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Developing an Artificial Hummingbird Algorithm for Probabilistic Energy Management of Microgrids Considering Demand Response

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This study proposes an artificial hummingbird algorithm (AHA) for energy management (EM) for optimal operation of a microgrid (MG), including conventional sources and renewable energy sources (RES), with an incentive-based demand response (DR). Due to the stochastic nature of solar and wind output power and the uncertainty of prices and load, a probabilistic EM with hybrid AHA and point estimation method (PEM) is proposed to model this uncertainty by utilizing the normal and Weibull distribution functions. The PEM method is considered a good tool for handling stochastic EM problems. It achieves good results using the same procedures used with the deterministic problems while maintaining low computational efforts. The proposed AHA technique is employed to solve a deterministic incentive DR program, with the goal of reducing the overall cost, which includes the cost of conventional generator fuel and the cost of power transaction with the main grid while taking into account the load demand. Two different case studies are tested. The simulation results of the proposed AHA is compared with the results of well-known metaheuristic algorithms to demonstrate its efficacy. According to AHA's results, a total reduction of energy consumption by 104 KWh for the first case study and 2677 MWh for the second case study is achieved while achieving the lowest overall operating cost. The results demonstrate that the AHA is adequate for tackling the EM problem. Then, to examine the effect of uncertainty on the MG state, a probabilistic EM problem is solved using AHA-PEM.

Keywords: energy management, Microgrid, renewable energy sources, generation uncertainty, optimization, artificial hummingbird algorithm

1 INTRODUCTION

In recent years, the integration of productive subsystems or distributed generation (DG), which are called microgrids (MGs), into the main grid has played an essential role in resolving many energy-related problems (Shivam and Dahiya, 2018). MG can be connected to other MGs or the main grid, thereby exchanging energy between them or in a stand-alone configuration (Asano et al., 2007). For supplying power demanded in MGs, both conventional and different types of RES, such as solar

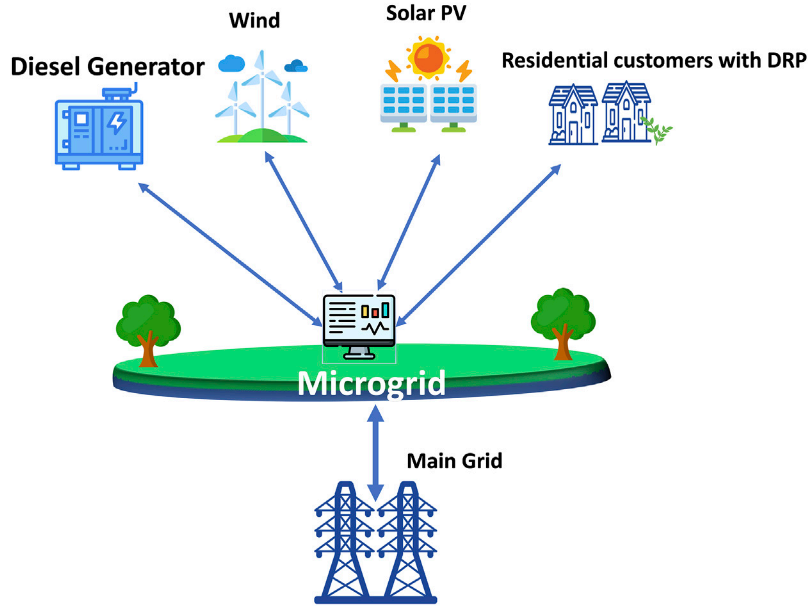

FIGURE 1 | Grid-connected MG structure with DR mode.

photovoltaic (PV), wind turbine (WT), biomass units, microturbine units, and energy storage systems (ESS) (Khalili et al., 2019), are used. MG energy management (EM) has received significant attention in research for the optimal operation of MGs. EM involves the maximization or minimization of one or more objective functions, such as maximizing profit or minimizing total cost. MG's optimal operation is essential for achieving effective EM at a low cost and maximum profit (Parisio et al., 2014).

A deterministic EM in MG is employed in (Aghajani and Ghadimi, 2018), in which the power generated from renewable sources, load profile, and market prices are considered. Many probabilistic EM approaches consider the uncertainties in renewable source generation, load demand, and energy prices (Tabatabaee et al., 2016, García Vera et al., 2019, Alavi et al., 2015). In (Arabali et al., 2013), the uncertainty of solar and wind generation, as well as the load demand, are considered. The EM problem is solved using GA optimization with the 2m point estimation method (PEM) in order to enhance the efficiency and reduce the total cost. In (Baziar and Kavousi-Fard, 2013), a probabilistic framework is modeled using the 2m PEM method, thereby considering uncertainties related to wind and solar power and market bid variations. A modified glowworm swarm optimization with PEM is proposed in (Ben Christopher and Carolin Mabel, 2020). Gravitational search algorithm (GSA) and 2m PEM are proposed in (Niknam et al., 2012a) to solve the EM problem of MGs involving the existing uncertainties in the MGs. Moreover, an improved bat algorithm is considered in (Li et al., 2014).

In (Nguyen et al., 2020) an improved stochastic fractal search algorithm is proposed to solve a multiobjective problem, get lower generation fuel cost, reduce power losses and emission, and enhance the voltage profile, with a faster execution. A new approach for reducing the power loss is proposed in (Nguyen et al., 2021), in which different optimization algorithms, such as particle swarm optimization (PSO), PPA, and TSA, are used.

Meanwhile, 2m + 1 PEM is used to solve the probabilistic EM of MG (Alavi et al., 2015, Mohammadi et al., 2013, Li et al., 2014); in (Alavi et al., 2015), PSO technique is used to reduce the total operating cost and enhance reliability. (Mohammadi et al., 2013) used 2m + 1 PEM with an adaptive modified firefly optimization algorithm while considering the uncertainties.

DR may be considered a tariff that motivates the customers to change their consumption as a response to the change in electricity price over time or to reduce the usage of electricity in response to incentive payments once the price of electricity in the market is high or in the case of grid reliability issues (Aalami et al., 2010).

DR is divided into two types: first, price-based DR (PDR), in which consumers' electricity prices are altered at varying periods. For example, high prices during peak hours, medium prices during off-peak hours, and low prices during low-peak hours. Second, incentive-based DR (IDR), in which consumers receive incentive awards for changing their consumption (Jordehi, 2019).

In (Aghaei and Alizadeh, 2013), utilizing a hybrid augmented weighted-constraint approach and lexicographic optimization, DR and optimal power flow in a combined heat and power (CHP) system were presented in a MG with an energy storage system. In (Majidi et al., 2017), a multiobjective optimization problem is described for using the DRP to reduce the emissions and cost of a hybrid system. PSO technique was used in (Faria et al., 2013) to manage MG resources and DR in order to reduce the MG operator's operating costs. Despite the previous studies, further study is needed to apply the DRP to power system issues to include customers and reduce MG fuel prices.

According to the studies mentioned above, several optimization techniques have been efficient in solving engineering challenges, particularly those incorporating EM. These research established the importance of applying new and improved optimization techniques for solving particular EM problems; moreover, according to Wolpert's (1997) No-Free-Lunch theorem, there are no metaheuristic optimization algorithms capable of addressing all optimization problems. These two considerations inspired us to apply a newly developed optimization technique, artificial hummingbird algorithm (AHA), to solve the EM problem in MGs.

To the best of the authors' knowledge, no similar study has been conducted. The uncertainties of load, market pricing, and PV and WT output power in grid-connected MG while considering DR and using AHA to solve the EM are investigated in this study. **Table 1** illustrates a comparative analysis of the relevant literature in terms optimization technique, uncertainty modeling and contribution.

The objective of this study is to use a newly developed optimization technique, AHA, to solve the EM problem for a MG with an incentive DR program. The proposed EM algorithm is compared to those achieved by other well-known algorithms to demonstrate its robustness. Also, a probabilistic EM using hybrid AHA-PEM to consider the uncertainties of renewable sources, load demand, and market prices is proposed. The main contributions of this study, however, may be stated as follows:

1- Proposing a new application for a recent optimization technique, AHA, for solving the EM problem of a MG while considering DR.
2- Studying two different scenarios; the first is deterministic EM with two different case studies. The first MG consists of one wind generator, one solar PV generator, three conventional generation units (diesel), and three residential customers with DRP, while the second one consists of an aggregated model for solar PV and wind, ten conventional generation units, and seven customers. The second scenario is used for probabilistic EM.
3- Considering the probabilistic nature of the market pricing, load, and produced power of the PV and WT generators and modeling a stochastic energy cost function.

The rest of this paper is organized as follows: **Section 2** presents the mathematical model for the MG with the DR model. **Section 3** presents the modeling for the EM optimization problem. The uncertainty modeling is discussed in **Section 4**. **Section 5** focuses on the recent optimization technique, AHA. **Section 6** presents the simulation results obtained. Finally, the paper is concluded in **Section 7**.

2 MATHEMATICAL MODEL FOR GRID-CONNECTED MICROGRID

The structure of MG connected to the grid for this paper is shown in **Figure 1**. This MG comprises conventional generation sources, renewable generation sources (PV power generator and WT generator), and customers with DR model.

2.1 Grid-Connected Microgrid Model

In this work, the MG is connected to the main grid, and a power transaction is assumed to be bought or sold to the main grid. In the case of surplus (more than the demand) in generation from MG, power will be sold to the main grid, and vice versa.

If P_{r_t} is the amount of power transaction MG and main grid at a time t; locational marginal prices are used (given as γ_t) (Nwulu and Fahrioglu, 2013) for purchasing power between main and MG. Therefore, the cost of power transactions ($C_r(P_{r_t})$) can be obtained as:

$$C_r(P_{r_t}) = \left\{ \begin{array}{cc} \gamma_t \times |P_{r_t}| & P_{r_t} > 0 \\ 0 & P_{r_t} = 0 \\ -\gamma_t \times |P_{r_t}| & P_{r_t} < 0 \end{array} \right\} \tag{1}$$

2.2 Modeling of DR

Let $C(\theta, x)$ be the cost customer incurred; where θ is customer type and x is the amount of consumption reduction in (KW or MW); thus, the benefit for the customer can be calculated as:

$$F_1(\theta, y, x) = y - C(\theta, x) \tag{2}$$

Equation 2 illustrates that the customer will participate in the DR program and reduce his consumption only in the case of $F_1 \geq 0$, with y representing the total incentive that customers will receive for consumption reduction.

Also, MG benefit can be expressed as:

$$F_2(\theta, \lambda, x) = \lambda x - y \tag{3}$$

where λ is the cost of power interruption from a particular customer. Power interruptibility can be calculated using optimal power flow analysis (Fahrioglu and Alvarado, 2000).

2.3 Customer Cost Function

The formulation for the customer's cost function ($C(\theta, x)$) can be expressed mathematically as:

$$C(\theta, x) = k_1 x^2 + k_2 x(1 - \theta) \tag{4}$$

where:

- $\boldsymbol{\theta}$ is the customer willing: its value varies between 0 and 1 so that the customer who has the most willing g has this value as 1 and the lower willing customer has a value of 0.
- k_1 and k_2 are cost coefficients.

Customers' contract formulation is computed as in (Fahrioglu and Alvarado, 2000); thus, if y_j is the payment for customer (j) payment, the benefit for the customer can be expressed as:

$$U_j = y_j - \left(k_1 x_j^2 + k_2 x_j (1 - \theta)\right), \text{for j} = 1, 2, \ldots\ldots, \text{J} \tag{5}$$

Moreover, MG benefit is calculated as:

$$U_0 = \sum_{j=1}^{J} \lambda_j x_j - y_j \quad (6)$$

3 FORMULATION OF THE EM PROBLEM

As previously mentioned, the grid-connected MG consists of different generation sources, conventional generators and RESs, and loads with a DR program. The operating cost consists of two components, conventional generation cost and power transaction cost. The main objective of MG management system is to optimize the operation of MG resources by lowering the generation cost and increasing the MG benefit while marinating customers' benefit and satisfying the operational constraints.

3.1 The Operating Cost Function

For EM in grid-connected MG, one of the objectives in the studied optimization procedure is the minimization of conventional generators' fuel cost and the transferred power's cost between the main grid and MG, and it is given as:

$$\min f_1(x) = min \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(P_{i_t}) + \sum_{t=1}^{T} C_r(P_{r_t}) \quad (7)$$

The fuel cost for conventional generators ($C_i(P_{i_t})$) is represented by a quadratic model as follows:

$$C_i(P_{i_t}) = a_i p_{i_t}^2 + b_i P_{i_t} \quad (8)$$

where a_i and b_i are the fuel cost coefficients for any conventional generator i.

3.2 MG Benefit Function

The objective of maximizing the expected MG benefits can be formulated as follows:

$$\max f_2(x) = max \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_j x_j - y_j \quad (9)$$

Equation 9 indicates that the MG operator can benefit if he selects not to supply specific customers with power or pay incentive payments.

3.3 Constraints of Generation Sources

At any period t, the total power generated from conventional generation and RESs units and power transacted between the MG and main grid must supply total load demand with the DR program. In this paper, the active power losses in the MG are ignored. Hence, the power balance equation's constraints can be expressed as:

$$\sum_{i=1}^{I} P_{i_t} + P_{w_t} + P_{s_t} + P_{r_t} = D_t - \sum_{j=1}^{J} x_{j,t} \quad (10)$$

$$P_{i_{min}} \le P_{i_t} \le P_{i_{max}} \quad (11)$$

$$-DR_i \le P_{i_{t+1}} - P_{i_t} \le UR_i \quad (12)$$

$$0 \le P_{s_t} \le P_{st_{max}} \quad (13)$$

$$0 \le P_{w_t} \le P_{wt_{max}} \quad (14)$$

$$-P_{r_{max}} \le P_{r_t} \le P_{r_{max}} \quad (15)$$

where

D_t (MW) is the total power demand at any time t.
$x_{j,t}$ is the customer (j) curtailed power at time t.
$P_{i_{min}}$ and $P_{i_{max}}$ are the minimum and maximum generation limits of a generator i, respectively.
P_{s_t} is the hourly output power from the solar PV generator.
$P_{st_{max}}$ is the maximum forecasted PV power at a time i.
P_{w_t} is the hourly wind power at a time t.
$P_{wt_{max}}$ is the maximum forecasted wind generator power at a time t.
$P_{r_{max}}$ is the maximum permissible transacted power between the MG and the main grid.
UR_i and DR_i are the maximum ramp up and ramp down rates for a generator i, respectively.

I and T are the total number of conventional generators and dispatch interval, respectively.

Constraint in **Eq. 10** describes the power balance to ensure that the total production and grid transacted power at any time t will equal the total demand. While **Eq. 11** ensures that any conventional generation's generation does not exceed its upper and lower limits, the constraint (**Eq. 12**) do not violate the ramp up and down rates for generators.

The constraints for maximum and minimum generation of solar and WT generators are represented in **Eqs 13** and **14**, respectively. **Eq. 15** represents the transacted power constraint, which limits the power transacted between the MG and the utility grid to not exceed the maximum limit $P_{r_{max}}$.

3.4 DR Constraints

$$\sum_{t=1}^{T} y_{j,t} - \left(k_1 x_{j,t}^2 + k_2 x_{j,t} - k_2 x_{j,t} \theta\right) \ge 0 \quad (16)$$

$$\sum_{t=1}^{T} y_{j,t} - \left(k_1 x_{j,t}^2 + k_2 x_{j,t} - k_2 x_{j,t} \theta\right) \ge \sum_{t=1}^{T} y_{j-1,t} - \left(k_1 x_{j-1,t}^2 + k_2 x_{j-1,t} - k_2 x_{j-1,t} \theta\right)$$
$$\text{For } j = 2, 3, \ldots\ldots, J \quad (17)$$

$$\sum_{t=1}^{T} \sum_{j=1}^{J} y_{j,t} \le UB \quad (18)$$

$$\sum_{t=1}^{J} x_{j,t} \le CM_j \quad (19)$$

where the upper limit for the MG budget limit is UB and the maximum daily power curtailment for customer j is CM_j.

The demand management contract formulations in **Eq. 5** are expanded to cover the entire 24 h-period (1 day) rather than just 1 h, making them more practical and cost effective. The constraint in **Eq. 16** ensures that the client receives a total incentive for any power curtailed that is more than the cost of interruption. In addition, if the client increases his or her curtailment (constraint in **Eq. 17**), the customer should receive a higher incentive. Constraint (**Eq. 18**) describes the total MG budget limit constraint, thereby ensuring that the daily budget is less than the maximum. **Eq. 19** ensures that any client's total curtailment is within the allowable limits.

The mathematical model of the objective function is given as:

$$\min w\left[\sum_{t=1}^{T}\sum_{i=1}^{I}C_i\left(P_{i_t}\right)+\sum_{t=1}^{T}C_r\left(P_{r_t}\right)\quad\right]+(1-w)\left[\sum_{t=1}^{T}\sum_{i=1}^{I}y_j-\lambda_j x_j\right] \tag{20}$$

4 UNCERTAINTY MODELING

This study presents a mathematical model for the MG EM that can deal with PV power, wind power generation, load consumption, and market price uncertainty. The chance of a discrepancy between the expected and actual components is defined as uncertainty. The operational cost of MG is substantially influenced by errors produced by the lack of uncertainty. As a result, km + 1 PEM is combined with AHA in this work to enhance MG EM on an uncertainty framework.

4.1 Probabilistic EM of the Micro Grid

In the presence of input variables, with random nature or uncertainty, the EM problem becomes probabilistic instead of deterministic. Because of the random nature of solar irradiance and wind speed, the output power from solar PV and WT generators are also random variables. Furthermore, load demand will not be exactly the same as the forecasted load due to forecasting errors, unexpected disturbances, load variations, or energy prices (Niknam et al., 2012a, Soroudi and Ehsan, 2011). Every probabilistic formulation requires statistical characterization of the random input variables and a method for evaluating statistical features of the output variables.

4.1.1 Statistical Characterization of the Input Random Variables (IRVs)

- Wind power

The power output and wind speed can be calculated as:

$$P_w=\begin{cases}0 & v\le v_{ci}\ and\ v\ge v_{co}\\ \dfrac{v^2-v_{ci}^2}{v_{nom}^2-v_{ci}^2}\cdot P_{nom} & v_{ci}\le v\le v_{nom}\\ P_{nom} & v_{nom}<v\le v_{co}\end{cases} \tag{21}$$

where P_{nom} is the rated power of WT, v_{nom} is the rated wind speed, v_{ci} is the cut-in wind speed, and v_{co} is the cutout wind speed, with P_w and v denoting the output power and the wind speed, respectively.

The power curve of WT is represented by the quadratic model (**Eq. 21**); thus, the quadratic approximation will be used to obtain the power probability density function (PDF) (Villanueva et al., 2011). Weibull distribution can be used to express the wind speed's PDF at a certain location, such as what has been expressed in **Eq. 22**:

$$f_v(v)=\begin{cases}0, & v<0\\ \dfrac{k}{C}\cdot\left(\dfrac{v}{C}\right)^{k-1}\cdot e^{\left(\frac{v}{C}\right)^k}, & v\ge 0\end{cases} \tag{22}$$

and cumulative density function (CDF) is given as:

$$F_v(v)=\begin{cases}0, & v<0\\ 1-e^{-\left(\frac{v}{C}\right)^k}, & v\ge 0\end{cases} \tag{23}$$

CDF and its inverse are utilized for computing the wind speed as following:

$$v=C\cdot(-\ln(r))^{1/k} \tag{24}$$

where C and k are the scale and shape parameters of the Weibull distribution, respectively and r is a uniformly distributed random number between 0 and 1. Different methods can be used for calculating C and K parameters (Atwa et al., 2011, Jangamshetti and Rau, 1999). Here, the parameters are approximately calculated using the mean wind v_m speed and the standard deviation (STD) σ as follows (Atwa et al., 2011):

$$k=\left(\frac{\sigma}{v_m}\right)^{-1.086} \tag{25}$$

$$C=\frac{v_m}{\Gamma\left(1+{}^{1}\!/_{k}\right)} \tag{26}$$

where gamma function ($\Gamma\ (x)$) can be defined as in **Eq. 27**:

$$\Gamma\ (x)=\int_0^\infty t^{x-1}\cdot e^{-t}dt \text{ for } x>0 \tag{27}$$

- Solar power

The output power of solar PV depends on the ambient temperature, solar irradiation, and characteristics of the module. The solar PV output power can be expressed as:

$$P_s=P_{STC}\frac{I}{1000}\left[1+\gamma(T-25)\right] \tag{28}$$

where I is the solar irradiation (w/m^2), T is the PV module temperature (°C), γ is the module temperature coefficient (°C $^{-1}$), and P_{STC} is the PV module maximum output power at slandered test conditions (I = 1000 w/m^2 and T = 25°C).

The PV module temperature can be calculated based on the module's nominal operating cell temperature (T_{NOCT} (°C)) as (Radosavljević et al., 2016):

$$T=T_a+\frac{I}{800}\left[T_{NOCT}-20\right] \tag{29}$$

where T_a is the ambient temperature.

In this paper, solar irradiance is suggested to have a normal distribution function. As a result, the PDF of any variable z_i can be expressed as:

$$f_{z_i}(z_i) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-(z_i-\mu)^2/2\sigma^2} \tag{30}$$

Normal distribution CDF can be formulated as:

$$F_{z_i}(z_i) = \frac{1}{2}\left[1 + erf\left(\frac{z_i - \mu}{\sqrt{2}\sigma}\right)\right] \tag{31}$$

CDF and its inverse are used for determining the variable z_i as follows:

$$z_i = \mu + \sqrt{2}\sigma \cdot erf^{-1}(2r - 1) \tag{32}$$

where r is a uniformly distributed random variable in the range [0,1], μ is the mean value for the variable z_i, σ is the variable STD, and erf and erf^{-1} are the error function and its inverse, respectively, which can be calculated as:

$$\mathrm{erf}(z) = \frac{2}{\sqrt{\pi}}\int_0^z e^{-t^2}dt \tag{33}$$

$$\mathrm{erf}^{-1}(z) = 1 - \mathrm{erf}(z) \tag{34}$$

In technical literature, there are many probabilistic approaches that deal with the uncertainties in renewable energy sources, load demand, and market prices for solving the EM problem. These approaches may be classified into three main categories (Morales and Perez-Ruiz, 2007): Monte Carlo simulation, analytical methods, and approximate methods.

Monte Carlo simulation (MCS) deals with uncertainties by generating random values for the variables. These values help solve the problem as a deterministic problem (Rubinstein and Kroese, 2016). However, MCS uses a deterministic routine to solve the problem in each simulation; its main drawback is that it requires a large number of simulations to attain convergence.

Analytical methods are more effective, but they are based on certain mathematical assumptions that simplify the problem to analyze the statistical characteristics of random output function y based on the statistical characteristics of random input variables p (Pei and Lee, 2004, Niknam et al., 2012b), and they do not yield optimal and accurate results (Ben Christopher and Carolin Mabel, 2020).

Approximate methods provide an approximate description of the statistical properties of output random variables. PEM is one of the approximation approaches. PEM uses a deterministic strategy to solve probabilistic problems, similar to MCS, but it has a much lower number of simulations than MCS. In addition, PEM has led to great reduction in calculation efforts in comparison with the MCS method.

It uses a deterministic strategy to solve a probabilistic issue, similar to MCS, but PEM has a significantly lower number of simulations than MCS.

PEM firstly was developed by Rosenblueth (1975), which was then modified in 1981 (Rosenblueth, 1981). However, this and similar approaches (Wang et al., Seo and Kwak, 2002) give more accurate estimates. The number of simulations required may be very large in a system with high random variables. Hong (1998) proposed PEM, where the number of required simulations grows linearly with the number of random or uncertain variables.

4.2 Point Estimation Method

The PEM approximation method is a scheme to linearize output variables with respect to IRVs. The basic idea of PEM is to compute the moments of a function y, a function of IRV (m), i.e., $y = F(p_1, p_2, \ldots, and\ p_m)$, and use the forecasted information of these variables to concentrate its first few central moments of the statistical information on $K = 2, 3, \ldots$, and 5 points for each variable. By using these points statistical moments of output function y, statistical information on y can be approximated. To obtain the central moments, function y should be evaluated based on the adopted scheme number of times equal to 2 m, 2 m + 1, and 4 m + 1.

- 2m + 1 PEM scheme

Generally, in this scheme, three concentration points are used for each IRV. One of them is the mean value. The standard locations are:

$$\xi_{t,k} = \frac{\lambda_{t,3}}{2} + (-1)^{3-k} \cdot \sqrt{\lambda_{t,4} - \frac{3}{4}\lambda_{t,3}^2} \quad k = 1, 2\ and\ \xi_{t,3} = 0 \tag{35}$$

where $\lambda_{t,3}$ and $\lambda_{t,4}$ denote the third and fourth standard central moments and they are the skewness and kurtosis, respectively, of the input random variable p_t.

Variable locations are:

$$p_{t,k} = \mu_{p_t} + \frac{\lambda_{t,3}}{2} + \xi_{t,k} \cdot \sigma_{p_t} \quad k = 1, 2, 3 \tag{36}$$

and weights are:

$$w_{t,k} = \frac{(-1)^{3-k}}{\xi_{t,k}(\xi_{t,1} - \xi_{t,2})} \quad k = 1, 2 \tag{37}$$

$$w_{i,3} = \frac{1}{m} - \frac{1}{\lambda_{t,4} - \lambda_{t,3}^2} \tag{38}$$

It is noted from (**Eq. 36**) that setting $\xi_{t,3} = 0$ yields $p_{t,k} = \mu_{p_t}$; thus, the third location of all IRV will be the same as $(\mu_{p_1}, \mu_{p_2}, \ldots, \mu_{p_t}, \ldots, \mu_{p_m})$. Hence, it is enough to evaluate the function F only once for this location, and the corresponding weight will be:

$$w_0 = 1 - \sum_{t=1}^{m}\frac{1}{\lambda_{t,4} - \lambda_{t,3}^2} \tag{39}$$

The moments' vector of output random variables are estimated as:

$$E(Y^j) = E(Y^j) + \sum_{i=1}^{2} w_{i,t} \cdot [F(P_i)]^j \tag{40}$$

After knowing these statistical moments of the output function, STD and mean can be obtained as:

$$\sigma_Y = \sqrt{E(Y^2) - \mu_Y^2} \tag{41}$$

$$\mu_Y = E(Y) \tag{42}$$

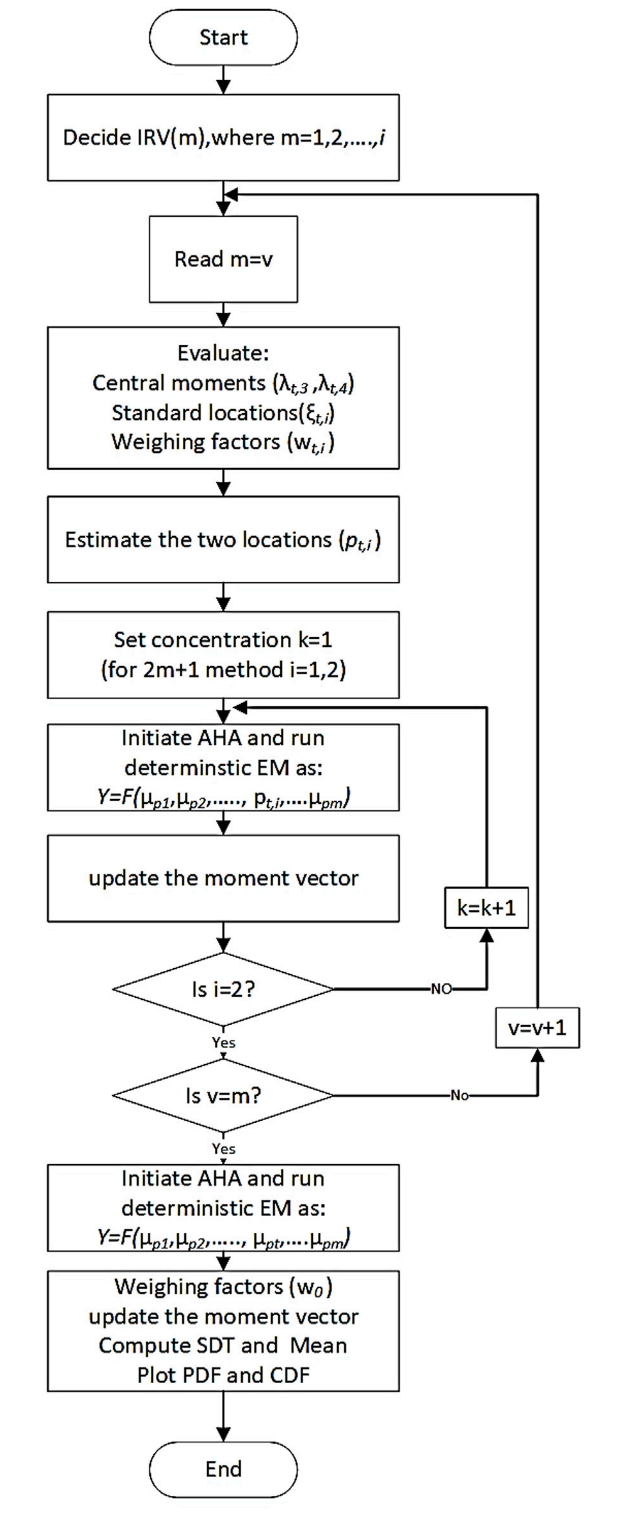

FIGURE 2 | Flow chart of proposed PEM-AHA.

Using the values of σ_Y and μ_Y, the Gram–Charlier series technique can be used to estimate the PDFs of the output random variables of interest based on statistical moments (Radosavljevic, 2018).

5 OPTIMIZATION ALGORITHMS

5.1 Description

This algorithm, AHA, is one of the bioinspired optimization techniques, which are better at balancing exploration and exploitation in the search for global optimum (Boussaïd et al., 2013). Recently, bioinspired algorithms have received the greatest traction (Darwish, 2018). Those algorithms transfer the biological activities of living organism algorithms into mathematical models, such as PSO, ant colony optimization, artificial bee colony, and cuckoo search, in an optimized manner. AHA was proposed in 2021 in (Zhao et al., 2022), although AHA belongs to the metaheuristics categories. It is pretty distinct from the previously developed bioinspired algorithms. The major difference is AHA's particular biology background. This algorithm is inspired by hummingbirds' unique flying abilities and sophisticated foraging techniques. AHA replicates three flying patterns: axial, omnidirectional, and diagonal, as well as three foraging strategies: guided, territorial, and migratory foraging search strategies. Additionally, for selecting the food source, the hummingbird's memory function is implemented as a visit table.

5.2 Mathematical Model for the AHA

5.2.1 Initialization

In first step, the population of N hummingbirds are initialized to be placed at N food sources as:

$$x_i = Lb + r_1\,(Ub - Lb) \quad i = 1, 2, \ldots\ldots, N \tag{43}$$

where X_i is the i^{th} food sources position (or solution) for the hummingbird; Lb and Ub are the lower and upper boundaries for the variables in search domain, respectively; and r_1 is a random vector between 0 and 1.

The visit table, which mimics the memory for hummingbirds, is initialized as:

$$VT_{i,j} = \begin{cases} 0 & if\ i \neq j \\ null & i = j \end{cases} i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, N \tag{44}$$

The visit table at i = j is set to null, which means that this hummingbird is taking its food from its food source, and it is zero ($VT_{i,j} = 0$) to indicate that in the current iteration, the ith hummingbirds visit the jth food source.

5.1.2 Foraging

In AHA, there are mainly two strategies for foraging, guided foraging and territorial foraging. Guided foraging involves visiting food sources with the highest refilling nectar rate, thereby choosing it to be the target food source, and then trying to fly toward its target. In territorial foraging, after eating from the target food source, hummingbirds try to find a different food source. Therefore, it attempts to go to a nearby location in the hope of discovering a new food source which is superior to the existing one.

During foraging, a direction vector is used to model the three flights patterns. The patterns for those flights in a d-D space, in which a diagonal flight is defined as following:

TABLE 1 | A summary of the relevant literature.

References	Formulation	Uncertainty modelling	Modeling approach	DR	Renewable PV and wind	Objective function
(Aghajani and Ghadimi, 2018)	PSO	No	-	NO	yes	Multi
(Arabali et al., 2013),	GA optimization	Yes	2m PEM	No	Yes	Multi
(Baziar and Kavousi-Fard, 2013),	Modified PSO	Yes	2m PEM	No	Yes	single
(Ben Christopher and Carolin Mabel, 2020)	modified glowworm swarm optimization (MOGSO)	Yes	2m and 2m + 1 PEM	No	Yes	Single
(Niknam et al., 2012a)	Gravitational search algorithm (GSA)	Yes	2m PEM	No	Yes	Multi
(Alavi et al., 2015)	PSO	Yes	2m + 1 PEM	No	Yes	single
(Mohammadi et al., 2013)	an adaptive modified firefly optimizations	Yes	2m + 1 PEM	No	Yes	single
(Li et al., 2014)	an improved bat algorithm	Yes	2m PEM	No	Yes	Single
(Aghaei and Alizadeh, 2013)	lexicographic optimization	No	-	Yes	No	Multi
(Majidi et al., 2017)	PSO	No	-	Yes	PV only	Multi
(Faria et al., 2013)	PSO	No	-	Yes	Yes	Multi
Proposed	AHA	Yes	2m + 1 PEM	Yes	Yes	Multi

TABLE 2 | Conventional generators and customers data (case study 1).

i,j	**Conventional generators**						**Customer**			
	a_i($/kW^{2}h)	**b_i($/KW h)**	**$P_{i,min}$ (KW)**	**$P_{i,max}$(KW)**	**DR_i (KW/h)**	**UR_i (KW/h)**	θ	**$K_{1,j}$**	**$K_{2,j}$**	***CM_j* (KW)**
1	0.06	0.5	0	4	3	3	0	1.079	1.32	30
2	0.03	0.25	0	6	5	5	0.45	1.378	1.36	35
3	0.04	0.3	0	9	8	8	0.9	1.847	1.64	40

TABLE 3 | $\lambda_{i,t}$ values and total initial hourly demand (case study 1).

Time (h)	λi_t($)	Total demand(KW)
t = 1	1.57	31.83
t = 2	1.4	31.4
t = 3	2.2	31.17
t = 4	3.76	31
t = 5	4.5	31.17
t = 6	4.7	32.1
t = 7	5.04	32.97
t = 8	5.35	34.1
t = 9	6.7	37.53
t = 10	6.16	38.33
t = 11	6.38	40.03
t = 12	6.82	41.17
t = 13	7.3	39.67
t = 14	7.8	41.7
t = 15	8.5	42.1
t = 16	7.1	41.67
t = 17	6.8	40.7
t = 18	6.3	40.07
t = 19	5.8	38.63
t = 20	4.2	36.4
t = 21	3.8	34.1
t = 22	3.01	32.8
t = 23	2.53	32.5
t = 24	1.42	32

TABLE 4 | Forecasted power from solar PV and wind generators (case study 1).

Time (h)	Solar (KW)	Wind (KW)
t = 1	0	7.56
t = 2	0	7.5
t = 3	0	8.25
t = 4	0	8.48
t = 5	0	8.48
t = 6	0	9.42
t = 7	0	9.82
t = 8	7.99	10.35
t = 9	10.56	10.88
t = 10	13.61	11.01
t = 11	14.97	10.94
t = 12	15	10.68
t = 13	14.78	10.42
t = 14	14.59	10.15
t = 15	13.56	9.67
t = 16	11.83	8.98
t = 17	10.17	8.37
t = 18	7.66	7.61
t = 19	0	6.7
t = 20	0	5.72
t = 21	0	7.21
t = 22	0	7.75
t = 23	0	7.88
t = 24	0	7.69

TABLE 5 | Forecasted power from solar PV and wind generators (Scenario-1, case study 2).

Time (h)	Solar (MW)	Wind (MW)
t = 1	0	113.44
t = 2	0	112.55
t = 3	0	123.76
t = 4	0	127.21
t = 5	0	127.33
t = 6	0	141.44
t = 7	0	147.39
t = 8	79.94	155.38
t = 9	105.69	168.33
t = 10	136.18	165.28
t = 11	149.75	164.23
t = 12	150	160.32
t = 13	147.89	156.31
t = 14	145.92	152.3
t = 15	135.65	145.05
t = 16	118.36	134.8
t = 17	101.71	125.64
t = 18	77.68	114.2
t = 19	0	100.63
t = 20	0	85.95
t = 21	0	108.26
t = 22	0	116.38
t = 23	0	118.33
t = 24	0	115.38

TABLE 7 | Coefficients of the customer cost function, customer type, and daily customer curtailment limitations (case study 2) (Scenario-1).

J	*θ*	$K_{1,j}$	$K_{2,j}$
1	0	1.847	11.64
2	0.14	1.378	11.63
3	0.26	1.079	11.32
4	0.37	0.9124	11.5
5	0.55	0.8794	11.21
6	0.84	1.378	11.63
7	1	1.5231	11.5

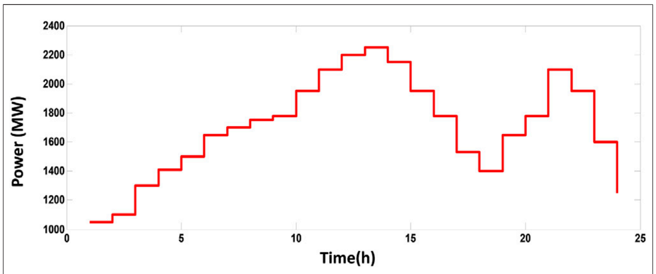

FIGURE 3 | Initial hourly load demand for case study 2 (Scenario -1).

TABLE 6 | Ten conventional generators units data (Scenario-1, case study 2).

i	a_i($/MW²h)	b_i($/MWh)	$P_{i,min}$(MW)	$P_{i,max}$(MW)	DR_i(MW/h)	UR_i(MW/h)
1	0.00043	21.6	30	370	200	200
2	0.00063	21.05	35	360	200	200
3	0.000394	20.81	33	240	150	150
4	0.0007	23.9	30	200	100	100
5	0.00079	21.62	33	143	80	80
6	0.00056	17.87	37	60	30	30
7	0.00211	16.51	20	30	30	30
8	0.0048	23.23	27	120	60	60
9	0.10908	19.58	20	80	40	40
10	0.00951	22.54	25	55	30	30

$$D^{(i)} = \begin{cases} 1 & if\ i = p(j),\ j \in [1, k], p\,randperm(k), k \in [2, r_2 \cdot (d-2) + 1] \\ 0 & else \end{cases} i = 1, 2, \ldots, d \tag{45}$$

The axial flight can be mathematically modeled:

$$D^{(i)} = \begin{cases} 1 & if\ i = randi([1, d]) \\ 0 & else \end{cases} i = 1, 2, \ldots, d \tag{46}$$

and the omnidirectional flight is defined as:

$$D^{(i)} = 1 \quad i = 1, 2, \ldots, d \tag{47}$$

where randperm(k) creates a random permutation of integers between 1 and k, randi([1, d]) creates a random integer between 1 to d, and r_2 is a random number in [0, 1].

Hummingbirds visit the target food source using their flights, and the resulting food source is obtained. The candidate food source is updated based on the target food source for guided foraging as:

$$\begin{aligned} v_i(t+1) &= x_{i,tar}(t) + a \cdot D \cdot [x_i(t) - x_{i,tar}(t)] \\ a &\sim N(0, 1) \end{aligned} \tag{48}$$

The mathematic simulation for territorial forging (local search) hummingbirds for a candidate food source is modeled as follows:

$$\begin{aligned} v_i(t+1) &= x_i(t) + a \cdot D \cdot x_i(t) \\ b &\sim N(0, 1) \end{aligned} \tag{49}$$

where $x_i(t)$ is the position of the ith food source at current iteration t, $x_{i,tar}(t)$+ is the position that ith hummingbirds

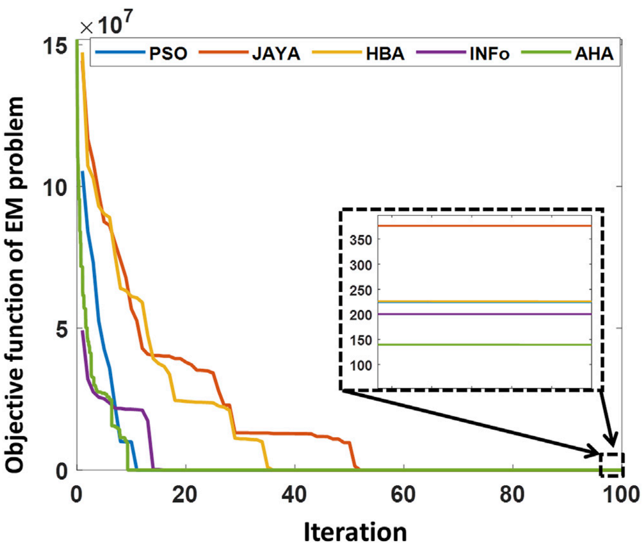

FIGURE 4 | Convergence characteristic curve of all studied techniques for Case 1.

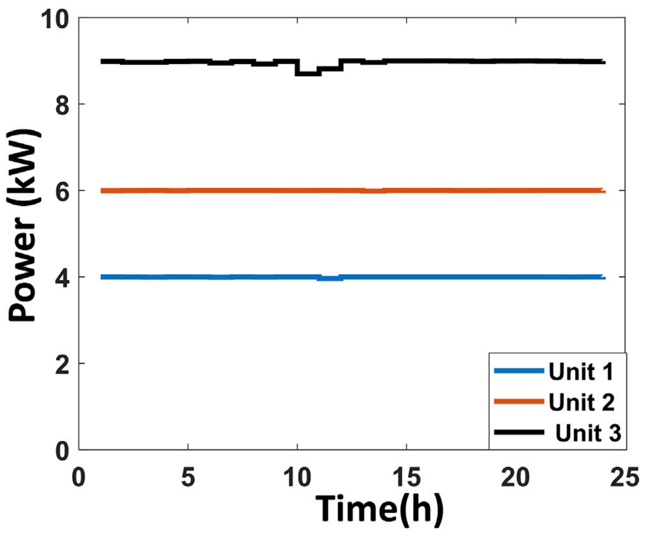

FIGURE 5 | Optimal output power for conventional generation units obtained by AHA (case 1).

TABLE 8 | Comparison of the EM problem for Case 1.

	Total operating cost ($)			
Technique	Worst	Best	Mean	SD
PSO (Moghaddam et al., 2011)	807.35	477.4	658.49	90.47
JAYA (Warid et al., 2016)	790.67	647.49	711.32	41.57
HBA (Hashim et al., 2021)	672.81	460.39	545.31	40.11
INFO (Ahmadianfar et al., 2022)	747.1355	509.374	615.9763	66.60
AHA	389.3867	279.7346	337.9311	33.85

intend to visit (target food source), and a and b are a guided factor and a territorial factor, respectively, which have a normal distribution with standard deviation = 1 and mean = 0.

Then, the position of the current food source for guiding foraging and territorial forging is updated as follows:

$$x_i(t+1) = \begin{cases} x_i(t) & if\ f(x_i(t)) \le f(v_i(t+1)) \\ v_i(t+1) & f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{50}$$

Equation 50 implies that if the current food source's nectar-refilling rate is less than that of the candidate, the hummingbirds leave the current position and stay at the candidate food source for feeding instead, with f(·) referring to the fitness function value for (.).

In AHA, the visit table serves as the memory for indicating how long it has been since this hummingbird visited that food source location. Each hummingbird tends to visit a food source with the highest visit level. The guiding foraging with the update process for the visit table is indicated in Algorithm 1 for guided foraging and in Algorithm 2 for territorial forging.

Algorithm 1. Guiding foraging for AHA.

For ith hummingbirds (from 1 to N)
Do Equation (48)
If $f(v_i(t+1)) \le f(x_i(t))$
$x_i(t+1) = v_i(t+1)$;
For jth food source(postion) from 1 to n
VisitTable(i, j) = VisitTable(i, j) + 1
End
$VisitTable(i, TargetSource) = 0$
For jth food source(postion) from 1 to n
VisitTable(i, j) = max(VisitTable(j, i)) + 1
VisitTable(j, j) = NAN
End
Else
For jth food source from 1 to n($j \neq tar, i$)
$VisitTable(i, j) = VisitTable(i, j) + 1$
$VisitTable(i, TargetSource) = 0$
End
End

Algorithm 2. Territorial forging for AHA.

For ith hummingbirds (from 1 to N)
 Do Equation **(49)**
 If $f(v_i(t+1)) \le f(x_i(t))$
  $x_i(t+1)$=$v_i(t+1)$;
  For jth food source(postion) from 1 to n($j \ne i$)
   $\text{VisitTable}(i,j) = \text{VisitTable}(i,j) + 1$
  End
  For jth food source(postion) from 1 to n
   $\text{VisitTable}(i,j) = \max(\text{VisitTable}(j,i)) + 1$
   $\text{VisitTable}(j,j) = \text{NAN}$
  End
 Else
  For jth food source from 1 to n($j \ne tar, i$)
   $VisitTable(i,j) = VisitTable(i,j) + 1$
  End
End

Migration foraging: migration for the hummingbird occurs when the most frequently visited region lacks food. The migration happened after a predefined number of iterations depending on the migration coefficient, given as:

$$m = 2N \tag{51}$$

In migration, the food source with the lowest (or worst) nectar-refilling rate will migrate to a new food source randomly generated across the search space. At this point, the hummingbird will leave the previous feeding location in favor of feeding on the new one. The migration from the source with the worst nectar-refilling rate to a new position is described in **Eq. 52**, and the visit table is updated, as described in Algorithm 3.

$$x_{wrst}(t+1) = LB + r_3\ (UB - LB) \tag{52}$$

Algorithm 3. Migration forging for AHA.

IF mod(t,2N)
 Do Equation **(52)**

  For jth food source(postion) from 1 to N($j \ne wrst$)
   $\text{VisitTable}(i,j) = \text{VisitTable}(wrst,j) + 1$
  End
  For jth food source(postion) from 1 to N
   $\text{VisitTable}(i,j) = \max(\text{VisitTable}(j,i)) + 1$
   $\text{VisitTable}(j,j) = \text{NAN}$
 End
End

In this paper, the advantages of two strategies were merged to address the MG EM problem and provide reliable statistical cost results. **Figure 2** illustrates the suggested PEM-AHA algorithm.

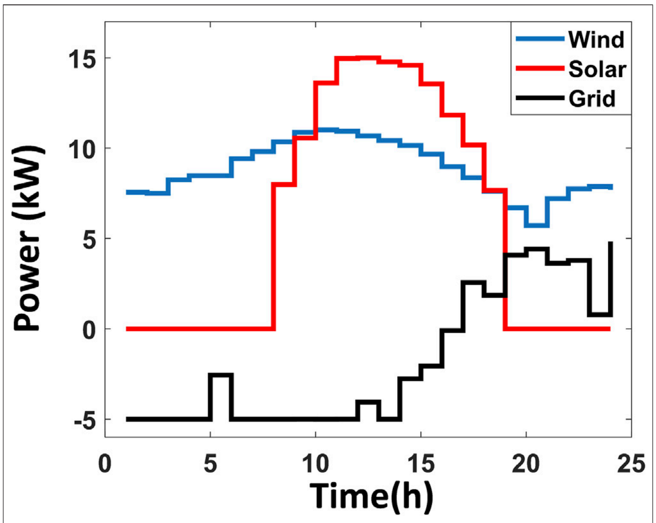

FIGURE 6 | Optimal output power for solar, wind and grid power transaction (case study 1) obtained by AHA.

6 RESULTS AND DISCUSSION

In this section, the proposed algorithm is validated as:

6.1 MG Design

To investigate the performance and the effectiveness of the EM using AHA, a simulated MG comprising DG units and customers with DR is used. The MG is equipped with PV modules and a WT unit with different ratings in different scenarios. In addition, diesel generators are used. A typical illustration of a simulated MG is shown in **Figure 1**.

6.2 Operating Scenarios

To show the behavior of the EM with AHA in the MG test system, two different scenarios have been formulated. Both deterministic and probabilistic frameworks have been used to solve EM in MG, thereby studying the influence of uncertainty on MG financial assessments and cost estimates. In the first scenario for deterministic EM, the output powers of renewable energy units, PV and WT generators, are assumed to be equal to their forecasted values and at the maximum available power at each hour. Two different case studies are evaluated.

Through 2m + 1 PEM, the uncertainty in random renewable power production, market bids, and total demand are evaluated for probabilistic analysis. In this case, three concentrations were determined for each IRV, one of which was estimated at its mean and the other two were estimated on either side of the mean in the associated distribution function.

6.1.1 Scenario-1 Deterministic EM

In this scenario, two separate case studies are given. Based on the MG shown in **Figure 1**, the first case study (case study 1) is a small MG that consists of one PV and wind generator, three conventional generating units (diesel), and three residential customers with DRP. This 6.2.1 scenario will last for only

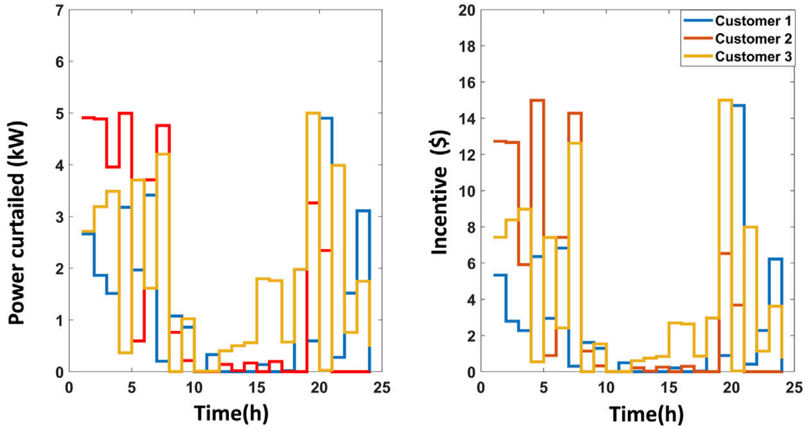

FIGURE 7 | Optimal power curtailed and incentive paid to customers obtained by the AHA.

TABLE 9 | Total amount of energy saved and the total amount of incentive received (case study 1).

	PSO	JAYA	HBA	INFO	AHA
	Saving (kWh)				
j					
1	25.02	27.21	25.18	30	29.61
2	33.20	32.599	32.49	34.79	34.92
3	35.38	39.15	35.03	38.81	39.90
Total(KWh)	93.6	98.96	92.70	103.60	104.44
	Incentive($)				
j					
1	69.18	77.78	61.62	58.74	57.95
2	82.23	88.05	77.71	74.28	81.33
3	84.56	111.72	85.42	80.16	89.21
Total ($)	235.97	277.56	224.77	213.1847	228.51

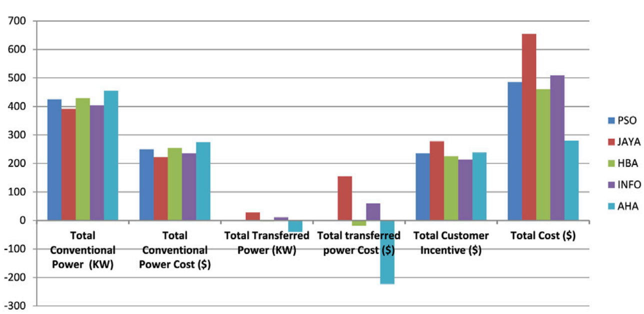

FIGURE 8 | Cost breakdown for the studied optimization techniques (case study 1).

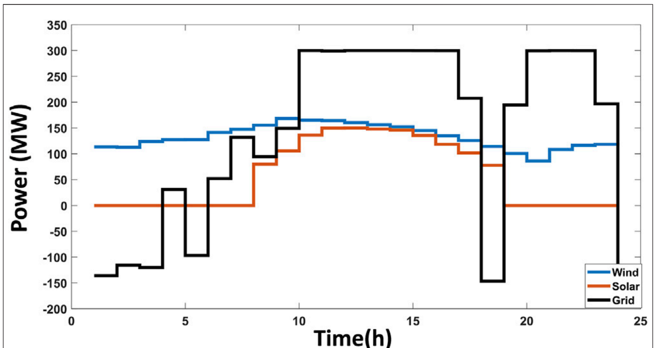

FIGURE 9 | Optimal output power for solar, wind and grid power transaction (case study 2) obtained by the studied optimization techniques.

1 day (24 h). **Table 2** presents the specifications of conventional generators (cost coefficients, upper and lower generating limits, and ramp up and down rates) and shows the customer information (customer type, cost function coefficients, and daily power curtailment maximum limit). The values of hourly power interruptibility ($\lambda i,t$) are presented in **Table 3**, as well as the hourly total initial MG demand; all customers are assumed to have the same hourly power interruptibility. **Table 4** presents the

TABLE 10 | Total amount of energy saved and the total amount of incentive received (case study 2).

	PSO	JAYA	HBA	INFO	AHA
	Saving (kWh)				
j					
1	179.47	179.8	179.92	179.03	179.86
2	229.74	226.42	229.87	229.96	229.91
3	309.8	306.80	309.34	309.87	309.32
4	389.58	389.14	389.9	389.87	389.45
5	394.73	439.33	439.97	438.488	438.89
6	529.86	528.10	528.93	529.48	529.09
7	594.18	598.81	598.57	599.82	599.98
Total(KWh)	2627.4	2668.40	2676.5	2676.50	2676.5
	Incentive ($)				
j					
1	8980.90	8994.90	8873.90	7748.892	8873.90
2	11,390.80	11,333.90	12,300.50	10,504.28	12,300.50
3	15,372.00	15,439.70	15,323.70	16,655.23	15,323.70
4	19,470.80	19,438.90	20,328.05	21,152.74	20,328.05
5	19,893.70	21,888.80	21,927.80	26,017.29	21,927.80
6	26,474.10	26,470.80	25,982.80	35,103.39	25,982.80
7	29,890.90	29,964.40	29,352.40	28,140.71	28,352.40
Total ($)	131,473.2	133,531.30	125,683.28	145,322.5	133,089.2

TABLE 11 | Cost breakdown for the studied optimization techniques (case study 2).

	PSO	JAYA	HBA	INFO	AHA
Total Conventional Power (MW)	29,621.88	30,330.53	30,032.43	29,997.52	30,383.60
Total Conventional Power Cost ($)	649,490	665,480	658,960	664,310	653,520
Total Transferred Power (MW)	4302.092	3229.667	3642.39	3781.241	3291.242
Total Transferred Power Cost ($)	31,835.48	23,899.536	26,317.925	28,358.34	24,355.1908
Total Power Curtailment	2670.26	2668.40	2676.50	2676.50	2676.5
Total Customer Incentive ($)	131,473.2	133,531.30	125,799.2	145,322.5	133,089.2
Total Cost ($)	812,798.7	822,910.84	811,077.1	837,990.84	810,964.4

solar PV and wind hourly data. The MG daily budget (UB) in this case study is $500 cost.

A second case with a larger MG is simulated for scalability validation of the algorithm. This case (case study 2) comprises an aggregated model for solar PV and wind and generators (data in **Table 5**), ten conventional generating units (parameters in **Table 6**), and seven customers to evaluate the algorithm's scalability (data in **Table 7**). The initial load demand for case 2 is shown in **Figure 3**, and the load data and values of power interruptibility utilized were given in (Nwulu and Xia, 2017).

The next subsections summarize the results of the two examples analyzed, which have been produced using various optimization approaches, including PSO, JAYA, and AHA:

i) Case study 1

All simulations have been executed using MATLAB 2021b on a 2.9 GHz i7 PC with 8 GB of RAM. A 20 independent run was performed, and the obtained results were compared with the results of the techniques reported in (Moghaddam et al., 2011, Warid et al., 2016, Hashim et al., 2021, Ahmadianfar et al., 2022), as shown in **Table 8**; the effectiveness of AHA with the best value of operating cost can be noticed when compared with other techniques. The convergence characteristic curve of the objective function for all studied techniques is shown in **Figure 4**, which demonstrates the effectiveness and robustness of the AHA technique in achieving faster convergence and the best value for the fitness function. Using the AHA technique, the optimal power produced by the three conventional generators (diesel generators) is depicted in **Figure 5**. **Figure 6** depicts the optimal power produced from solar PV generators, wind generators, and electricity transacted between the main grid and the MG. The optimal curtailed power from all customers and their incentives during the day are shown in **Figure 7**. **Table 9** shows the total power curtailed for each customer using all studied techniques and AHA during the day. A comparison of the total cost for the studied techniques is shown in **Figure 8**.

i) Case study 2

Using the AHA technique, the output power from PV and wind generator and the power transacted with the main grid is illustrated in **Figure 9**. **Table 10** presents the total curtailed power

TABLE 12 | Locations of the input random variables for EM and corresponding costs.

t (h)	PV1 KW	PV2 (KW)	WT1 (KW)	WT2 (KW)	Load1 (KW)	Load2 (KW)	$\lambda1_{,t}$($)	$\lambda2_{,t}$($)	PVμ	WTμ	Loadμ	λ_t($)μ
1	0.0000	0.0000	8.5469	7.2273	33.4839	30.1761	1.7060	1.4340	0.0000	7.8871	31.8300	1.5700
2	0.0000	0.0000	8.4810	7.1719	33.0316	29.7684	1.5212	1.2788	0.0000	7.8264	31.4000	1.4000
3	0.0000	0.0000	9.3054	7.8653	32.7896	29.5504	2.3905	2.0095	0.0000	8.5853	31.1700	2.2000
4	0.0000	0.0000	9.5582	8.0780	32.6108	29.3892	4.0856	3.4344	0.0000	8.8181	31.0000	3.7600
5	0.0000	0.0000	9.5582	8.0780	32.7896	29.5504	4.8897	4.1103	0.0000	8.8181	31.1700	4.5000
6	0.0000	0.0000	10.5914	8.9471	33.7680	30.4320	5.1070	4.2930	0.0000	9.7692	32.1000	4.7000
7	0.0000	0.0000	11.0310	9.3169	34.6832	31.2568	5.4765	4.6035	0.0000	10.1740	32.9700	5.0400
8	8.6820	7.2980	11.6136	9.8070	35.8719	32.3281	5.8133	4.8867	7.9900	10.7103	34.1000	5.3500
9	11.4745	9.6455	12.1961	10.2970	39.4801	35.5799	7.2802	6.1198	10.5600	11.2465	37.5300	6.7000
10	14.7887	12.4313	12.3390	10.4172	40.3217	36.3383	6.6935	5.6265	13.6100	11.3781	38.3300	6.1600
11	16.2664	13.6736	12.2621	10.3525	42.1100	37.9500	6.9325	5.8275	14.9700	11.3073	40.0300	6.3800
12	16.2990	13.7010	11.9763	10.1121	43.3093	39.0307	7.4106	6.2294	15.0000	11.0442	41.1700	6.8200
13	16.0600	13.5000	11.6905	9.8717	41.7313	37.6087	7.9322	6.6678	14.7800	10.7811	39.6700	7.3000
14	15.8535	13.3265	11.3937	9.6220	43.8668	39.5332	8.4755	7.1245	14.5900	10.5079	41.7000	7.8000
15	14.7343	12.3857	10.8661	9.1782	44.2876	39.9124	9.2361	7.7639	13.5600	10.0222	42.1000	8.5000
16	12.8545	10.8055	10.1077	8.5403	43.8352	39.5048	7.7149	6.4851	11.8300	9.3240	41.6700	7.1000
17	11.0507	9.2893	9.4373	7.9763	42.8148	38.5852	7.3889	6.2111	10.1700	8.7068	40.7000	6.8000
18	8.3234	6.9966	8.6019	7.2736	42.1521	37.9879	6.8456	5.7544	7.6600	7.9377	40.0700	6.3000
19	0.0000	0.0000	7.6017	6.4322	40.6373	36.6227	6.3023	5.2977	0.0000	7.0169	38.6300	5.8000
20	0.0000	0.0000	6.5245	5.5261	38.2914	34.5086	4.5637	3.8363	0.0000	6.0253	36.4000	4.2000
21	0.0000	0.0000	8.1622	6.9037	35.8719	32.3281	4.1291	3.4709	0.0000	7.5330	34.1000	3.8000
22	0.0000	0.0000	8.7558	7.4030	34.5043	31.0957	3.2707	2.7493	0.0000	8.0794	32.8000	3.0100
23	0.0000	0.0000	8.8987	7.5232	34.1887	30.8113	2.7491	2.3109	0.0000	8.2109	32.5000	2.5300
24	0.0000	0.0000	8.6898	7.3475	33.6628	30.3372	1.5430	1.2970	0.0000	8.0187	32.0000	1.4200

TABLE 13 | Statistical moments of total expected cost for Case 1.

$E(Y)$ ($)	$E(Y^2)$ ($)^2	$E(Y^3)$ ($)^3	$E(Y^4)$ ($)^4	μ_Y ($)	σ_Y ($)
378.9548	1.6026e + 05	7.4056e + 07	3.6618e + 10	378.9548	129.0465

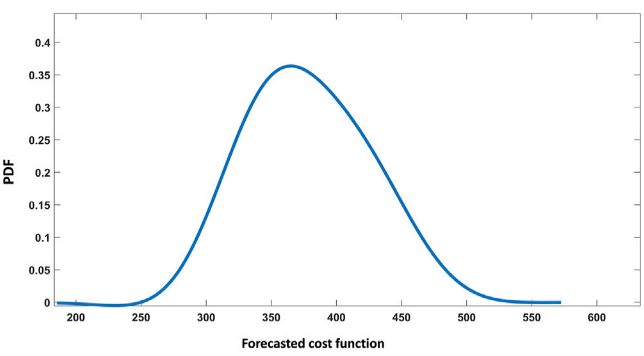

FIGURE 10 | Probability density function (PDF of forecasted cost function based on the AHA for Scenario 2.

and total incentive for each customer (seven customers) during the day for all studied techniques. **Table 12** details a thorough comparison of the studied optimization strategies for generation cost, incentive payment cost, and power-transacted cost. **Supplementary Appendix Table S1** presents the optimum power produced from ten conventional units in the Appendix, and **Supplementary Appendix Table S2** presents a comprehensive curtailed power from seven customers.

Looking at the simulation results for case study 1, **Table 9** reveals that in the case of AHA, the overall power curtailment is the highest compared with other techniques. Also, it can be noted from **Figure 8** that the overall amount of power transacted with the grid is substantially lower in the case of AHA as well as the total cost.

In case study 2, the results in **Table 10** show that AHA has a larger overall power curtailment than the PSO and the JAYA cases. **Table 11** shows that employing the AHA approach has a lower overall cost than the other procedures.

6.1.2 Scenario-2 Probabilistic EM

In this scenario, the point estimation technique (2m + 1) is combined with the AHA algorithm in order to provide the optimal solution for probabilistic EM. The WT and PV output power, market price, and demand load level are utilized as uncorrelated RIVs. Furthermore, the PV and WT generators' output power, market price, and demand load level are determined using proper PDF modeling for hourly data of wind power and solar power, as specified in Section 4.1.1. It is assumed that PV output power, market prices, and load demand follow a normal distribution, with a standard deviation of 5% for PV and market prices (Radosavljevic, 2018) and 3% for load demand. The Weibull distribution is considered for the output power of the WT units, with an STD of 5%. Following that, the 2m + 1 approach is used to solve the probabilistic EM problem; IRVs' concentrations (locations) during the implementation of 2m + 1 are calculated, as indicated in **Table 12**. AHA approach is employed using data acquired from (2m + 1) for each case. Finally, the statistical moments are calculated, and then, the mean value (μ_Y) and standard deviation (STD) of the EM output random variables (MG's operating cost) are calculated; the results are shown in **Table 13**.

The PDF of the total expected cost for case study 1 is shown in **Figure 10**. These results demonstrate that the proposed strategy with AHA could solve the EM problem in unpredictable environments.

7 CONCLUSION

In this paper, a new application of an efficient optimizer, AHA, has been proposed for solving the EM problem of grid-connected MG with DRP. Moreover, a probabilistic EM using hybrid AHA and 2m + 1 PEM has been investigated. The main objective of this study is to get the lowest conventional generating and transaction costs to maximize the MG operator benefit. For deterministic operation, different optimization techniques have been utilized to solve the EM problem in MG over 24 h (1 day) to achieve the optimum operation on both sides of generation and demand. According to AHA's results, in the first case study, energy consumption has been reduced by 104 KWh, while that in the second case study was reduced by 2677 MWh. The results of two case studies for the studied optimization strategies evaluated have been discussed, thereby proving that the AHA has the lowest overall cost. A probabilistic EM is solved using AHA-PEM, which allows operators of the MG system to make more realistic decisions and examine the effect of input random variable uncertainties on the statistical indicators, which describe the MG system state.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors contributed to manuscript revision, read, and approved the submitted version.

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The icons used in this paper were developed using Freepik, AmethystDesign, Arkinasi, and Smashicons from www.flaticon.com.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.905788/full#supplementary-material

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NOMENCLATURE

Variables and parameters

$\boldsymbol{C_r}\,(\boldsymbol{P_{r_t}})$ Transaction cost

$\boldsymbol{\gamma_t}$ Locational Marginal Prices

$\boldsymbol{P_{r_t}}$ Power truncationTransacted power

$\boldsymbol{F}_1$ Customer benefit function

$\boldsymbol{y}$ Incentive payment

$\boldsymbol{C}\,(\theta, \mathbf{x})$ Customer cost

$\boldsymbol{F}_2$ MG operator benefit function

λ power interruption cost

$\boldsymbol{\theta}$ customer willing

$\boldsymbol{k}_1$ **, and** $\boldsymbol{k}_2$ Customer cost coefficients

$\boldsymbol{C_i}\,(\boldsymbol{P_{i_t}})$ fuel cost for conventional generator

$\boldsymbol{P_{i_{min}}}$ **and** $\boldsymbol{P_{i_{max}}}$ Minimum and maximum generation limits generator i

$\boldsymbol{P_{s_t}}$ PV output power

$\boldsymbol{P_{w_t}}$ Wind turbine output power

$\boldsymbol{P_{r_t}}$ Power truncationTransacted power

$\mathbf{D_t}$ Total power demand

$\boldsymbol{f_v}$ Probability Density Function

$\boldsymbol{F_v}$ cumulative density function (CDF)

$\boldsymbol{\xi_{t,k}}$ Concentration points

$\lambda_{\mathbf{t},3}$ **and** $\lambda_{\mathrm{t},4}$ skewness and kurtosis

$\boldsymbol{E}\,(\boldsymbol{Y^j})$ Moments vector

$\boldsymbol{\sigma}$ Slandered deviation

$\boldsymbol{\mu}$ mean

N Hummingbirds number (population)

$\boldsymbol{VT}$ Visit Table

Abbreviations

MG Microgrid

DR Demand response

AHA Artificial Hummingbird Algorithm

EM Energy Management

RES Renewable Energy Sources

PEM Point Estimation Method

PV Photovoltaic

WT Wind turbine

PDR price-based DR

IDR incentive-based DR

PSO Particle swarm optimization

HBA Honey Badger Algorithm