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Flexible optimum sizing of a hybrid renewable power system based on Metaheuristics in the presence of storage system

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ABSTRACT

This paper addresses one of the most important challenges in utilization of renewable energy source the design of a system that incorporates this type of energy sources, which is the size determination of system component. A meta-model of hybrid renewable power system is studied here which can include many sorts of renewable and nonrenewable energy sources as well as energy storage. This system is then optimized in terms of component size to supply the load with minimum overall cost. In addition, a novel optimization algorithm is proposed here named modified marine predators optimization technique which addresses the shortcomings observed in classic and metaheuristic optimization algorithm which are slow convergence, local optima, and immature convergence. Moreover, a real-world case study in an isolated location is analyzed here and a hybrid renewable power system with diesel generator, PV panels, and battery and the proposed optimization algorithm are implemented to determine optimum component size. The results suggest that, due to high investment cost, only a battery with very small capacity is economically advisable. Utilization of the proposed methodology here can help the system designers and operators to increase renewable energy penetration with higher reliability and lower costs.

Keywords: *modified marine predators optimization technique, PV panel, diesel generator, battery storage system, meta-model, hybrid renewable power system, renewable energy source, distributed generation*

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1. INTRODUCTION

There have been many scientific works discussing the impact of consumption of fossil fuels has on global warming [1-5]. This has been a concern for years and the best suggested solution has been implementation of more clean renewable energy or improving the efficiency of existing ones [6]. To fully utilize this new type of source, the power system around world has had to change dramatically by changing to decentralized from centralized form, which requires sophisticated control made possible with new optimization tools which are able to optimize the power with various configurations [7]. In decentralized power system, on the contrary to centralized one in which there are few power plant whose generation is transferred by a high capacity transmission system to distant consumers, there are multiple generation with local consumers either in islanded mode or grid-connected mode to import or export power in times of lack of generation or high generation, respectively [8]. Decentralized power systems are robust in case of system failures, i.e. when one section has failed only a small part experiences outage rather than the majority of even the whole of the grid. High penetration of renewable energy system can be realized by decentralization [9, 10].

On the other hand, it is worth mentioning that there is a barrier on the path of renewable source to high penetration. Their intermittent nature leads to unreliability which can cause system outage in case of high penetration. The solution is incorporation of a group of renewable sources and/or adding

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one or more fossil fuel generation units with high reliability [11, 12]. This form of generation is named hybrid renewable power system (HRPS). A HRPS can work in three states of local load supplement, power export to the grid, or the combination of both [13]. Each of these operation condition call for their own management or possibility of optimization. In case of local load supplement, the management of renewable power sources is the most difficult, since generation insufficiency or excess cannot be compensated or dumped or demand change might not be dynamically responded [14]. This is why another more reliable power source such as diesel generation (DG) or connection to is essential in distributed generation [15]. In case of direct connection to the upstream grid, optimization is not needed, since the goal is to maximize generation with given amount of investment and limits caused by situations and laws. In case of combination of grid connection and local load, management is easier, however, optimization is still required to minimize the cost and power import from the main grid since it is more expensive than generating in the system [16, 17]. In addition to management, optimization is also required in initial size determination for each component. In summary, the instantaneous demand must be met by the HRPS instantly, which is difficult with high intermittency caused by renewable energy sources, through optimum size determination of component and optimum energy management [18, 19]. To add some tolerance to the system, a variant of energy storage, e.g. battery, hydro storage, etc., can be used which increases the investment cost but it can save energy in times of excess energy and spend it when needed. It should be noted that the size of the energy storage is associated to the management, i.e. if the system management is optimal, smaller storage is required, and smaller storage system makes more accurate management essential. An example diagram of HRPS and utilization of its generation are shown in Fig. 1.

The system designers must have flexible means when designing a HRPS which means that their tools must be able to model any variant of HRPS settings with the all three type of aforementioned power utilization path. They must also be able to optimize the system sung their own optimization tool. The proposed system modeling satisfies these requirements.

Utilization of hybrid renewable power system has been the focus of many scientific works which

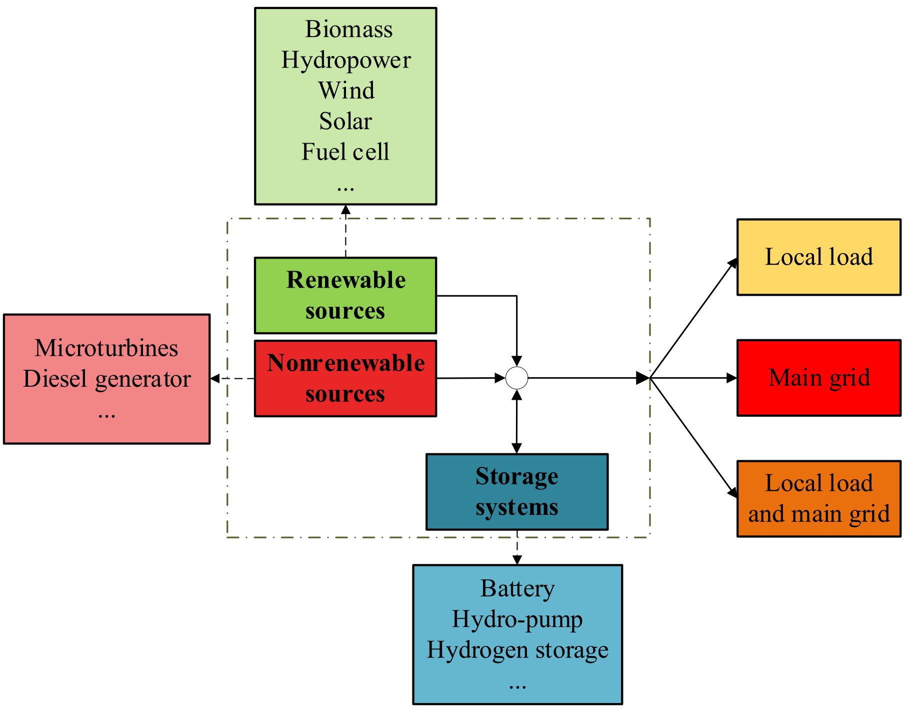

Fig. 1. The general schematic of a HRPS supplying three possible types of loads

have contributed to this field using many different methods [20-22]. A hybrid power system coupled magnetically is studied in [23]. The proposed power system here consists of photovoltaic, battery, and fuel cell which has the task of providing power to a local residential section, which can work in both islanded and grid-connected modes [24]. The system incorporates a rule-based control method and a dynamic programming as energy management tools to minimizing the system operation cost. The proposed power system, control method, and optimization technique are simulated with different meteorological conditions which impact the PV generation [25, 26]. The general hybrid renewable systems are studied in [27]. To determine operational variation over a pre-specified time plan, the sequential linear programming algorithm embedded with trust area is proposed. This optimization can model vast range of equipment including controllable and responsive load, fixed load, energy storage system, CHP, fossil fuel generation and sustainable source with different capacity [28, 29]. The proposed method is capable of finding an efficient optimum solution for the HRPS. The proposed optimization is also implemented on a real-world hybrid power system in Tuscany to show the capability of the algorithm. An HRPS consisted of a PEMFC and Li-ion battery is studied in [30]. The authors have tried to optimize the system with real-time energy management using Pontryagin optimization algorithm to achieve minimum operational cost (through minimum fuel consumption) and maximum component longevity. The study develops an efficiency degradation model for the fuel cell and battery. The optimum trade-off between operational cost and system durability is achieved using the aforementioned optimization algorithm. The results are compared to other works that have used rule-based and dynamic programming energy management which has proved the better performance of the proposed system [31].

The reviews presented above are some the papers published on optimization of hybrid power system using classical optimization algorithm. However, the classic optimization methods converge slowly, are difficult to use on complicated systems and optimize nonlinear systems with low accuracy not cannot do it at all. Therefore, in most of the new scientific works, metaheuristic optimization algorithms are used. A hybrid renewable power system with numerous components is optimized in [32] using modified PSO. This power system was implemented in Sierra Leone and includes battery, solar panel, wind turbines, biomass generation, and diesel generator as backup. The goals of the optimization are unmet demand, fraction of diesel power, cost of replacement, greenhouse gas emission. A hybrid renewable power system in household size is studied in [33]. This hybrid system consists of PV panels, solar thermal collectors and required components, wind turbines, battery storage system. The paper also proposes utilization of the novel thermal insulation thickness for the hybrid system. This system can operate in both grid-connected mode, or islanded mode (backed up by a diesel generator). The single objective genetic algorithm is used to twice to get the minimum cost and minimum environmental impacts, between which Pareto-optimum solution is found. There has been many papers studying the HRPS with different techniques of optimization, however, using the optimization methods sometimes give slow convergence or yield to local optimum. Therefore, a new optimization method named modified marine predators optimization technique is proposed in this paper to face the aforementioned drawbacks.

The sections of the paper are as explained here. Section 2 presents the methods and materials which will study each component of the simulated HRPS, model the grid and load and present the objective function. Section 3 present the optimization algorithm and its background. The results of simulation are given in section 4. finally, the conclusion of the paper is given in section 5.

2. MATERIALS AND METHOD

The Hybrid system studied here consists of many parts, including photovoltaic panels as main power source, Battery as storage system, Diesel as the backup generation for main power source. In addition, grid connection can be added to the system in addition to the DG or as a replacement to it. Below, the modeling of each component is presented. It is also worth mentioning that the time horizon of the study is one year with time step of 1 hour.

2.1. Photovoltaic system model

Photovoltaic systems generate electricity using the energy of futons. The panels used here are CS6U-330P each with rated power of 330W, efficiency of 16.97%, and price tag of 205$. The

Table 1. The technical specification of the solar panels

Investment	621 $/kW
Operation and maintenance	14.18 $/kW.year
Efficiency	19.97%
Degradation factor (D_{sol})	88%

cost of operation and management is 4.68 $ per panel per year [34, 35]. The lifespan of the panels is long enough to is as long as that of project. More practical information regarding this solar panel is given in Table 1.

The instantaneous power generation from PV panels can be calculated as follows [36]:

$$P_{PV}(t) = P_{PV,\ Nom} \times \frac{I(t)}{I_{Nom}} \times D_{Sol} \times \left(C_{Temp} \left(T_{Panel}(t) - 25 \right) + 1 \right) \tag{1}$$

Where, $P_{PV}(t)$ and $P_{PV,\ Nom}$ are the instantaneous power generated and nominal power of the photovoltaic system, respectively. $I(t)$ and I_{Nom} are instantaneous and nominal solar radiation for the panels, respectively. D_{Sol} is the degradation factor. C_{Temp} and $T_{Panel}(t)$ are temperature coefficient and instantaneous temperature in the PV panel, respectively.

2.2. Battery storage system

Batteries storage system can be used to dam sudden changes in the consumption from the generation point of view. When the generation cannot increase quickly enough to meet the demand or when it cannot decrease fast enough, the battery helps the system by discharging or charging, respectively. The instantaneous power stored in the battery is calculated as follows [37]:

$$E_{Bat}(t) = E_{Bat}(t - \Delta t) + \Delta E_{Bat} \tag{2}$$

$$\Delta E_{Bat} = \begin{cases} E_{E/D} \times \eta_{BT} \times \eta_{Ch}, & E_{E/D} \geq 0 \\ \dfrac{E_{E/D}}{\eta_{BT} \times \eta_{Dch}}, & E_{E/D} < 0 \end{cases} \tag{3}$$

$E_{Bat}(t)$ and $E_{Bat}(t - \Delta t)$ are the stored energy in the battery at present moment and last moment, respectively. ΔE_{Bat} is the energy that will be added to or subtracted from the battery. $E_{E/D}$ denotes the excess or deficit generation which must be saved or provided, which is positive if there is extra generation and negative in generation is inadequate. η_{BT}, η_{Ch}, and η_{Dch} are battery controller, battery charge and battery discharge efficiency. The battery state of charge (SOC) must be less than or higher than its minimum and maximum values:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{4}$$

This limit increases the battery operational condition and lifespan in Li-ion batteries which are mostly used nowadays.

2.3. Diesel generation

This system also includes a diesel generator to help with the power supplement when the main source and battery cannot fully supply power to the load. Although this generator consumes fossil fuel with all its disadvantages, it can start generating power regardless of meteorological conditions with high dynamic response. Power generated by a diesel generator can calculated as follows [38]:

$$U_{Fuel,DG}(t) = \left(C_{FCI} + P_{DG,nom} \right) + \left(C_{FCS} + P_{DG}(\mathrm{t}) \right) \tag{5}$$

Here, $U_{Fuel}(t)$ is the fuel utilization by the DG, C_{FCI} denotes the coefficient of fuel curve intercept, $P_{DG,nom}$ is the nominal output power of the DG, C_{FCS} coefficient of fuel curve slope, and $P_{DG}(\mathrm{t})$ is the instantaneous power generated by the DG.

2.4. Upstream grid

The HRPS can also be connected to the upstream grid to sell extra power or buy needed power from it. The following equation can be used to related the load, PV generation, battery power, DG generation and power trade with the upstream grid.

$$P_{Grid}(t) = P_{Load}(t) - \left(P_{Bat}(t) + P_{DG}(t) + P_{PV}(t) \right) \tag{6}$$

$P_{Grid}(t)$ denotes the power trade with upstream grid, which is positive if power is purchased from the main grid and negative if power is sold to the main grid. $P_{Load}(t)$ is the power demand by the consumer, and $P_{PV}(t)$, $P_{DG}(t)$, and $P_{Bat}(t)$ are generated power by PV panels, DG, and battery, respectively.

2.5. The Load

The considered load here is a factory in a tropical location and because of the locational features, the power consumption pattern does not change significantly each season. Therefore, the consumption of the factory is measured for month and the data is averaged to obtain an average day with hourly time steps. Then this consumption sequence is duplicated to make up a year. Also, in case of off days, the consumption is zero. It should be noted that when there is no solar radiation in operation time of the factory, either the battery or the DG must be used. In addition, there day that the factory is not operational, which make the energy management more challenging.

2.6. Economics of the system

The Investment cost $M_{Inv}(y)$ and operational cost M_{Op} are calculated in the fallowing

$$M_{Inv} = M_{Inv,PV} \times P_{PV,Nom} + M_{Inv,Bat} \times P_{Bat,Nom} + M_{Inv,DG} \times P_{DG,Nom} \tag{7}$$

Where, M_{Inv} is total investment cost, and $M_{Inv,PV}$, $M_{Inv,Bat}$, and $M_{Inv,DG}$ are PV system, battery, and DG investment costs per kW, respectively. In addition, $P_{PV,Nom}$, $P_{Bat,Nom}$, and $P_{DG,Nom}$ are nominal power of the PV system, battery, and DG, respectively.

$$M_{Op} = M_{Op,PV} \times M_{Inv,PV} \times P_{PV,Nom} + M_{Op,Bat} \times M_{Inv,Bat} \times P_{Bat,Nom} + M_{Op,DG} \times M_{Inv,DG} \times P_{DG,Nom} \tag{8}$$

Here, M_{Op} is total operational cost, and $M_{Op,PV}$, $M_{Op,Bat}$, and $M_{Op,DG}$ are PV system, battery, and DG operational costs per power or energy unit, respectively

The overall cost (OC) of the system in Y_{Op} years and taking account of interest rate (i) is as follows:

$$OC = M_{Inv} + \sum_{y=1}^{Y_{Op}} M_{Op} \times (1+i)^{-y} \tag{9}$$

The experimental data regarding the costs are given in Tab. 2 which are obtain by consulting to experts.

Table 2. The value of economic parameters

$M_{Inv,PV}$	794 $/kW
$M_{Op,PV}$	23.82 $/kW
$M_{Inv,Bat}$	510.48 $/kW
$M_{Op,Bat}$	20.42 $/kWh
$M_{Inv,DG}$	260.91 $/kW
$M_{Op,DG}$	20.88 $/kWh
i	0.6
Y_{Op}	25 years

2.7. The Objective function

The goal in this paper is minimizing the OC per amount of generated energy unit, which is equivalent to minimizing levelized cost of energy (LCOE), which is calculated as follows:

$$\text{LCOE} = \frac{OC}{overall\ geneerated\ energy} \tag{10}$$

The total amount of produced power is not constant making the equation nonlinear, thus, when supplying the power to the main grid or supplying both local load and grid, in which consumption is not equal to generation, the optimization is nonlinear. However, in case of supplying the power to the local load, where consumption and generation are equal, the optimization is linear. The present condition demands an optimization powerful enough to handle both linear and nonlinear optimization with high robustness, accuracy and speed. The optimization used here is modified marine predators optimization (MMP) technique, which is another novelty of this paper.

3. Modified marine predators optimization technique

The optimization algorithm proposed here is based on marine predators optimization algorithm, which is one the newest metaheuristic optimization algorithms which has been used in numerous recent works [39-42]. This algorithm has proved to be powerful technique for finding solutions in various problems, however, sometimes, it yields inaccurate results because of converging prematurely or being trapped in local optima. The modifications embedded into the algorithm are explained in section 3.2 after explaining the original MPA.

3.1. The original MPA

This optimization algorithm is a metaheuristic technique based on population distributed in uniform and random manner in the search space. The procedure of this method is mathematically explained below:

$$Z_0 = Z_{min} + (Z_{max} - Z_{min}) \times \overrightarrow{C_{Rand}} \tag{11}$$

Here, $C_{rand,i}$ is a vector with random entries distributed uniformly in range of [0 1]. Z_{max} and Z_{min} are upper and lower range of the search agents. The best hunters are the ones with the best hunting ability. Mathematically speaking, the best hunter is the best solution based on which the Elite matrix is made. This matrix traces the search of prey and its entries are positions of the prey. The elite matrix is made up as follows:

$$E = \begin{bmatrix} Z^{I}_{1,1} & \cdots & Z^{I}_{1,n} \\ \vdots & \ddots & \vdots \\ Z^{I}_{c,1} & \cdots & Z^{I}_{c,n} \end{bmatrix}_{c\times n} \tag{12}$$

Here, is the elite matrix, c and n is the count of search agents and agents, respectively. Z^{I} is the vector of best hunter. The predator and prey are both agents in this technique, which means that hunter looks for prey and the prey itself look for its own food. The entries of the elite matrix is renewed at the end of each iteration by replacing the best hunter by the better one if available. Another matrix is constructed for the preys (matrix P) which has similar dimension as the elite matrix. The predators renew their location using this matrix.

$$P = \begin{bmatrix} Z_{1,1} & \cdots & Z_{1,n} \\ \vdots & \ddots & \vdots \\ Z_{c,1} & \cdots & Z_{c,n} \end{bmatrix}_{c\times n} \tag{13}$$

Here, P denotes the prey matrix, and c and n are same as the elite matrix. The optimization is wholly based on these matrices.

The algorithm is divided into three stages, where the relative speed of prey and predator are different. Each of the stages happen in one third of the iteration. The relative speed is calculated as follows:

$$v_{relative} = \frac{v_{Prey}}{v_{Predator}} \tag{14}$$

- First stage

In the first stage, the prey is faster than the predator (relative speed is high) and the algorithm is in exploration phase, which means that the bigger step size (movement velocity) favors the exploration ability. When the relative speed is high ($v_{relative} \geq 10$), the predator does not move at all. It should be noted that this stage occurs when $Iter < \frac{1}{3} Iter_{max}$. This procedure is as follows:

$$\overrightarrow{stepsize_i} = \overrightarrow{C_{Rand,B}} .* \left(\vec{E}_i - \overrightarrow{C_{Rand,B}} .* \vec{P}_i\right) \tag{15}$$

$$\vec{P}_{(i+1)} = \vec{P}_i + \frac{\overrightarrow{C_{Rand}} .* \overrightarrow{stepsize_i}}{2} \tag{16}$$

$$i = 1, 2, \ldots, n \tag{17}$$

Here, $\overrightarrow{C_{Rand,B}}$ is vector of random number create using Brownian pattern [43]. $.*$ denotes entry by entry multiplication. $\overrightarrow{C_{Rand,B}} .* \vec{P}_i$ signifies the movement of the preys. $Iter$ and $Iter_{max}$ are present iteration and maximum iteration, respectively.

- Second stage

This stage occurs when the predator and prey are moving with similar speed (relative velocity is normal) in foraging for their own food. This stage happens when $\frac{1}{3} Iter_{max} < Iter < \frac{2}{3} Iter_{max}$, which is a transition phase from exploration to exploitation. Since both of the search procedures, i.e. exploration and exploitation occur in this stage, the populations is separated into two parts of exploration (predator) and exploitation (prey). In this stage, the movement pattern of the prey and the predator are Lévy and Brownian, respectively. The exploitation in this stage is mathematically modeled as follows:

$$\overrightarrow{stepsize_i} = \overrightarrow{C_{Rand,L}} .* \left(\vec{E}_i - \overrightarrow{C_{Rand,L}} .* \vec{P}_i\right) \tag{18}$$

$$\vec{P}_{(i+1)} = \vec{P}_i + \frac{\overrightarrow{C_{Rand}} .* \overrightarrow{stepsize_i}}{2} \tag{19}$$

$$i = 1, 2, \ldots, \frac{n}{2} \tag{20}$$

Here, $\overrightarrow{C_{Rand,L}}$ is vector of random number create using Lévy distrinution [43]. $\vec{R}_B .* \vec{P}_i$ signifies the movement of the preys. Since the step sizes in the Lévy is small, the algorithm favors the exploitation. Moreover, the exploration in this stage is as follows:

$$\overrightarrow{stepsize_i} = \overrightarrow{C_{Rand,B}} .* \left(\vec{E}_i - \overrightarrow{C_{Rand,B}} .* \vec{P}_i\right) \tag{21}$$

$$\vec{P}_i = \vec{E}_i + \frac{C_s .* \overrightarrow{stepsize_i}}{2} \tag{22}$$

$$C_s = \left(1 - \frac{Itr}{Iter_{max}}\right)^{2\times \frac{Iter}{Iter_{max}}} \tag{23}$$

$$i = 1, 2, \ldots, \frac{n}{2} \tag{24}$$

Here, C_s is a dynamic variable which changes by iteration and controls the predator's step size. $\overrightarrow{C_{Rand,B}} .* \vec{P}_i$ models the prey's Brownian-based movement such that predator updates its position based on the prey's movement.

- Third stage

In this stage, the prey is moving slower than the predator (relative velocity is low), which occurs in the last portion of the iterations ($\frac{2}{3} Iter_{max} < Iter$) and focuses far more on the exploitation. When the relative speed is low ($v_{relative} \leq 0.1$), the movement of the predator is based on the Lévy distribution. This stage is modeled as follows:

$$\overrightarrow{stepsize_i} = \overrightarrow{C_{Rand,L}} .* \left(\overrightarrow{C_{Rand,L}} .* \vec{E}_i - \vec{P}_i \right) \tag{25}$$

$$\vec{P}_i = \vec{E}_i + \frac{C_s .* \overrightarrow{stepsize_i}}{2} \tag{26}$$

$$i = 1, 2, \ldots, n \tag{27}$$

Here, $\overrightarrow{C_{Rand,L}} .* \vec{E}_i$ models the predator's Lévy movement, in which, after updating the position of the predator, the position of the prey is updated accordingly.

In addition to the stages above, fish aggregating devices (FAD) and Eddy formation can affect the algorithm directly. According to FAD, the sharks spend four fifth of their time in vicinity of FADs and the remaining one fifth is on jumping to other dimensions to look for a different location with different preys. The FADs are considered local optima, therefore, the bigger jump helps prevent being trapped in these local optima. To implement this concept, the following equation must be utilized:

$$\vec{P}_i = \begin{cases} \vec{P}_i + C_s \times \left(\begin{matrix} \overrightarrow{Z_{min}} + \overrightarrow{C_{Rand}} .* \\ \left(\overrightarrow{Z_{max}} - \overrightarrow{Z_{min}} \right) \end{matrix} \right) .* \vec{B}, & c_{Rand} \leq C_{FAD} \\ \vec{P}_i + \left(C_{FAD} \times (1 - c_{Rand}) + c_{Rand} \right) \times \left(\vec{P}_{r_1} - \vec{P}_{r_2} \right) & c_{Rand} > C_{FAD} \end{cases} \tag{28}$$

Here, $\vec{B}$ is a vector of ones and zero, C_{FAD}. is the coefficient of FAD effect which denotes its intensity and is 0.2 here, c_{Rand} is uniformly a random number with random distribution between 0 and 1, $\vec{P}_{r_1}$ and $\vec{P}_{r_2}$ are randomly chosen entries of the prey matrix. $\overrightarrow{Z_{max}}$ and $\overrightarrow{Z_{min}}$ are two vectors composed of upper and lower limits of dimensions, respectively.

3.2. Incorporated modifications

Self-adaptive weight allocation is the first modification used here to increase the probability of moving towards the fittest solution and preventing the worst ones. To enhance population quality, the population should reach a desirable area of solutions in the initial stage of the MPA search, and a local search must be conducted in the last stage. To do so, the approach angle must be tune by allocating weights, which is done by adding the following equation to the optimization algorithm.

$$\overrightarrow{Z_{0,new}} = \overrightarrow{Z_{min}} + C_{weight} \times \overrightarrow{C_{Rand}} \times \left(\overrightarrow{Z_{max}} - \overrightarrow{Z_{min}} \right) \tag{29}$$

Here, C_{weight} is the coefficient of weight which is calculated as follows:

$$C_{weight} = \begin{cases} \left(\frac{f(Z_{best})}{f(Z_{worst})} \right), & f(Z_{worst}) \neq 0 \\ 1, & Else \end{cases} \tag{30}$$

Here, $f(Z_{best})$ and $f(Z_{worst})$ are the objective functions of the best and the worst solution, respectively. The size of the weight depends on the size difference of the best and worst solutions, i.e. the bigger the distance between them, the bigger the C_{weight}. Because of the dynamicity of the weighting method, both exploitation and exploration are done in their suitable times and transition is done automatically based on the feedback received from the results.

Moreover, another modification is embedded to enhance the quality of the best solution in each generation which uses chaos learning principle. In an optimization algorithm, the role of the best solution is leading other search agents to the best solution space, however, it sometimes gets stuck in a local optima, which can lead to prematurely converged algorithm. This can be thwarted by a chaotic term added to the algorithm which can produce ergodic and random agents that can be better than the previous best solution. This modification is incorporated into stage 3 and uses the prominent logistic map, which yield the following equation:

$$\vec{P}_i = \begin{cases} \vec{P}_i + C_s \times \left(\begin{matrix} \overrightarrow{Z_{min}} + \overrightarrow{C_{Rand}} .* \\ \left(\overrightarrow{Z_{max}} - \overrightarrow{Z_{min}} \right) \end{matrix} \right) .* \vec{B}, & c_{Rand} \leq C_{FAD} \\ \vec{P}_i + \left(C_{FAD} \times (1 - c_{Rand}) + Q_t \right) \times \left(\vec{P}_{r_1} - \vec{P}_{r_2} \right) & c_{Rand} > C_{FAD} \end{cases} \tag{31}$$

$$Q_i = 4 Q_{i-1} \left(1 - Q_{i-1} \right) \tag{32}$$

Here, Q_i is value associated to the $i-th$ generation, where Q_0 is a random number between 1 and 0, and i is generation number.

4. SIMULATION AND RESULTS

The goal of this work is obtaining minimum component sizing for a HRPS generating power for a factory in tropics, which is shown in Fig. 2. The studied time period is 52×7 days which is approximately equal to one year. The energy required by the factory is 490 MWh/y which is a result of six days of operation and one day off in each week. The power demand curve is shown in Fig. 3 which is obtained from real the factory. The simulation is conducted on a core i7-10510u CPU @1.8 GHz and 16 GB of ram using MATLAB application which took 156s. The simulations results are shown in Tab. 3, which show that the generated energy is higher than the demand. In addition to power consumption, Fig. 3 shows the generated power by PV panels, DG, and battery for a week. Note that positive value for battery power means it is losing energy and giving it to the load. Even though the maximum generation capacity of the PV panels are higher than the demand, because the operation time of the factory is longer than the sunny time and sudden increase from zero to full consumption value, PV panels alone are sufficient for supplying the load. This where the battery and DG start helping. It also should be noted that in seventh day, there is no consumption and the battery is charged fully. This could have been a good opportunity to charge the battery with bigger capacity and decrease the need for air-polluting DG if the battery investment cost was not high, however, with current cost given in Tab. 2, the determined very small battery size by the optimization is economically optimum. However, the impact of battery is not significant if removed from system, only 6500$ (0.32%) increase in TLCC will be observed which can be neglected by the system designer to avoid complications. In addition, the battery state of charge changes as the battery charges and discharges according to power excess or insufficiency.

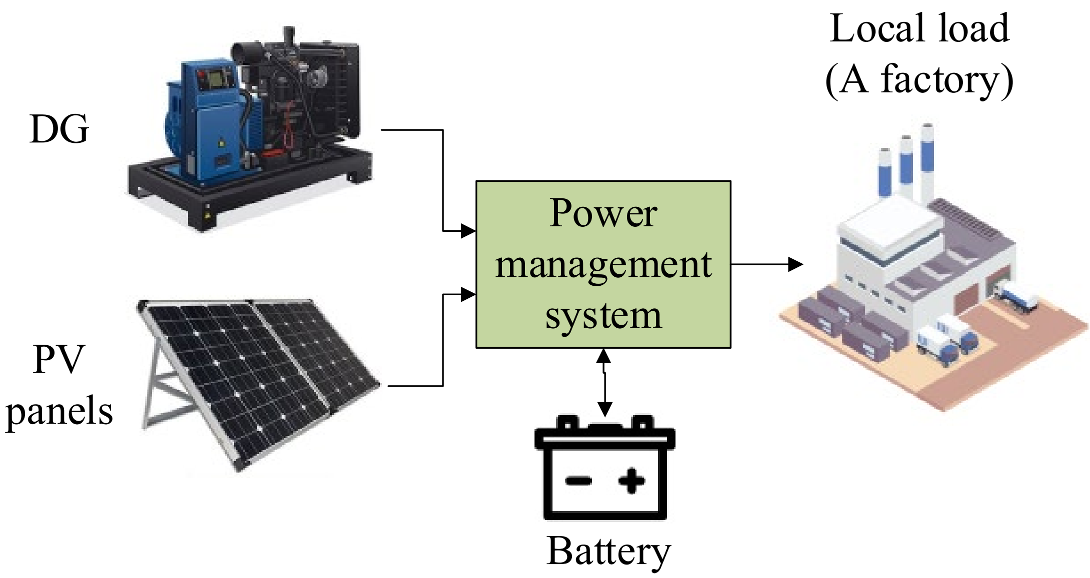

Fig. 2. The proposed HRPS supplying power to a local load

Table 3. The simulations results obtained for one year of simulated operation

Nominal power of PV panels ($P_{PV,Nom}$)	289 kW
Total energy generated by the PV panels	520 MWh
Nominal power of DG ($P_{DG,Nom}$)	128 kW
Total energy generated by DG	145 MWh
Battery storage capacity	33 kWh
Battery power output capacity	17 kW
Total energy exchanged by the battery	11 MWh
Total investment cost (M_{Inv})	284646 $
Total operational cost (M_{Op})	10698 $
LCOE	740984 $

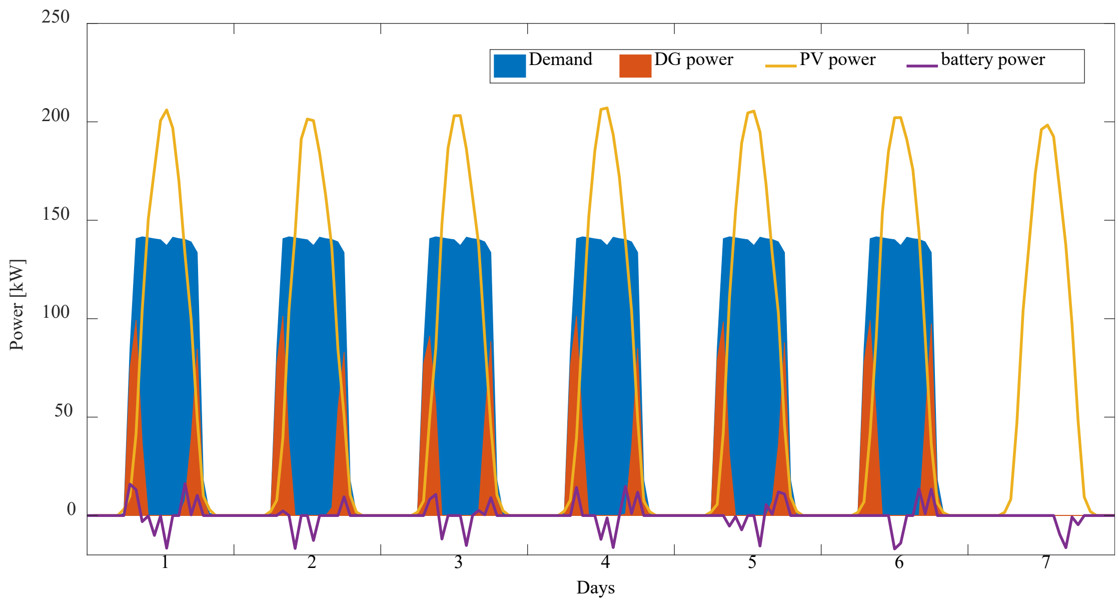

Fig. 3. The load, PV, DG and battery power for random 7 consecutive days.

5. CONCLUSION

A new meta-model of HRPS is studied here and optimized using the proposed novel modified marine predators optimization technique, which is a very powerful optimization algorithm with multi-objective optimization ability and has high performance and speed. This modeling resolves the shortcoming of others tools such as HOMER in term of generality to all configurations. The studied system consists of PV panels, battery, and DG. The three possible type of power output is studied here which include local load, export to main grid, and both local load and main grid. The power system and optimization are implemented in a real-world case study in which a factory in tropics is supplied. The results can be used by system designers and operators to establish their own HRPS with their specific needs. The results also suggest that battery's high investment cost is a barrier in its high-capacity usage. Therefore, a low-capacity battery is suggested by the optimization algorithm, which is close to the one in electric vehicle in terms of size.

The proposed procedure is very flexible and can be utilized in many different HRPS configuration and target for power generation. Moreover, the economics in terms of initial investment and operational costs are also taken into account.

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