in the DSGRWMO-BS Model to allocate the fitness rate for every model to accomplish optimality. The memetic aptness value of each system data is determined with its reliable limitations (i.e., the increased output of the generators, low running cost, longer lifetime of energy storage structures, and lower environmental cost). The memetic fitness value of every individual is computed as,

$$MemeticFitness(MF) = Pminmaxmin_{max} \tag{1}$$

From (1), P_{max} symbolize generator maximum power output, OC_{min} denotes minimum operating price, EL_{max} symbolizes a lifetime of energy storage, and EC_{min} represents the minimum environmental cost.

3.4. Roulette Wheel Selection

After determining the fitness value, roulette wheel assortment is done by the DSGRWMO-BS Model in order to select every individual (i.e., system data) with a higher fitness rate. Consider a wheel to select the fittest individuals (i.e., those with the highest fitness) from the population. This wheel is split into 'S' no. of modules, where the 'S' is the number of system data in the population. Depending on the fitness value, each system statistic will be displayed on the roulette wheel during the selection process. Figure 2 deliberates the best individual.

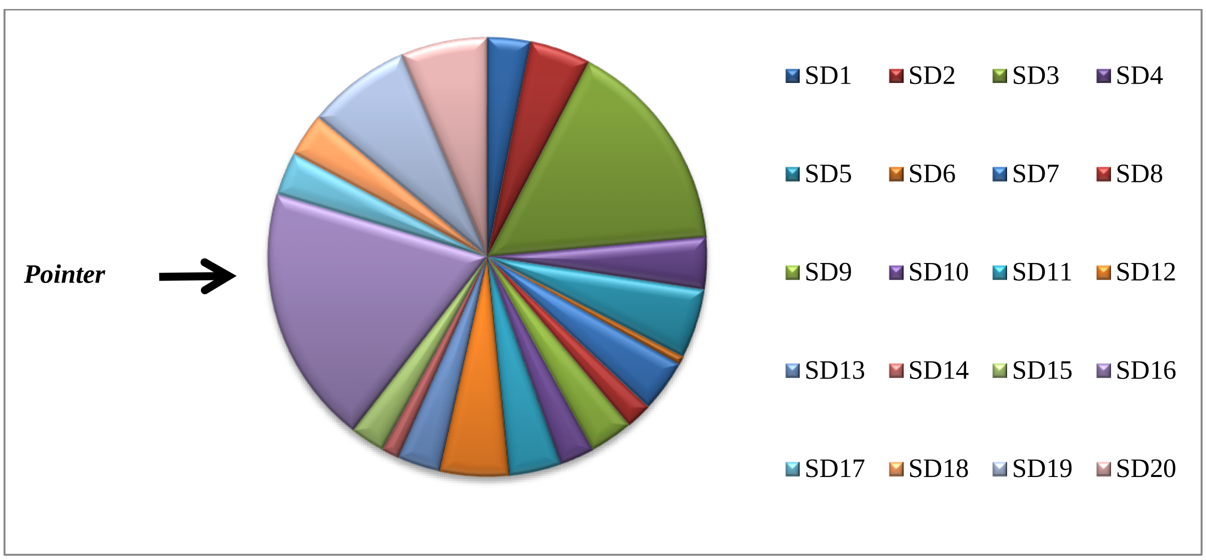

Fig. 2 Roulette wheel-based system data selection

Figure 2 explains that the individual (i.e., system data) selection is done by a roulette wheel using a wheel pointer. The various segments represent the suitable value for dissimilar system data. $(SD_1, SD_2, SD_3, \ldots, SD_{20})$. To identify the exact system data, the roulette wheel is moved. The system data identified by the pointer is taken, and it shows the maximum fitness value. The assortment of top individuals in the population is represented as,

$$RWS_P = \frac{MF_n}{\sum_{i=1}^{n} MF_i} \tag{2}$$

From (2), 'RWS_P denotes the roulette wheel selection probability, MF_i and represents the fitness of system data in the population i. n denotes the number of system data in the population. After that, the system data with higher fitness are selected for performing the crossover operation.

3.5. Two-Point Crossover

The new operator employed in the DSGRWMO-BS Model is a two-point crossover. Two-point crossover operators are employed to vary the chromosomes from one generation to the next. The crossover process has taken more than one parent chromosome and produced an offspring from them. Crossover is applied to two selected individuals (i.e., system data) along with probability. Two-point crossover is considered the two points chosen, depending on the parent individuals. Chromosome swapping provides the two offspring. Let us consider two selected system data for detecting the maximum relevance between them (i.e.SD_1, SD_2)$SD_1 = 1101000$ and$SD_2 = 1011110$. Each chromosome has a binary string value.

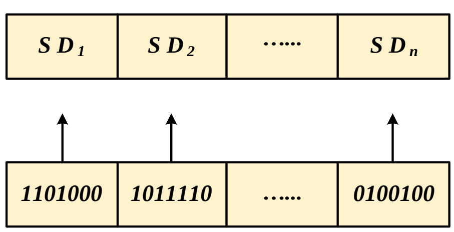

Fig. 3 Chromosome representations with selected system data

Figure 3 clearly explains the chromosome representation with chosen system data. From the figure, $SD_1, SD_2 \ldots SD_n$ The selected system data and the length are changed along with the size of the number of system data. However, the length of the chromosome is equal to the size of every chromosome. After the illustration, the crossover is performed between the two chromosomes to generate new offspring. Therefore, the crossover point is selected randomly among the chromosomes, as shown in Figure 4.

Figure 4 depicts a two-point crossover to alter the genes to attain the finest offspring to identify the best system data subclasses. A crossover is carried out in the DSGRWMO-BS Model. Depending upon the grouping of two chromosomes, an adapted one is generated. Crossover aids the study of feature space to identify data close to the optimum subsequent system data. A crossover operator on two chromosomes produces similar chromosomes when all of the population's individuals are equal. However, variety within the population is not produced by the two-point crossover mechanism. As a result, the Adaptive Lévy mutation operator is used to continue the assortment process.

Mutation is the procedure of random deviation carried out for a definite string. It is employed to save the genetic variety from one generation to the next. The proposed DSGRWMO-BS Model uses adaptive lévy mutation for arbitrarily interchanging the bits to attain enhanced outputs. The adaptive mutation operation randomly varies the worth of every bit of chromosomes in addition to the probability, which is called the mutation probability.

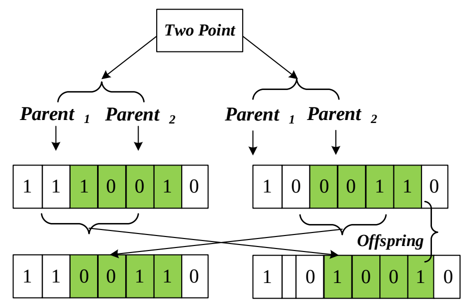

Fig. 4 Two-point crossover

3.6. Adaptive Lévy Mutation Operator

Mutation happens in the progression process, which depends on the probability function. The mutation probability is used to increase the probability that the memetic algorithm determines optimal system data under a simple hypothesis. The mutation operator considers the newly generated offspring from two-point crossovers and flips the bit '1' to '0' or '0' to '1' at a random position. In the DSGRWMO-BS Model, the Lévy Density Probability Density Function ($LDPDF$) is computed as,

$$LDPDF(x) = \frac{1}{\pi}\int_0^\infty e^{-\sigma q \rho}\, Cos(qx)\, dq \tag{3}$$

From (3), ρ it σ symbolizes the parameters categorizing the dispersal. A bit-flip mutation is shown in Figure 5.

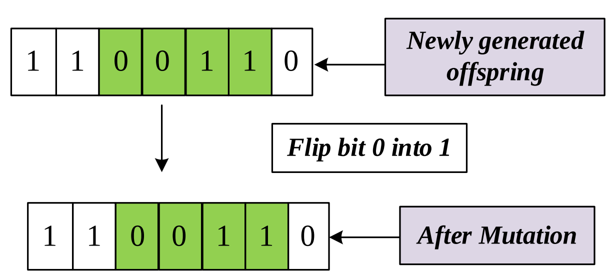

Fig. 5 Adaptive lévy mutation

Figure 5 depicts the procedure of lévy mutation to obtain the new resolution by arbitrarily varying the bit '0' into '1'. A new individual is chosen in place of the previously chosen one.

3.6.1. Condition for Termination

The termination condition is the DSGRWMO-BS Model's termination point. When the maximum number of epochs is reached, the memetic approach is terminated. By updating the population, Till the predetermined number of repetitions is reached, repeat the procedure.

The following procedure illustrates the algorithmic procedure of the Derived Self Generative Roulette Wheel Memetic Optimization led Bidding Policy.

Algorithm 1: Derived Self-Generative Roulette Wheel Memetic Optimization-based Bidding Strategy Algorithm

Derived Self Generative Roulette Wheel Memetic Optimization based Bidding Strategy Algorithm
Input: Number of system data.$SD_1, SD_2, SD_3, \dots., SD_{20}$'
Output: Identify the system data for increasing the profit of power manufacturers
Step 1: Start the procedure
Step 2: Set the initial amount of system data
Step 3: For every 'SD'
Step 4: Identify the memetic fitness 'MF'
Step 5: Place the Roulette Wheel Selection procedure
Step 6: Interchange the two entities to create the new offspring by the two-point crossover function
Step 7: Apply the mutation process by the Adaptive Lévy approach
Step 8: Change the old individual with a new one
Step 9: If the condition is satisfied, then go to the next step
Step 10: Choose the best switching angle
Step 11: If not
Step 12: Proceed to step 4
Step 13: Stop the process

Based on the DSGRWMO-BS Model, Algorithm 1 describes how to select the finest system data to increase power producers' profits. The amount of system data is first initialized. The fitness of the individual system data is then measured using the memetic fitness function. The best system data from the population is then identified by using a Roulette Wheel Selection Procedure based on the memetic fitness function.

To generate new offspring by a swapping procedure, two-point crossover is used. The input bit is flipped at an arbitrary point based on the adaptive lévy mutation. It can be concluded whether the prerequisite is met or not. Till the best system data is chosen to increase power producers' profits, the procedure is repeated. As a result, the optimization technique improves the performance of renewable Energy interconnected with the microgrid.

4. Simulation Settings

A preconfigured VPP with 60 PEVs, 5 PV models, and 5 MTs is considered. An improved IEEE-33 distribution system over 24 hours is considered in this simulation. The PJM market offers the power load data and the electricity market tariff. Ten scenarios are developed using annual data and probability distributions to account for uncertainty. These situations include loads, PV, energy market pricing, and other variables. The solar energy data is taken from the National Renewable Energy Laboratory.

The data considered in this simulation is taken from March 21, 2019, which is a typical day. With a maximum power of 5 kW, the electric vehicle's charging and discharging efficiency is fixed at 95%. The mounted dimensions of each MT are 50 kW, and the different running costs are 0.055, 0.065, 0.075, 0.085, and 0.095 \$/kWh, respectively. The power load's hourly amendment ranges from 0.9 to 1.1 times the original data. VPP has a supreme bidding capacity of 250 kW. Various parameters are used to evaluate the effectiveness of the DSGRWMO-BS Model.

- Accuracy of the Energy Management
- Cost of Running
- Solar Energy

5. Discussion About the Simulation Analysis and Findings

Three different metrics, ie, the energy management accuracy, operation cost, and solar Energy, are used to compare the suggested DSGRWMO-BS Model, energy management system, and stochastic model. Tables and graphs are used to describe the comparative investigations.

5.1. Outcome of Accurate Energy Management

The quantity of Energy that positively controls the bidding policy related to the total amount of Energy is known as energy management accuracy. The percentage (%) is used to measure it. The precision of Energy Management Accuracy (EMA) is computed by,

Table 1. Percentage of energy management accuracy

Time Spell in 24-hour format (hrs)	Energy Running accuracy (%)		
	Energy Running System	Stochastic Model	DSGRWMO-BS Model
2	90	92	96
4	91	93	95
6	89	91	93
8	88	90	91
10	81	85	89
12	78	82	87
14	75	80	86
16	73	77	84
18	70	74	82
20	74	76	91
22	78	80	95
24	82	85	97

$$EMA = \frac{Amountofenergycorrectlymanagedbiddingstratergy}{Totalamountofenergy} \quad (4)$$

Equation (4) computes the exact level of energy management. The exactness of the obtainable and current procedure is enlightened in Table 1.

The accuracy of energy management performance against time in an hourly setup, which varies from '2, 4, 6 ... 24', is given in Table 1. The precision of all the approaches, specifically the Energy Management System, the Stochastic Model, the existing model, and the proposed DSGRWMO-BS Model, is discussed in Table 1.

Assume that the DSGRWMO-BS Model achieves 91% of energy management accuracy at time instant "10,". In contrast, the energy management precision of the current Energy Management System and the Stochastic Models is 81% and 85%, respectively.

Likewise, the comparison with the precision of energy management investigation of the DSGRWMO-BS module with the two available methodologies. Graphical illustration of energy management precision is presented in picture 6.

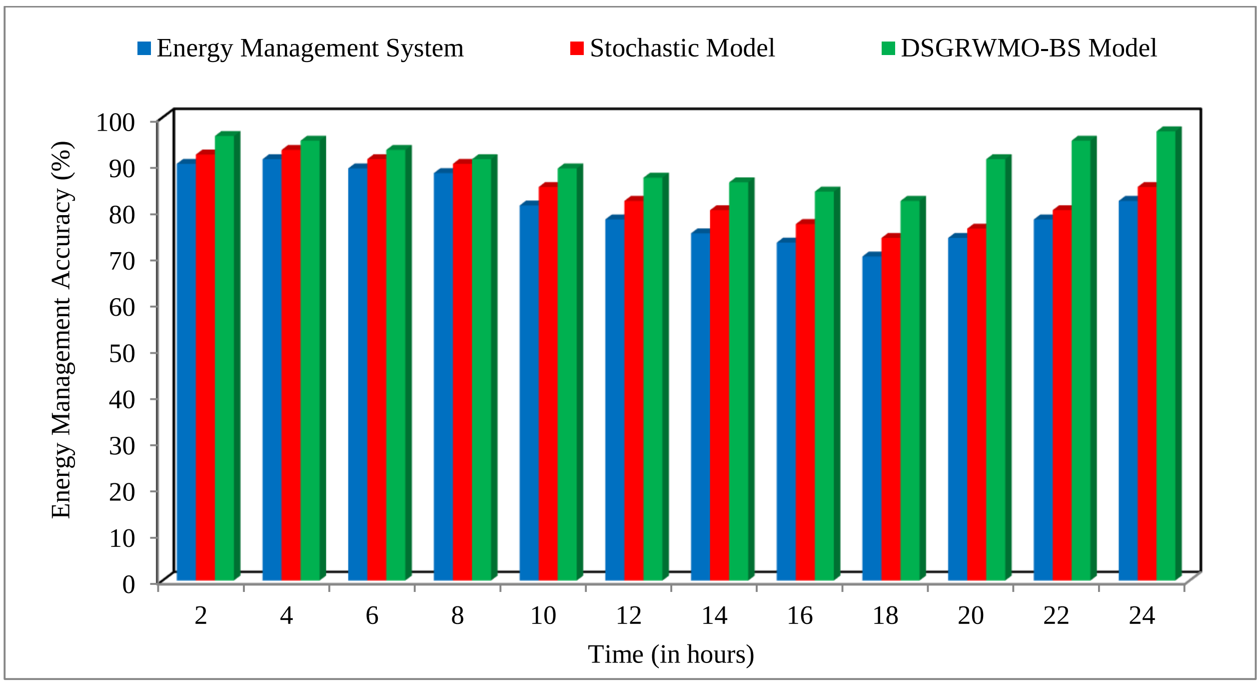

Fig. 6 Measurement of energy management accuracy

Figure 6 shows the analysis of energy management accuracy evaluation with three distinct approaches: the suggested DSGRWMO-BS Model, the existing Energy Management System, and the existing Stochastic Model. As indicated in Figure 6, the period in a 24-hr setup is considered for the 'x' axis, and in the 'y' direction, energy management accuracy solutions are presented. Blue and red colors represent the energy management accuracy study of the Energy Managing Scheme and the Stochastic Model; the green color represents the energy management accuracy of the DSGRWMO-BS Module. The complete Energy management precision of the new approach DSGRWMO-BS Model is substantially higher o compared with the preceding methods. This is because of the memetic optimization approach. A fitness function is established for the selection, crossover, and mutation processes, subsequently initializing the system data population. To determine the ideal system data for boosting power providers' profits, the DSGRWMO-

BS Module accomplishes the three above-discussed procedures. Consequently, this improves the exactness of energy management performance. Rendering the average of twelve evaluation findings from three distinct approaches, the DSGRWMO-BS Model accomplishes the Energy Management Scheme and the Stochastic Model of energy management accuracy by 13% and 8%, correspondingly.

5.2. Impact of Operation Cost

Energy management operation costs are typically calculated depending on the time used. It is the amount of time spent managing Energy during the bidding process. The unit of this dimension is Milliseconds (ms). The formulation for the operation costs is,

$$Operation\,Cos\,t = EndingTime - StratingofTimeofEnergyManagement \quad (5)$$

The operation cost is computed by the above Equation (5). The operating costs of the already discussed and the recent approaches are enlightened in Table 2. The 24-hour operation cost of energy management is displayed in Table 2. The solution illustrates the operation cost for various time instants. Out of the three methods, the DSGRWMO-BS Model uses bidding policies to achieve the lowest cost for energy management.

In Table 2, altogether ten different results are achieved for every strategy. The experiments are primarily conducted for the time instant “18.” The DSGRWMO-BS Model has an operating cost of 40 milliseconds, whereas the Energy Management Scheme and the Affinely Adaptable Strong Bidding Policy have operation costs of 53 and 49 milliseconds, respectively. The remaining runs are also completed with ten different outcomes. Figure 7 compares the DSGRWMO-BS model’s total operating costs with those of the other two available approaches.

Table 2. Operation cost indices

Time in 24-hour format (hours)	Operation Cost (ms)		
	Energy Management Scheme	Stochastic Model	DSGRWMO-BS Model
2	25	20	15
4	27	24	18
6	31	27	21
8	35	30	28
10	40	34	30
12	45	37	31
14	48	42	34
16	51	46	37
18	53	49	40
20	45	38	25
22	40	35	20
24	36	30	12

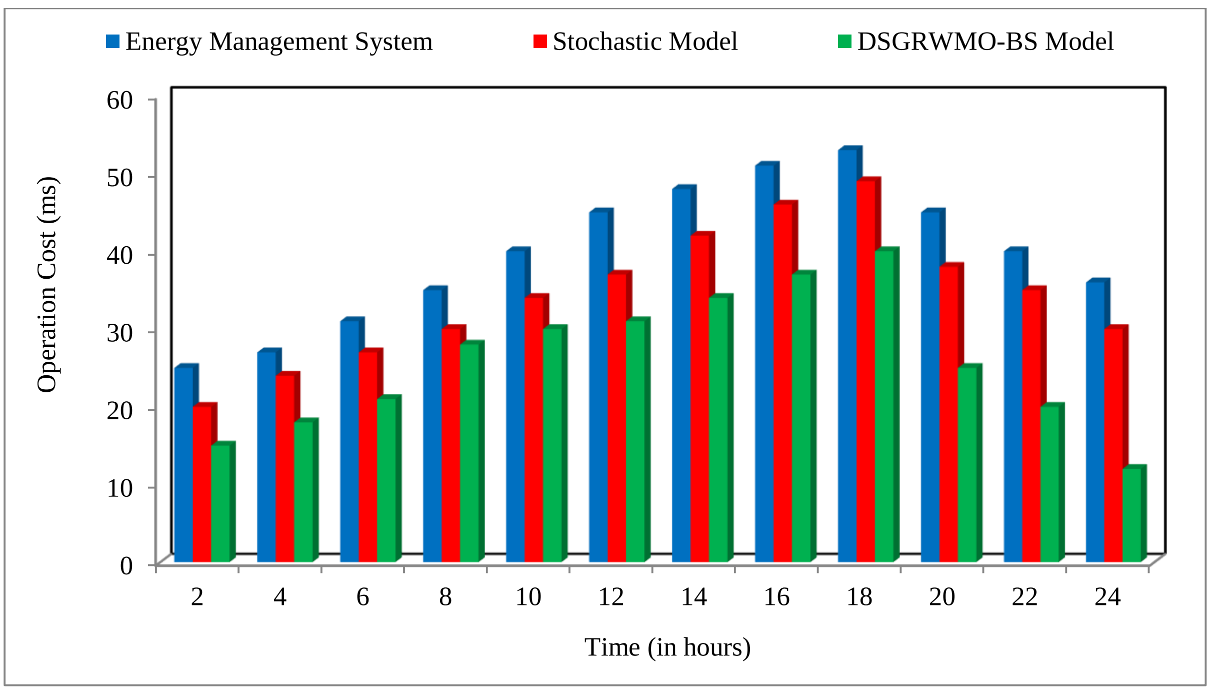

Fig. 7 Measurement of operation cost

Figure 7 depicts the analysis of the operating cost compared with the three distinct approaches: the suggested DSGRWMO-BS Model, the Energy Management Scheme, and the current Stochastic Model. Figure 7 illustrates that time in 24-hour format is entered into the "x" axis, and the results of operating costs are examined at the "y" axis. The DSGRWMO-BS Model's operation cost performances are indicated by the green color, followed by the Energy Management System and Stochastic Models, which are indicated by blue and red colors, respectively.

The complete operational cost solution of the projected DSGRWMO-BS Model is comparatively smaller than the other prevailing methods. This is because of the use of memetic optimization. The system data population is created, and a memetic fitness function is calculated to carry out the selection, crossover, and mutation operations. The above three processes are working to find the ideal system data to increase the profit of energy producers. In this way, the operation cost gets minimized. On average, twelve assessment solutions by means of three dissimilar approaches show that the DSGRWMO-BS model diminishes operation cost by 35% and 25% associated with the Energy Management System and Stochastic Model, respectively.

5.3. Impact of Solar Energy

The amount of Energy attained from a photovoltaic panel for a particular period of time is known as solar Energy. It is calculated in Kwh (Kilowatt-hour). The Energy is calculated as

$$SolarEnergy = EnergyObtained * Timeins\tan t \quad (6)$$

By Equation (6), solar Energy is computed. Table 3 describes solar Energy for the planned and prevailing methods.

Table 3. Tabulation of solar energy

Time in 24-hour format (hours)	Solar Energy (kWh)		
	Energy Management System	Stochastic Model	DSGRWMO-BS Model
2	3000	3300	3700
4	2800	3100	3550
6	2700	3000	3400
8	2800	3150	3700
10	3000	3300	3900
12	3100	3400	4200
14	3050	3200	4000
16	3200	3400	4200
18	3400	3500	4500
20	3500	3700	4600
22	3300	3600	4400
24	3500	3800	4700

Table 3 shows the analysis of solar Energy and the period of time on an hourly basis, which can vary from $2\ to\ 24$ hrs. Solar Energy of three approaches, the Energy Management System, the existing Stochastic Model, and the proposed DSGRWMO-BS Model are accomplished in Table 3 considering the instant of time '16'.

Solar Energy for the DSGRWMO-BS Module is achieved $4200\ kWh$ while the solar Energy for the two prevailing methods achieved $3200kWh$ and $3400kWh$. The graphical depiction of solar Energy is shown in Figure 8.

Performance outcomes of solar Energy with the assessment of all three distinct approaches, such as the existing Energy Management System, existing Stochastic Model, and proposed DSGRWMO-BS Module, are described in Figure 8. As shown in Figure 8, the solar energy outputs are displayed on the "y" axis, and the time in a 24-hour arrangement is considered the input on the "x" axis. The solar energy analysis of DSGRWMO-BS Module is indicated by green color. In contrast, the solar energy representation of the Energy Management Scheme and the Stochastic Model is represented by blue and red colors.

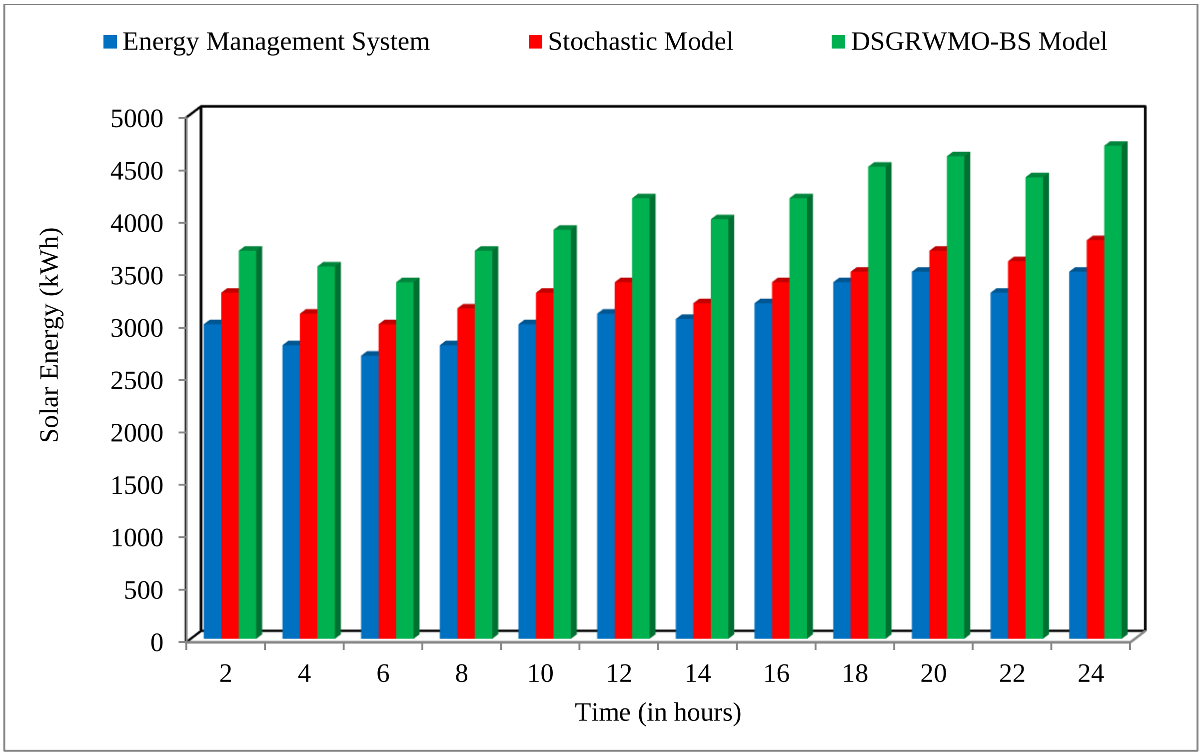

Fig. 8 Measurement of solar energy

On relating with the Energy Management Scheme and the Stochastic Model, the DSGRWMO-BS Module increases solar Energy by 31% and 21%, respectively, according to the average of twelve related solutions based on three distinct methodologies.

5.4. Discussion About the Simulation Performance and Findings

The projected DSGRWMO-BS module yields better results due to the proper balance between the global exploration and the local refinement of its hybrid memetic optimization structure. High-fitness bidding coefficients propagate through self-generative Roulette Wheel Selection, while two-point crossover accelerates convergence toward the optimal solutions. Furthermore, adaptive Lévy mutation injects controlled diversity into the approach, helping the algorithm to avoid premature convergence and subsequently tackle renewable uncertainty in a more proficient manner. Compared with other existing stochastic and deterministic methods, the proposed algorithmic approach will reduce the computation burden and enhance the convergence speed. These algorithmic advantages directly translate to enhanced accuracy in energy management, reduced operation cost, and enhanced solar-energy utilization against other pioneering approaches.

6. Conclusion

A novel model termed DSGRWMOBS is introduced to reduce the computational cost for price takers and customers. In the DSGRWMOBS Model, all collected data are considered as an initial population. DSGRWMOBS Model creates the initial random population of bidding coefficient rivals. The market-clearing prices are estimated using bidding coefficients. The fitness value of every population rate is determined depending on generation, demand, and the dispatch schedule that addresses the reliability constraints to achieve the maximum profit. After determining the fitness function, the DSGRWMOBS Model performs the selection, crossover, and mutation to achieve the optimal solution.

This, in turn, the DSGRWMOBS Model helps the Microgrid interconnected system at negligible computing cost. Simulation is carried out to determine the performance of the DSGRWMOBS Model over the two conventional bidding strategies oriented to three performance indicators, such as operation cost, energy management precision, and solar Energy. The results validate that the analysis of the DSGRWMOBS system attains enhanced outputs in terms of solar Energy with diminished operating overheads and the precision of energy management.

Declaration of Interests

Data Availability Statement

All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real-world data with appropriate permissions.

Author's Contributions

Author 1: Carried out methodology, implementation, and wrote the original manuscript.

Author 2: Given guidance, suggestions, reviewed, and edited the manuscript.

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