# A Novel Metaheuristic Algorithm for Electrical Generation Cost Optimization of Photovoltaic-Hydro-Thermal Power Systems

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A R T I C L E I N F O

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A B S T R A C T

In this paper, the optimal generation cooperation problem of thermal power plant (TPP), hydropower plant (HPP) and photovoltaic power plant (PVP) is successfully solved by slime mould algorithm (SMA). The problem aims to cut electricity generation cost of thermal power plants and photovoltaic power plants, and satisfy all operation constraints in these power plants and power system. The uncertainty of solar radiation is considered during the calculation of power generation and generation cost while limits of reservoir volume and discharge in hydropower plants are taken into account. In addition, general constraints regarding limits of generators such as minimum and maximum power output have to be exactly met. Two systems are run to test the performance of SMA and two other applied methods including Marine predator algorithm (MPA) and Moth Swarm Algorithm (MSA). The two systems are optimally scheduled over twenty-four hours and the PVP in the second system considers the uncertainty in generation and cost. SMA can reach smaller electricity generation cost than MPA, MSA and other previous methods in finding the best generation for all plants and reaching the lowest cost. Thus, SMA is recommended as an effective optimization tool in optimally cooperating three different power plants with the uncertainty of solar radiation.

## 1. INTRODUCTION

In traditional power systems, electrical energy produced from thermal power plants (TPPs) and hydropower plants (HPPs) is supplied to bundle loads such as urban consumers, commercial centers, and industrial zones via transmission lines. These plants use various fuels for generating electricity. TPPs, seized a dominated part of total electricity capacity, use fossil fuel such as gas, coal and oil; however, they are not low-priced and become exhausted in the near future. On the other hand, water that is used to produce electricity in hydropower plants costs approximately zero. Regarding the ability to adapt to the electrical load variation, HPPs are preferred to TPPs because by controlling the water flow HPPs can quickly adjust the generating power from very small power to rated power in only several minutes. Unlike HPPs, the startup and the response time of TPPs corresponding to the variation of load are quite slow. Moreover, increasing or decreasing the generating power of TPPs leads to consume more fuels or even waste of fuel, so we should restrict large adjustment volumes of generating power as well as the completely shut down circumstances. Therefore, TPPs need to operate in full-time periods once they have been started. Based on the previous analysis, to operate effectively and economically as well as save cost for power system, the coordination of TPPs and HPPs, called hydro-thermal system operation scheduling (HTSOS), becomes essential. The scheduling of hydro-thermal systems is more complicated than other systems with only TPPs or only HPPs. The core objective of HTSOS problem is how to minimize electrical generation fuel costs of thermal plants while satisfying the physical and operational constraints of HPPs and TPPs [1]. Constraints of TPPs are the limits of generating power within lower and upper boundaries while those of HPPs are upper and lower generation limits, available water resources, continuity water, water discharge limits and reservoir volume limits [2]. Available water resources, continuity water, water discharge limits and reservoir volume limit, called the hydraulic constraints, are dependent on the mathematical model of HPPs. Normally, HTSOS problem has two basic types that are short-term scheduling (STHTSOS) and long-term scheduling (LTHTSOS). The comer investigates

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optimization horizon of from one day to one week involving hour-by-hour generation planning of all generating units while the latter considers the scheduled plan in a long period, namely one week to one year.

For solving STHTSOS problem, a huge number of methods has been developed by scholarships in the past few decades, such as Lagrange multiplier theory based efficient method (EM) [1], genetic algorithm (GA) [2], improved GA (IGA) [2], Cuckoo search (CS) [3-5], gravitational search (GS) [6], GS with non-dominated sorting procedure (NSGS) [7], GS with combination of krill herd search and particle swarm optimization (GS-KHS-PSO) [8], symbiotic organisms optimizer (SOO) [9-10], accelerated PSO (APSO) [11], hybrid grey wolf optimizer and dragonfly search (HGWODS) [12], krill herd search (KHS) [13], quasi-reflected ions motion optimization search (QRIMOS) [14], evaporation rate-based water cycle optimizer (ERWCO) [15], parallel differential evolution algorithm (PDE) [16], sine cosine search (SCS) [17], two-stage linear programming with special ordered sets (TLPSOS) [18] and backtracking search (BA) [19]. Among methods, EM [1] and GA [2] are the oldest methods but their structure is completely different. EM is a mathematical technique whilst GA is an evolutionary algorithm. In [1], authors have linearized coordination equations and the constraint of availability water of each unit has been separately handled by using Lagrangian function. Based on the obtained results from solving the constraint, the Lagrangian multiplier for the energy balance equation is determined and the outputs of thermal and hydro units are then determined. However, due to using derivative equation, EM cannot solve the problems with consideration of nonconvex objective function or complicated constraints. GA can solve the drawback of EM by employing the mechanics of natural selection and natural genetics. And GA can reach a global optimal solution as proved by obtained result comparisons [2]. Except for EM, other methods have the best solution by using population that are randomly initialized. Anyway, the above studies have proven a promising ability of algorithms in searching the global optimum of the STHTSOS problem. In mentioned papers, authors only focused on minimizing the fuel cost function of thermal unit and ignoring cost of HPPs. However, fuel resources for electricity generation of TPPs will be exhausted and scarce in the future. It is therefore essential to find different resources. Solar energy and wind energy are considered as suitable solutions that can meet the above issue. Recently, these renewable energy sources have been connected in conventional power system with hydro and thermal plants for tackling HTSOS problem [20-25]. In [20], two approaches are proposed for dealing with HTSOS problem considering uncertain model of photovoltaic power plants (PVPs). An efficient 2m-point estimate method (E2PEM) is employed to determine the uncertainty of solar radiation and whale optimization optimizer (WOO) is utilized for finding power of TPPs and HPPs. In [21-23], multi-objective hydro-thermal-wind scheduling with consideration of wind power cost is proposed for testing the ability of bee colony optimization (BCO), NSGA-III and SCS, respectively. In these papers, three wind power costs such as direct cost, underestimation cost and overestimation cost have been established as a part of the objective function of such problem. In [24], cascaded hydropower plants are considered together with TPPs and wind power plants (WPs) while [25] considers the wind-thermal-hydropower-pumped storage system. Like [21-23], the two studies also considered three costs of wind turbines.

In this study, Slime mould algorithm (MSA) [26] is nominated to tackle STHTSOS problem considering the integration of PVPs, the uncertain solar radiation along with complex practical operating constraints. For demonstrating the efficacy and practicality of MSA, its results are compared with many different algorithms available in recent literature and two other implemented methods including Marine predator algorithm (MPA) [27] and Moth Swarm Algorithm (MSA) [28] that were introduced in 2016 and 2020, respectively. MSA and MPA are applied to successfully solve some different problems such as economic load dispatch [29], network reconfiguration [30] and optimal reactive power dispatch [31].

Briefly, the main contributions of the study are as follows:

1. Formulate an optimal scheduling problem for a new complex integration structure consisting of Photovoltaic, Hydro and Thermal power plants,
2. Select the suitable decision variables for methods,
3. Scrutinize performance of SMA, MPA and MSA,
4. Consider the uncertainty of solar radiation.

The remaining sections of this paper are as follows. Problem formulation is shown in Section Problem Formulation. The application of slime mould algorithm for the problem is presented in Section Application. Obtained results, analyses and discussions are reported in Section Numerical Result. Lastly, the conclusion is provided in Section Conclusion.

## 2. PROBLEM FORMULATION

For supplying electricity to loads involving urban consumers, commercial centers and industrial zones, a photovoltaic-hydrothermal power system with TPPs, HPPs and PVPs scheduled in optimization periods is constructed and depicted in Figure 1. This is one of two approaches used to evaluate the effectiveness of the applied algorithms in the study. To operate the system, it is essential to determine the optimal parameters of the power plants. This issue can be solved by using the optimal photovoltaic-hydrothermal system operation scheduling problem (OPHTSOS) through objective function and constraints. The model of TPPs, HPPs and PVPs, the objective function and all constraints can be mathematically expressed as follows: Thermal power plants

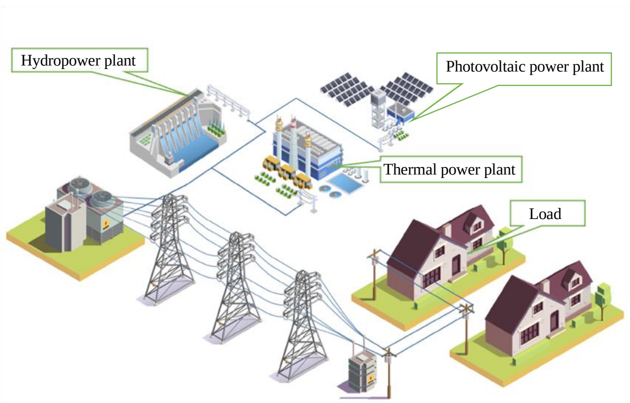


**Fig. 1. A typical photovoltaic hydrothermal power system**

### *2.1. Thermal power plants*

Among these plants, the cost of buying fuels for generating the electricity of TPPs is very high. So, the generation cost of TPPs is regarded as the fuel cost function objective that need to be minimized. The fuel cost (FC) model of all the TPPs available in the system is expressed as a quadratic function below:

$$FC_{TPP}=\sum_{i=1}^{N_1}\sum_{n=1}^{K} a_{si}+b_{si}T_{si,n}+c_{si}\left(T_{si,n}\right)^2 \tag{1}$$

where $N_1$ is the number of TPPs; $T_{si,n}$ denotes the power generation of the *ith* TPP over the subinterval $n$; $a_{si}$, $b_{si}$ and $c_{si}$ are the fuel coefficients of the TPP $i$ and $K$ signifies the number of subintervals.

However, the real cost model of the TPPs is non-convex function as taking the effects of valve on the process of increasing and decreasing power output into account. As result, Eq. (1) is rewritten by adding a sinusoidal term as the following equation below:

$$FC_{TPP}=\sum_{i=1}^{N_1}\sum_{n=1}^{K}\left(\begin{array}{c} a_{si}+b_{si}T_{si,n}+c_{si}\left(T_{si,n}\right)^2 \\ +\left|d_{si}\times sin\left(e_{si}\times\left(T_{si,min}-T_{si,m}\right)\right)\right| \end{array}\right) \tag{2}$$

where $d_{si}$ and $e_{si}$ are the fuel burnt coefficients of the *ith* TPP. $T_{si,min}$ represents the lower power generation of the TPP $i$

### *2.2. Hydropower plants*

Unlike TPPs, HPPs use water from the river to generate electrical power. Thus, their generation cost is low and can be ignored [32]. From this viewpoint, HPPs exploit the maximum power and do not consider the cost but their hydraulic and generator constraints must be seriously administered.

### *2.3. Photovoltaic power plants*

As predicted from Department of Energy [33], a world energy consumption will significantly grow in the future. Regarding energy security, emission problem and a high fluctuation of oil prices, it boosts to expand the non-fossil source use such as renewable energy resource, nuclear power and natural gas. Besides, the policy and support of the governments help renewable energies like solar energy become the world's fastest-growing energy source. Like HPPs, PVPs do not use any fossil fuel for producing the electricity, so their generation cost is negligible. However, if we consider the owner of the plant and the difference between the generated power and the forecasted power of PVPs, their cost model involving direct cost, underestimation cost and overestimation cost should be added [34]. Specifically, as PVPs belong to private owners, three mentioned costs are regarded as a part of objective function that must be minimized. The formulations of these costs are constructed as follows [34]:

$$FC_{DPVP}=g_d.T_{pvf} \tag{3}$$

$$FC_{UPVP}=h_u.\int_{T_{pvf}}^{T_{rpvf}}\left(t_{pvf}-T_{pvf}\right).f_{pv}\left(t_{pvf}\right).dt_{pvf} \tag{4}$$

$$FC_{OPVP}=k_o.\int_{0}^{T_{pvf}}\left(T_{pvf}-t_{pvf}\right).f_{pv}\left(t_{pvf}\right).dt_{pvf} \tag{5}$$

where, $FC_{DPVP}$, $FC_{UPVP}$ and $FC_{OPVP}$ are the direct, underestimation and overestimation costs of the considered PVP; $g_d$, $h_u$, and $k_0$, are the direct, underestimation and overestimation cost price coefficients of PVP; $T_{pvf}$ and $T_{rpvf}$ are the predicted power and the rated power of the *fth* PVP; $f_{pv}\left(t_{pvf}\right)$ is the solar power probability density function for the *fth PVP*.

### *2.4. Objective function*

The main target of the OPHTSOS problem is to cut the total generation cost from TPPs and PVPs as follows:

$$Reduce\ FC=FC_{TPP}+FC_{DPVP}+FC_{UPVP}+FC_{OPVP} \tag{6}$$

### *2.5. The constraint sets*

The solutions of Eq. (6) are subjected to the following equality and inequality constraints:

*2.5.1. System power balance constraint*

This is one of the most important constraints in the problem. This constraint is to ensure the balance between supply side and consumption side. In which, the supply side consists of power generation of TPPs, HPPs and PVPs whilst the consumption side involves the load demand and total power losses. Its mathematical equation is given by:

$$\sum_{i=1}^{N_1}T_{si,n}+\sum_{j=1}^{N_2}T_{hj,n}+\sum_{f=1}^{N_3}T_{pvf,n}=T_{L,n}+T_{D,n} \tag{7}$$

$$with\ n=1,\dots,K$$

where $T_{hj,n}$ denotes the power generation of the *jth* HPP over the subinterval *n*; $T_{L,n}$ and $T_{D,n}$ are power losses in transmission lines and load demand over the subinterval n.

*2.5.2. Discharge limits*

Water discharge via turbines for generating electricity are restricted within their boundaries as follows:

$$wq_{hj,min} \leq wq_{hj,m} \leq wq_{hj,max} \tag{8}$$

where $wq_{hj,n}$ is the discharge at the *nth* subinterval of the *jth* HPP; and $wq_{hj,min}$ and $wq_{hj,max}$ are the lower and upper discharges of the *jth* HPP.

In Eq. (8), $wq_{hj,n}$ is a quadratic function as follows [32]:

$$wq_{hj,n}=o_{hj}+p_{hj}T_{hj,n}+q_{hj}T_{hj,n}^2 \tag{9}$$

where $o_{hj}, p_{hj}$ *and* $q_{hj}$ are discharge coefficients of the HPP *j*

*2.5.3. Water availability constraint*

The total water discharge over *K* intervals must be equal to available as given by Eq. (10) [32]:

$$\sum_{n}^{K} wq_{hj,n} = WV_{h,avai} \quad ;j=1,\dots,N_2 \ ;n=1,\ \dots,K \tag{10}$$

where $WV_{h,avai}$ denotes available water of the *jth* HPP for power generation over *K* intervals

*2.5.4. Power generation constraints*

Power generations generated by TPPs, HPPs and PVPs must be restricted by their bounds as follows [4]:

$$T_{si,min} \leq T_{si,n} \leq T_{si,max};i=1,\dots,N_1;\ n=1,\dots,K \tag{11}$$

$$T_{hj,min} \leq T_{hj,n} \leq T_{hj,max};j=1,\dots,N_2;\ n=1,\dots,\ K \tag{12}$$

$$T_{pvf,min} \leq T_{pvf,n} \leq T_{pvf,max};f=1,\dots,N_3;\ n=1,\dots,\ K \tag{13}$$

where $T_{si,max}$ is the upper power generation bound of the *ith* TPP; $T_{hj,min}$ and $T_{hj,max}$ are the lower and upper power generation limitations of the *jth* HPP; and $T_{pvf,min}$ and $T_{pvf,max}$ are the lower and upper power generation limitations of the *fth* PVP

***2.6. The uncertainty description of solar power***

For determining the uncertainty of solar irradiance, lognormal probability distribution (PDF) [35] can be used and is given by

$$PDF\left(A_{pvf}\right) = \left( \frac{1}{A_{pvf}.\ \sigma.\sqrt{(2.\pi)}} \right) \times exp\ .\left[ -\frac{\left(ln\left(A_{pvf}\right)-\mu\right)^2}{2.\sigma^2} \right] with\ A_{pvf} > 0 \tag{14}$$

where $\sigma$ is the scale parameter and $\mu$ is the location parameter; $A_{pvf}$ is solar irradiance of the *fth* PVP

As solar irradiance is known, the power output of PVPs is resultant from the energy conservation of solar radiation as stated in Eq. (15) below [34]

$$T_{pvf}\left(A_{pvf}\right)=\begin{cases} T_{rpvf}\times\dfrac{A_{pvf}^2}{A_{std}+R_c}\ for\ \ 0<A_{pvf}<R_c \\ T_{rpvf}\times\dfrac{A_{pvf}}{A_{std}}\ \ for\ \ A_{pvf}>R_c \end{cases} \tag{15}$$

$$with\ n=1,\dots,K$$

where $A_{std}$ is the standard environmental solar radiation in W/m$^2$; $R_c$ is radiation intensity in W/m$^2$.

In Eq. (14) and Eq. (15), probability distribution and the power output of PVP are two functions with solar radiation variable. Their values are determined by the sun's radiations at each time period.

## 3. THE APPLICATION OF SLIME MOULD ALGORITHM

***3.1. Slime Mould Algorithm***

The main inspiration for forming SMA is based on the simulation of the food searching process of Slime Mould fungus. This process is divided into two main phases: the body-transforming phase and the surrounding food source phase. In the first phase, the whole body of Slime Mould is transformed like a starfish. In this shape, their limbs are spread out in all directions. This behavior aims to improve the probability of catching foods from the environment. In the second phase, while the food source is already determined, the Slime Mould starts to surround the food source and release a special enzyme to digest the food. The update mechanism of SMA is described in the Equation (16) below:

$$Sm(t+1)= \begin{cases} Lb+r_1(Ub\text{-}Lb) & ;if\ r_1\leq\varepsilon \\ \begin{cases} Sm_{best}(t)+pr.(M.S_{RA}\text{-}S_{RB}), & r_2\leq k \\ dp.Sm(t), & r_2>k \end{cases} & ;if\ r_1>\varepsilon \end{cases} \tag{16}$$

where *Sm(t+1)* is the position of Slime Mould in the *(t+1)th* iteration; *t* is the *tth* iteration; $Sm_{best}$ is the position with the highest flavor that the Slime Mould already detected; *Sm(t)* is the current position of Slime Mould; *dp* is the linear decreasing parameter picked up from the interval of [0, 1]; $S_{RA}$ and $S_{RB}$ are the random positions taking by the Slime Mould on the way to detect food sources; *M* is the mass of Slime Mould; $r_1$ and $r_2$ are respectively the random values with a range of [0 1]; and *pr* is varied in the interval between –*q* and *q*. *Lb* and *Ub* are respectively the lower and upper limitations of search spaces. $\varepsilon$ is the predetermined value and is set to 0.03. The values of *q* and *k* is calculated by:

$$q = arctanh\left( -\left(\frac{t}{H_i}\right)+1\right) \tag{17}$$

$$.k = tanh\ |F(m)\ \text{-}\ BestF\ |;\ m=1,\ \dots,\ N_s \tag{18}$$

where, *F(m)* is the fitness of the *mth* Slime Mould; *BestF* is the best fitness obtained in all iterations; $N_s$ is the population; $H_i$ is the highest iteration.

**Table 1. The comparison of cost values for Case 1**

| Method | EM [1] | GA [2] | IGA [2] | CS [3] | MSA | MPA | SMA |
|---|---|---|---|---|---|---|---|
| Min. Cost ($) | 96024.37 | 96028.65 | 96024.34 | 96024.68 | 96024.76 | 96024.41 | 96024.35 |
| Aver. Cost ($) | - | 96050.15 | 96024.37 | 96024.68 | 96039.74 | 96026.37 | 96024.46 |
| Max. Cost ($) | - | 96086.70 | 96024.42 | 96024.69 | 96105.19 | 96039.22 | 96024.57 |
| STD | - | - | - | 0.003 | 13.051 | 2.758 | 0.036 |
| $N_s$ | - | - | - | 20 | 50 | 25 | 50 |
| $H_i$ | - | - | - | 1000 | 200 | 200 | 200 |

### *3.2. The whole search of SMA for the problem*

The SMA implementation for determining the power output of the plants to reduce cost is presented in the steps below and summarized in flowchart of Figure 2.

Step 1: Set the values for $N_s$, $H_i$ and set $t$ =1

Step 2: Generate solutions in the population $S_m$ ($m$=1,…, $N_s$)

Step 3: - Calculate fitness function using Eq. (6)

- Find $BestF$ and $Sm_{best}$

Step 4: Calculate $k$ and $q$ by using Eq. (17) and Eq. (18)

Step 5: Update new solutions using Eq. (16)

Step 6: Check violated new solutions

Step 7: If $t$=$H_i$, stop the iterative algorithm. Otherwise, set t=t+1 and back to Step 3.

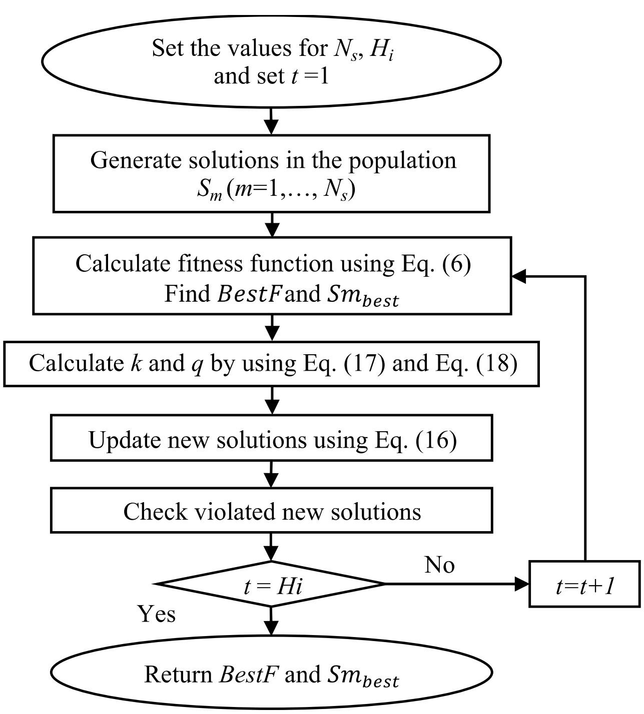


**Fig. 2. The search process of SMA.**

## 4. RESULTS

In this section, SMA is compared to MPA, MSA and other methods such as EM [1], GA [2], IGA [2] and CS [3] to find the best one. Two test systems are handled for determining the optimal parameters. System 1 considers the operation cooperation of one hydro power plant and one thermal power plant and System 2 comprises of one hydro power plant, one thermal power plant and one photovoltaic power plant. The whole schedule timeline is 24h and this schedule is divided into 24 intervals separately. The entire work of programing, simulating and data arrangement is implemented in a personal computer with 2.4 Ghz of Processing unit and 16 GB of RAM. For each system, each method is run for getting 50 successful trial runs.

### *4.1. Comparison and discussion on system 1*

Data of System 1 are given in Table A1 and Table A2 and load demand is reported in Figure A1 in Appendix. The whole data can be read by referring to [3]. For comparisons with other approaches, the minimum cost (Min. Cost), average cost (Aver. Cost), maximum cost (Max. Cost) and standard deviation (STD) are determined to demonstrate MPA's strong search. To reach good results, the most important parameters should be selected effectively to be population ($N_s$) and the greatest iteration ($H_i$). These parameters are chosen for solving two test systems under consideration based on the system dimension and the settings of previously used methods in order to achieve good results and a fair comparison. The two parameters have an impact on the final results as well as the computation time. High values of these parameters usually help applied methods discover very good results, but they take a long time to compute. Conversely, if these parameters are set to low values, the applied procedures will produce poor results. However, in this scenario, short computation time is a significant benefit. As a result, $N_s$ and $H_i$ were chosen to achieve both the good result and reasonable computation time. To solve System 1, by the experiment, $N_s$ of SMA, MPA and MSA are respectively set to 50, 25 and 50. The $H_i$ is set 200 for the three methods. The obtained results by using the methods are reported in Table 1 and plotted in Figure 3, Figure 4 and

Figure 5. Namely, Figure 3 is the best cost obtained from 50 independent runs for System 1. It points out that MSA is the method with extremely high fluctuation between each independent run. The average fluctuation of 50 independent runs given by MPA method is smaller than MSA. In contrast to MSA, SMA has the smallest fluctuations of the fitness values during 50 independent runs. So, SMA is the most stable method among the three applied methods.

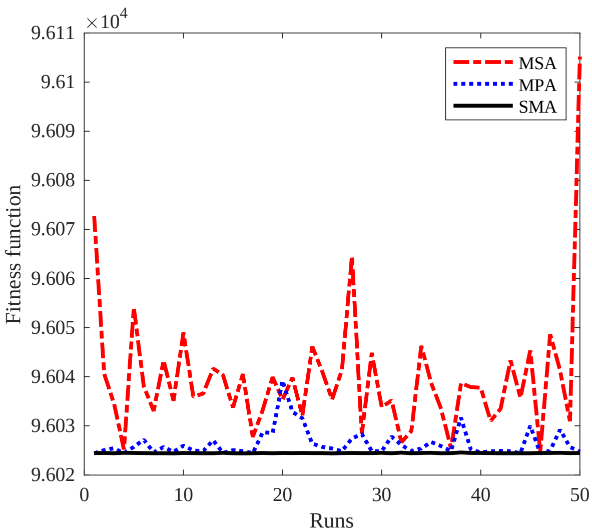


**Fig. 3. The best cost obtained form 50 independent runs for System 1.**

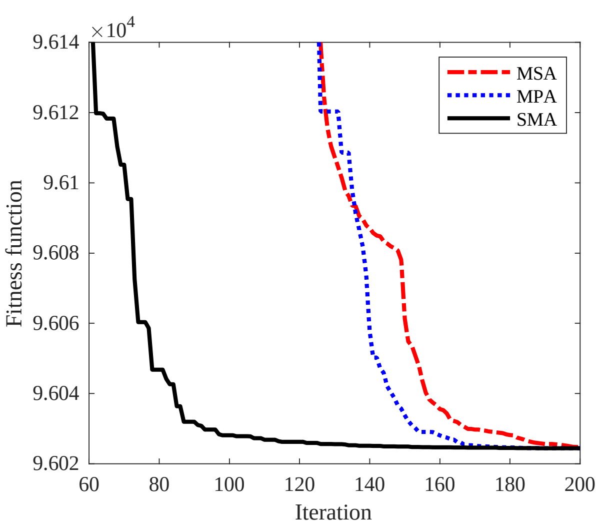


**Fig. 4. The convergence curve of three methods of System 1.**

Figure 4 shows the convergence curves reached by three applied methods for the system. The black curve represents the convergence of SMA method while the blue and red ones are for the convergence of MPA and MSA, respectively. In this figure, SMA shows its outstanding performance because the black curve reaches the optimal fitness value much earlier than both MPA and MSA. Specifically, SMA can reach the best cost at the 155th iteration while MPA and MSA can reach this value at the 170th and 195th iteration, respectively. Clearly, SMA is much faster and more effective than MPA and SMA for the system.

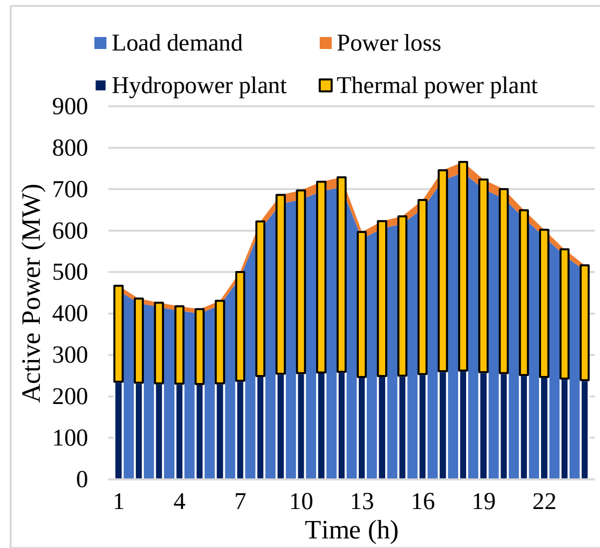


**Fig. 5. The power output generation by two type of power plant at particular time period found by SMA.**

According to Figure 5, the power demand is represented as the light blue bars while the power supplied by HPP and TPP are modelled by the yellow bars and the dark blue bars, respectively. During 24 intervals of the entire schedule, the total amount of power generated by both hydro power plant and thermal power plant surely satisfied the power demand.

In Table 1, the cost values in terms of Min. Cost, Aver. Cost, Max. Cost and STD obtained by three applied methods are compared with the similar values from others. Among three applied methods, SMA is the most effective method about the Min. Cost. Namely, the Min. Cost given by SMA is \$96024.35 while that reached by MPA method and MSA method are \$96024.41 and \$96024.76, respectively. Even the Max. Cost of SMA is better than the Min. Cost of MSA and approximatively equals the Min. Cost of MPA. That means that the application of SMA helps save more costs than MPA and MSA. As compared to other methods, the Min. Cost of SMA is better than the similar values reported by EM [1] with \$96024.37, GA [2] with \$96028.65, CS [3] with \$96024.68, and slightly greater than that of IGA [2] with \$96024.34. However, the results in terms of STD, $N_s$, and $H_i$ of IGA were not reported. Therefore, it lacks adequate information in order to make a final conclusion that the IGA method is more effective than SMA. Regarding to STD, that of SMA is 0.036 and smaller than that of MPA, MSA but higher than that of CS [3]. It is noted that CS [3] was run by using 1000 iterations but SMA was run by using 200 iterations.

### *4.2. Comparison and discussion on system 2*

System 2 is formed from System 1 by adding one PVP. So, data of HPP and TPP of such system are the same as those in System 1. The data of PVP are taken from [35] and reported in Table A3 in Appendix. Due to the presence of PVP, the number of control variables are increased, so System 2 is more complicated than System 1. In addition, the uncertainty of solar radiation is also considered. Therefore, factor electricity prices such as the direct, underestimation and overestimation costs are used for determining the cost of PVP. These costs are considered as a part in function objective of the OPHTSOS problem. Similar to System 1, these parameters such $N_s$ and $H_i$ for running SMA, MPA and MSA remain unchanged as reported in Table 2. The costs from fifty solutions obtained by implementing the three methods are displayed in Figure 6.

**Table 2. The comparison of cost values for Case 2**

| Method | MSA | MPA | SMA |
|---|---|---|---|
| Min. Cost ($/h) | 93475.33 | 93442.89 | 93438.83 |
| Aver. Cost ($/h) | 93550.64 | 93457.14 | 93440.44 |
| Max. Cost ($/h) | 93681.23 | 93505.85 | 93468.65 |
| STD (s) | 47.22 | 14.08 | 4.11 |
| $N_s$ | 50 | 25 | 50 |
| $H_i$ | 200 | 200 | 200 |

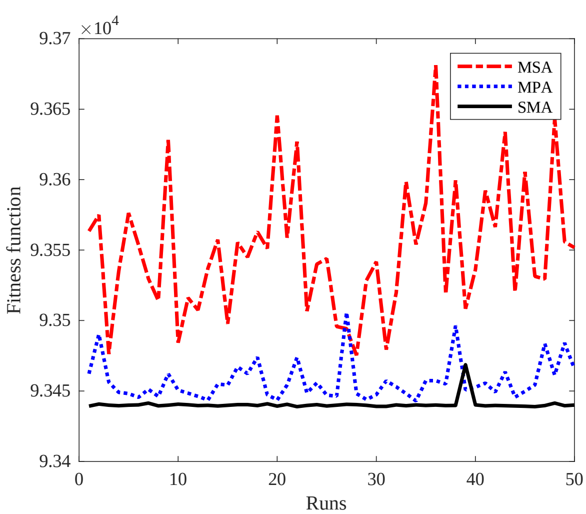


**Fig. 6. The best cost obtained from 50 independent runs for System 2.**

The observation of Figure 6 indicates that the fluctuation between each independent run of the SMA method is very small. The values of SMA are below those of MPA and SMA, excepting the solution at the 39$^{th}$ iteration. In contrast to SMA, the fluctuations of MSA are the highest. Clearly, the SMA method is the most stable method whilst the MSA method is still the most unstable method. Figure 7 shows the convergence curves. The convergence speed in the whole process of finding the optimal results of SMA is the quickest among the three methods. Specifically, the SMA needs only around 150 iterations for reaching the optimal results. The value of MSA is about 175 iterations meanwhile MPA cannot reach the optimal value even for one solution after running out of 200 iterations.

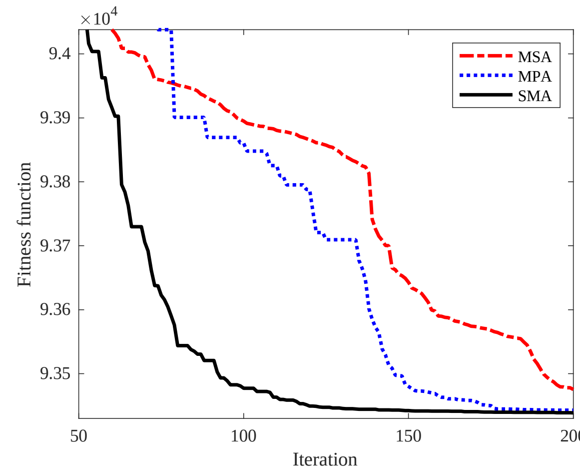


**Fig. 7. The convergence curve of three methods of System 2**

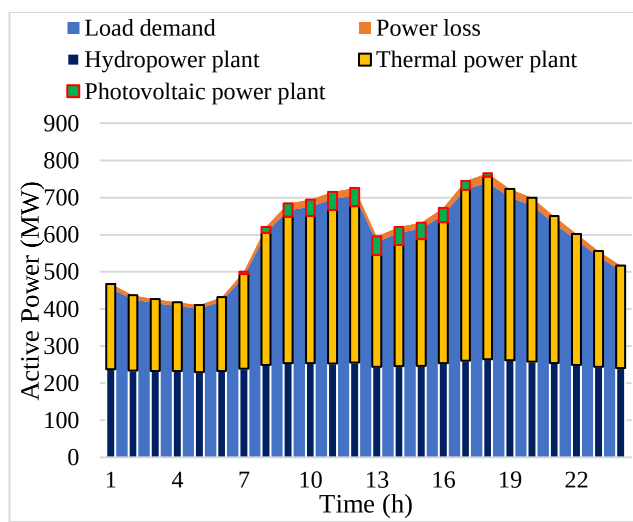


**Fig. 8. The power output generation by two type of power plant at particular time period found by SMA.**

Figure 8 presents the distribution of power output generated by HPP, TPP and PVP over 24 intervals given by SMA. The power output from HPP, TPP and PVP are shown by different color bars. The power output allocation of HPP is the same values over 24 intervals. This proves that HPP always generates the maximum power output because HPP's cost is insignificant. The contribution of TPP vividly fluctuates following each particular interval. That of PVP only exists at 8h until 17h. On the remaining intervals, the solar radiation does not happen, leading to power of zero. The power output from PVP is much less than that from HPP and TPP during the entire day. In addition, total generation of the three plant types can meet the power demand illustrated by the light blue bars. The results obtained by three applied methods in terms of Min. Cost, Aver. Cost, Max. Cost and *Std* are tabled in Table 2. The results obtained by SMA method are $93438.83, $93440.44, $93468.65 and better than those of both MPA and MSA method.

The exact calculation indicates that SMA can find less cost than MPA and MSA by $4.06 and $36.5 for Min. Cost, by $16.70 and $110.20 for Aver. Cost, by $37.199 and $212.58 for Max. Cost. Also, STD reached by the SMA is also smaller than that of MPA and MSA. Essentially, SMA's STD is only 4.11 while the similar values of MPA and MSA are 14.08 and 47.22. Clearly, SMA is the most efficient method among three methods applied in this case and the MSA is the most inefficient method.

## 5. CONCLUSIONS

In this paper, Slime mould algorithm (SMA), Marine predator algorithm (MPA) and Moth Swarm Algorithm (MSA) are applied to find the optimal operation parameters for thermal power plants, hydroelectric plants and photovoltaic power plants in OPHTSOS problem. The performance of three methods is investigated on two test systems. The second system is modified from the first system, so it becomes more complicated by considering PVP and the uncertainty of solar radiation. Results from two systems indicate that SMA could reach the best performance among the three applied methods. Namely, the minimum cost, the average cost, the maximum cost and standard deviation found by the SMA method are better than those of MPA and MSA. As compared to previously published optimization tools, SMA is also superior to almost all compared methods. Clearly, SMA demonstrated its promising ability to deal with the optimization problem of reducing the cost of electricity generation from thermal power plants and photovoltaic power plants while satisfying all system and generator constraints. In the future, it will be applied for larger systems with higher number of power plants and wind power plants considering the uncertainty of solar and wind.

## REFERENCES


[1] A. H. A. Rashid and K. M. Nor, "An efficient method for optimal scheduling of fixed head hydro and thermal plants," IEEE Transactions on Power Systems, vol. 6, no. 2, pp. 632-636, 1991, doi: 10.1109/59.76706.

[2] J. Sasikala and M. Ramaswamy, "Optimal gamma based fixed head hydrothermal scheduling using genetic algorithm," Expert Systems with Applications, vol. 37, no. 4, pp. 3352-3357, 2010, doi: 10.1016/j.eswa.2009.10.015.

[3] T. T. Nguyen, D. N. Vo and A. V. Truong, "Cuckoo search algorithm for short-term hydrothermal scheduling," Applied Energy, vol. 132, pp. 276-287, 2014, doi: 10.1016/j.apenergy.2014.07.017.

[4] T. T. Nguyen, D. N. Vo and W. Ongsakul, "One rank cuckoo search algorithm for short-term hydrothermal scheduling with reservoir constraint," In 2015 IEEE Eindhoven PowerTech (pp. 1-6). IEEE, 2015, doi: 10.1109/PTC.2015.7232825.

[5] T. T. Nguyen and D. N. Vo, "Modified cuckoo search algorithm for multiobjective short-term hydrothermal scheduling," Swarm and evolutionary computation, vol. 37, pp. 73-89, 2017, doi: 10.1016/j.swevo.2017.05.006.

[6] C. Li, J. Zhou, P. Lu and C. Wang, "Short-term economic environmental hydrothermal scheduling using improved multi-objective gravitational search algorithm," Energy Conversion and Management, vol. 89, pp. 127-136, 2015, doi: 10.1016/j.enconman.2014.09.063.

[7] G. Nadakuditi, V. Sharma, and R. Naresh, "Application of non-dominated sorting gravitational search algorithm with disruption operator for stochastic multiobjective short term hydrothermal scheduling," IET Generation, Transmission & Distribution, vol. 10, no. 4, pp. 862-872, 2016, doi: 10.1049/iet-gtd.2014.1137.

[8] X. Xiao and M. Gao, "Improved GSA based on KHA and PSO algorithm for short-term hydrothermal scheduling," In 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (Vol. 1, pp. 2311-2318). IEEE, 2019, doi: 10.1109/IAEAC47372.2019.8998021.

[9] S. Das and A. Bhattacharya, "Symbiotic organisms search algorithm for short-term hydrothermal scheduling," Ain Shams Engineering Journal, vol. 9, no. 4, pp. 499-516, 2018, doi: 10.1016/j.asej.2016.04.002.

[10] S. Das, A. Bhattacharya and A. K. Chakraborty, "Solution of short-term hydrothermal scheduling problem using quasi-reflected symbiotic organisms search algorithm considering multi-fuel cost characteristics of thermal generator," Arabian Journal for Science and Engineering, vol. 43, no. 6, pp. 2931-2960, 2018, doi: 10.1007/s13369-017-2973-5.

[11] M. S. Fakhar, S. A. R. Kashif, N. U. Ain, H. Z. Hussain, A. Rasool and I. A. Sajjad, "Statistical performances evaluation of APSO and improved APSO for short term hydrothermal scheduling problem," Applied Sciences, vol. 9, no. 12, pp. 2440. 2019, doi: 10.3390/app9122440.

[12] G. Chen, M. Gao, Z. Zhang and S. Li, "Hybridization of chaotic grey wolf optimizer and dragonfly algorithm for short-term hydrothermal scheduling," IEEE Access, vol. 8, pp. 142996-143020, 2020, doi: 10.1109/ACCESS.2020.3014114.

[13] P. K. Roy, M. Pradhan and T. Paul, "Krill herd algorithm applied to short-term hydrothermal

scheduling problem," Ain Shams Engineering Journal, vol. 9, no. 1, pp. 31-43, 2018, doi: 10.1016/j.asej.2015.09.003.

[14] S. Das, A. Bhattacharya and A. K. Chakraborty, "Quasi-reflected ions motion optimization algorithm for short-term hydrothermal scheduling," Neural Computing and Applications, vol. 29, no. 6, pp. 123-149, 2018, doi: 10.1007/s00521-016-2529-8.

[15] S. S. Haroon and T. N. Malik, "Evaporation rate-based water cycle algorithm for short-term hydrothermal scheduling," Arabian Journal for Science and Engineering, vol. 42, no. 7, pp. 2615-2630, 2017, doi: 10.1007/s13369-016-2262-8.

[16] J. Zhang, S. Lin, H. Liu, Y. Chen, M. Zhu and Y. Xu, "A small-population based parallel differential evolution algorithm for short-term hydrothermal scheduling problem considering power flow constraints," Energy, vol. 123, pp. 538-554, 2017, doi: 10.1016/j.energy.2017.02.010.

[17] S. Das, A. Bhattacharya and A. K. Chakraborty, "Solution of short-term hydrothermal scheduling using sine cosine algorithm," Soft Computing, vol. 22, no. 19, pp. 6409-6427, 2018, doi: 10.1007/s00500-017-2695-3.

[18] C. Kang, M. Guo and J. Wang, (2017). "Short-term hydrothermal scheduling using a two-stage linear programming with special ordered sets method," Water Resources Management, vol. 31, no. 11, pp. 3329-3341, 2017, doi: 10.1007/s11269-017-1670-1.

[19] K. Dasgupta and P. K. Roy, "Short Term Hydro-Thermal Scheduling Using Backtracking Search Algorithm," International Journal of Applied Metaheuristic Computing (IJAMC), vol. 11, vol. 4, pp. 38-63, 2020, doi: 10.4018/IJAMC.2020100103.

[20] S. Das, A. Bhattacharya, A. K. Chakraborty and V. Pandey, "Fixed head short-term hydrothermal scheduling using whale optimization algorithm considering the uncertainty of solar power," In 2017 Ninth International Conference on Advanced Computing (ICoAC) (pp. 179-185). IEEE, 2017, doi: 10.1109/ICoAC.2017.8441177.

[21] J. Zhou, P. Lu, Y. Li, C. Wang, L. Yuan and L. Mo, "Short-term hydro-thermal-wind complementary scheduling considering uncertainty of wind power using an enhanced multi-objective bee colony optimization algorithm," Energy conversion and management, vol. 123, pp. 116-129, 2016, doi: 10.1016/j.enconman.2016.05.073.

[22] X. Yuan, H. Tian, Y. Yuan, Y. Huang and R. M. Ikram, "An extended NSGA-III for solution multi-objective hydro-thermal-wind scheduling considering wind power cost," Energy Conversion and Management, vol. 96, pp. 568-578, 2015, doi: 10.1016/j.enconman.2015.03.009.

[23] K. Dasgupta, P. K. Roy and V. Mukherjee, "Power flow based hydro-thermal-wind scheduling of hybrid power system using sine cosine algorithm," Electric Power Systems Research, vol. 178, p. 106018, 2020, doi: 10.1016/j.epsr.2019.106018.

[24] H. M. Dubey, M. Pandit, and B. K. Panigrahi, "Ant lion optimization for short-term wind integrated hydrothermal power generation scheduling," International Journal of Electrical Power and Energy Systems 2016, vol. 83, pp. 158–174, doi: 10.1016/j.ijepes.2016.03.057.

[25] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare and S. Asadi, "Two-stage stochastic programming model for optimal scheduling of the wind-thermal-hydropower-pumped storage system considering the flexibility assessment," Energy, vol. 193, p. 116657, 2020, doi: 10.1016/j.energy.2019.116657.

[26] S. Li, H. Chen, M. Wang, A. A. Heidari and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," Future Generation Computer Systems, vol. 111, pp. 300-323, 2020, doi: 10.1016/j.future.2020.03.055.

[27] A. Faramarzi, M. Heidarinejad, S. Mirjalili and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic," Expert Systems with Applications, vol. 152, p. 113377, 2020, doi: 10.1016/j.eswa.2020.113377.

[28] A. A. A. Mohamed, Y. S. Mohamed, A. A. El-Gaafary and A. M. Hemeida, "Optimal power flow using moth swarm algorithm," Electric Power Systems Research, vol. 142, pp. 190-206, 2017, doi: 10.1016/j.epsr.2016.09.025.

[29] P. T. Ha, H. M. Hoang, T. T. Nguyen and T. T. Nguyen, "Modified moth swarm algorithm for optimal economic load dispatch problem," Telkomnika, vol. 18, no. 4, pp. 2140-2147, 2020, doi: 10.12928/TELKOMNIKA.v18i4.15032.

[30] T. T. Nguyen and D. T. Long, "Network Reconfiguration for Minimizing Power Loss by Moth Swarm Algorithm," Network, vol. 11, no. 7, 2020.

[31] M. A. Shaheen, D. Yousri, A. Fathy, H. M. Hasanien, A. Alkuhayli and S. M. Muyeen, "A novel application of improved marine predators algorithm and particle swarm optimization for solving the ORPD problem," Energies, vol. 13, no. 21, p. 5679, 2020, doi: 10.3390/en13215679.

[32] D. P. Kothari, " Power system optimization," In 2012 2nd National conference on computational intelligence and signal processing (CISP) (pp. 18-21). IEEE, 2012, doi: 10.1109/NCCISP.2012.6189669.

[33] J. Conti, P. Holtberg, J. Diefenderfer, A. LaRose, J. T. Turnure and L. Westfall, (2016). *International energy outlook 2016 with projections to 2040* (No. DOE/EIA-0484 (2016)). USDOE Energy Information Administration (EIA), Washington, DC (United States). Office of Energy Analysis, doi:10.2172/1296780

[34] F. Daqaq, M. Ouassaid, R. Ellaia, and A. T. Zeine, "Optimal Power Flow Solution Including Stochastic Renewable Resources," In 2018 6th International Renewable and Sustainable Energy Conference

(IRSEC) (pp. 1-6). IEEE, 2018, doi: 10.1109/IRSEC.2018.8702843.
[35] P. P. Biswas, P. N. Suganthan and G. A. Amaratunga, "Optimal power flow solutions incorporating stochastic wind and solar power," Energy conversion and management, vol. 148, pp. 1194-1207, 2017, doi: 10.1016/j.enconman.2017.06.071.

## APPENDIX

**Table A1. Data of TPP in System 1**

| $i$ | $a_{si}$ | $b_{si}$ | $c_{si}$ | $P_{si,min}$ (MW) | $P_{si,max}$ (MW) |
|---|---|---|---|---|---|
| 1 | 373.7 | 9.606 | 0.001991 | 0 | 505 |

**Table A2. Generation function coefficients and generation limits of HPP of System 1**

| $j$ | $a_{hj}$ | $b_{hj}$ | $c_{hj}$ | $wq_{hj,min}$ (Acre-ft) | $wq_{hj,max}$ (Acre-ft) | $WV_{hj}$ (Acre-ft) |
|---|---|---|---|---|---|---|
| 1 | 61.53 | -0.009079 | 0.007749 | 61.53 | 128.5473 | 2559.6 |

**Table A3. Optimal discharges (Acre-ft/h) found by three applied methods for System 1**

| $n$ | MSA | MPA | SMA | $n$ | MSA | MPA | SMA |
|---|---|---|---|---|---|---|---|
| 1 | 102.312 | 102.302 | 102.387 | 13 | 106.463 | 106.616 | 106.537 |
| 2 | 101.190 | 101.222 | 101.439 | 14 | 107.683 | 107.420 | 107.357 |
| 3 | 100.512 | 101.009 | 101.005 | 15 | 107.923 | 107.922 | 107.800 |
| 4 | 100.878 | 100.801 | 100.764 | 16 | 109.280 | 109.148 | 109.219 |
| 5 | 100.768 | 100.513 | 100.489 | 17 | 112.367 | 111.648 | 111.843 |
| 6 | 101.450 | 101.304 | 100.977 | 18 | 112.683 | 112.335 | 112.462 |
| 7 | 102.526 | 103.247 | 103.320 | 19 | 110.872 | 110.878 | 110.865 |
| 8 | 107.679 | 107.335 | 107.413 | 20 | 110.191 | 110.277 | 110.205 |
| 9 | 109.812 | 109.660 | 109.585 | 21 | 107.981 | 108.345 | 108.413 |
| 10 | 110.073 | 110.081 | 110.045 | 22 | 106.522 | 106.798 | 106.619 |
| 11 | 110.870 | 110.705 | 110.761 | 23 | 105.024 | 105.226 | 105.018 |
| 12 | 110.712 | 111.000 | 111.257 | 24 | 103.831 | 103.808 | 103.820 |

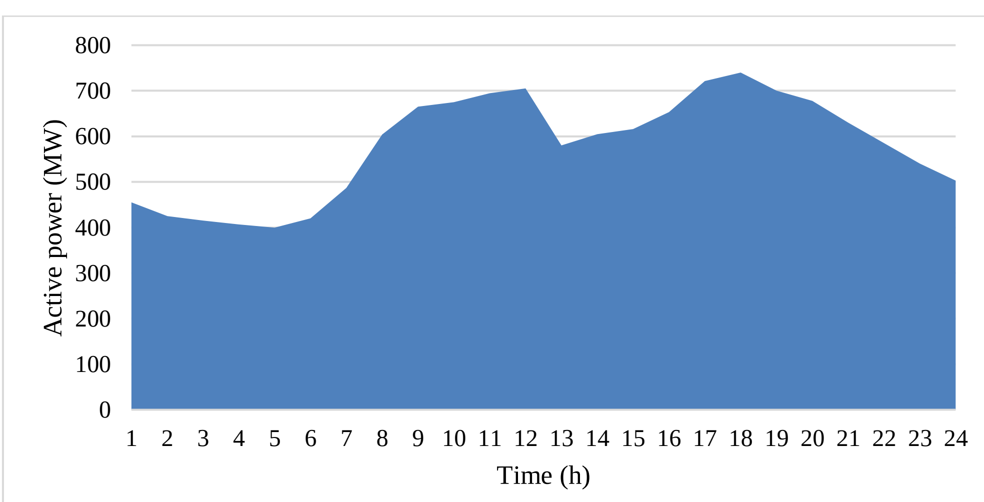


**Fig. A1. Load demand of Systems 1 and 2**

**Table A5. Optimal solutions found by three methods for System 2**

| *n* | MSA | | MPA | | SMA | |
|---|---|---|---|---|---|---|
| | *wq* (Acre-ft) | $T_{pvf}$ (MW) | *wq* (Acre-ft) | $T_{pvf}$ (MW) | *wq* (Acre-ft) | $T_{pvf}$ (MW) |
| 1 | 104.753 | 0.000 | 103.602 | 0.000 | 103.095 | 0.000 |
| 2 | 102.686 | 0.000 | 102.304 | 0.000 | 101.847 | 0.000 |
| 3 | 102.416 | 0.000 | 100.673 | 0.000 | 101.587 | 0.000 |
| 4 | 100.232 | 0.000 | 102.407 | 0.000 | 101.629 | 0.000 |
| 5 | 100.572 | 0.000 | 100.200 | 0.000 | 100.249 | 0.000 |
| 6 | 103.257 | 0.000 | 103.463 | 0.000 | 101.604 | 0.000 |
| 7 | 105.638 | 6.699 | 104.044 | 6.708 | 103.548 | 6.721 |
| 8 | 102.901 | 16.144 | 107.563 | 16.329 | 107.410 | 16.329 |
| 9 | 108.418 | 35.480 | 108.397 | 35.500 | 109.110 | 35.500 |
| 10 | 108.098 | 43.912 | 108.463 | 44.020 | 109.107 | 44.020 |
| 11 | 108.727 | 48.259 | 108.219 | 48.280 | 108.714 | 48.280 |
| 12 | 108.227 | 49.698 | 108.611 | 49.700 | 109.688 | 49.700 |
| 13 | 104.047 | 49.683 | 106.026 | 49.700 | 105.442 | 49.700 |
| 14 | 106.942 | 48.911 | 106.643 | 48.988 | 106.253 | 48.990 |
| 15 | 113.876 | 45.256 | 106.356 | 45.440 | 106.524 | 45.440 |
| 16 | 108.297 | 38.288 | 107.817 | 38.340 | 109.144 | 38.333 |
| 17 | 109.852 | 22.658 | 112.315 | 22.720 | 111.866 | 22.720 |
| 18 | 110.165 | 8.235 | 113.512 | 8.518 | 113.329 | 8.520 |
| 19 | 116.754 | 0.000 | 111.318 | 0.000 | 112.238 | 0.000 |
| 20 | 109.720 | 0.000 | 110.895 | 0.000 | 110.855 | 0.000 |
| 21 | 106.739 | 0.000 | 110.451 | 0.000 | 109.294 | 0.000 |
| 22 | 104.095 | 0.000 | 109.250 | 0.000 | 107.482 | 0.000 |
| 23 | 107.148 | 0.000 | 103.715 | 0.000 | 105.390 | 0.000 |
| 24 | 106.042 | 0.000 | 103.355 | 0.000 | 104.194 | 0.000 |