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Novel Approach for Optimal Sizing of Stand-alone Hybrid Photovoltaic/Wind Systems Using Evolutionary Algorithms

Zakieh Tolooi[1*], Hadi Zayandehroodi[2], Alimorad Khajehzadeh[3]
[1, 2, 3] Science and research, Islamic Azad University, Kerman, Iran
[1]Zakiye_tolooee@yahoo.com, [2]H.zayandehroodi@yahoo.com, [3]Ali.khajezadeh@yahoo.com

Abstract
Nowadays using of new energies in the form of dispersed resources in the worlds is wide spreading. In this article we will design a dispersed production source in the form of a solar/wind hybrid power plant in order to supply the energy of a residential unit according to a sample load pattern based on evolutionary algorithms such as GSA and PSO algorithms to optimize. The aim of aforementioned design is to reduce its costs in a period of 20 years. In order to optimize system costs we will use a new algorithm which is based on collective intelligence namely gravitational search algorithm and also we will use particle swarm optimization algorithm. Finally we can conclude that with an appropriate design of dispersed production resources we will be able to effectively reduce costs and make renewable energy usage more economically.

Keywords: *Energy Hybrid Systems, GSA, Optimal Sizing, PSO, Renewable Energies.*

1. Introduction

Today new energy usage in different regions of the world is rising. But with respect to the low efficiency of these kinds of energy production units, in many cases we cannot economically justify their usage. One way for solving this problem is to increase the efficiency with the help of multiple sources in the form of hybrid power plants for energy supplying in subsystems and independent loads. Because of PV specifications and WG specifications, solar - wind hybrid unit is one of the usual hybrid power plants. In Fig. 1 we can see a diagram of our hybrid power plant [1]. Outputs of energy production units are attached to a dc bus bar which with the help of a battery, is used for battery bank charging. Parallel to the battery bank we have an inverter (dc/ac convertor) which supplies load required energy. Energy surplus saves in the battery bank with the help of energy production units and when the energy is not enough with respect to load demand, saved energy will be used. One of the most important things in designing of such systems is reliable load supply in subsystems at different weather conditions which is considered as the main constraint [2]. In our problem, the number and types of needed equipment for load supplying with minimized cost is the main aim. System costs include purchasing costs, installation costs and maintenance costs in a period of 20 years. With respect to the nature of the presented model, problem parameters include number and types of solar cells, number and types of wind power plants, number and capacities of battery banks and the type of charger battery. Other parameters of the model such as anemometry data, radiation data, load demand and other information are considered as inputs for the problem. In recent years many researches are established about solar - wind hybrid power plant designing and optimization. In [1] with the help of GA or generic algorithm sizing problem of a solar - wind hybrid system is optimized.

Also in [3] sizing of such system is performed with reliability criterion and with the help of PSO algorithm. In some studies energy transforming network is considered in order to minimize the loss [4]. In [5] we have an algorithm for optimized modelling and arrangement of a solar- wind hybrid power plant. Also in [6] and [7] we have a good review of solar/wind hybrid system designing and modelling and after that, some recommendations and suggestions are presented in order to guideline future studies. In recent years using of intelligent algorithms for optimization problems is increasing significantly. Our study in this article because of its nature also shows the ability of these algorithms and altogether, relative studies represent their success in optimization activities.

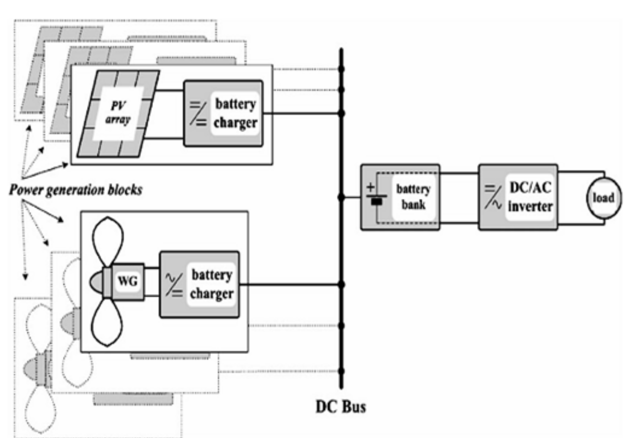

Fig. 1. Block diagram of the studied hybrid system

For example hybrid power plant designing problem is optimized by GA [1], PSO [2] [3] [8] and Markov chain [9]. So in this article, we will use a new method which is based on collective intelligence in order to optimize wind/solar hybrid power plant problem. In suggested method, we will use gravitational search algorithm or GSA which employs gravity rule and object interactions.
For using this algorithm to optimize the problem, variable parameters (number of equipment) are considered as problem dimensions. For model simplification we will waiver the type of equipment. So we have 3 variables which are: number of solar cells, number of wind power plants and number of batteries needed for battery bank. In each iteration, problem variables are determined with respect to system constraints.
We will evaluate the effectiveness of our proposed method with using anemometry data and solar radiation data in one area of Ardebil and Mashhad province in which, our systems are used for satisfying load demand of a rural region with 1 kW load pick and 10kW load pick for 20 years period of time. Moreover this problem is also solved by PSO and the results are compared. In this article we first use sys fluent software for Kite simulation and calculate resultant force, then we use MATLAB software and convert the resultant force to moment and then calculate useful power. In next sections we will explain the procedure and make a comparison in different wind speeds.

2. Modelling and Simulation of System Performance

In this section we will survey system main relations. Also for system simulation, each year is represented by an hourly period of time and simulations all are ran in these periods.

2.1. Solar Cells

With respect to Fig. 2, maximum output power of a solar cell in Ith day and tth hour can be calculated by (1):

$$P_M^i(t) = N_S.N_P.V_{OC}^i(t).I_{SC}^i(t).FF^i(t) \quad (1)$$

$$I_{SC}^i(t) = \{I_{SC,STC} + K_I[T_C^i(t) - 25^o C]\}.\frac{G^i(t)}{1000} \quad (2)$$

$$V_{OC}^i(t) = V_{OC,STC} - K_V.T_C^i(t) \quad (3)$$

$$T_C^i(t) = T_A^i(t) + \frac{NCOT - 20^o C}{800}.G^i(t) \quad (4)$$

In which N_s and N_p are numbers of cells in serial and parallel forms respectively. Also $V_{OC}^i(t)$ is the open circuit voltage (v), $I_{SC}^i(t)$ is the open circuit current (A), $FF^i(t)$ is fill factor, $I_{SC,STC}$ is the open circuit current in standard state (A), K_I is the thermal coefficient of open circuit current (A/°C) , $G^i(t)$ is the amount of radiation absorbed by cell area (W/m^2), $V_{OC,STC}$ is the open circuit voltage in standard state (v), K_V is the thermal coefficient of open circuit voltage (V/°C), $T_A^i(t)$ is the temperature (˚C) and NCOT is the nominal temperature of cell performance(˚C). Serial cell numbers can be calculated as:

$$N_S = \frac{V_{DC}^m}{V_{OC}^m} \quad (5)$$

In which V_{DC}^m is the maximum input voltage to charger batteries and V_{OC}^m is the maximum open circuit voltage of solar cells.

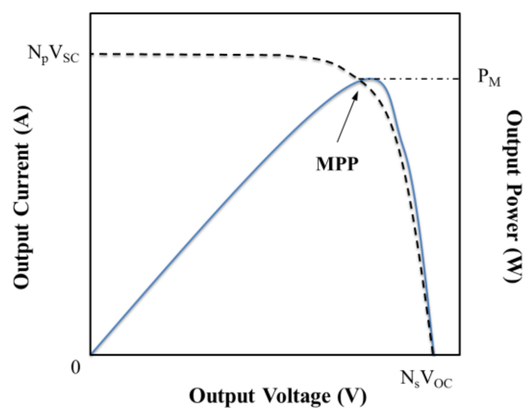

Fig. 2. PV module current–voltage and power–voltage characteristics

2.2. Battery Charger Batteries

Power transferred from a solar cell to a battery bank can be calculated as:

$$n_S = \frac{P_{PV}^i(t)}{P_M^i(t)} = n_1.n_2 \quad (6)$$

In which n_S is charger battery conversion factor, $P_{PV}^i(t)$ is the real power transferred from solar cell, $P_M^i(t)$ is the maximum output power from solar cell, n_1 is the efficiency of power electronic equipment and n_2 is the conversion faction which is dependent on battery charge algorithm [2]. The number of charger batteries is equal to total number of solar cell block and can be calculated as (7), In which N_{ch}^{PV} is the number of solar cell charger batteries, N_{PV} is the total number of solar cells, P_{PV}^m is the

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maximum output power of a solar cell and P_{ch}^{m} is nominal power of charger battery.

$$N_{ch}^{PV} = \frac{N_{PV}.P_{PV}^{m}}{P_{ch}^{m}} \quad (7)$$

2.3. Wind Unit

As shown in Fig. 3, output power of a wind unit is related to wind speed and can be formulated as:

$$P_{WG}^{i}(t) = P_1 + [v^{i}(t) - v_1].\frac{P_2 - P_1}{v_2 - v_1} \quad v_1 < v^{i}(t) < v_2 \quad (8)$$

In which $P_{WG}^{i}(t)$ is the delivered power to battery bank from wind turbine in Ith day and tth hour (W) and (P_1,v_1) and (P_2,v_2) are (wind speed and wind turbine power) couples with respect to tables available in [2] . The amount of wind speed is proportional to turbine installation height and can be calculated as:

$$v^{i}(t,h) = v_{ref}^{i}(t).(\frac{h}{h_{ref}})^{a} \quad (9)$$

In which $v^{i}(t,h)$ is the wind speed at turbine installation height, $v_{ref}^{i}(t)$ is the amount of reference wind and h_{ref} is the amount of reference height. Also (a) is a constant (named power low constant) and its amount varies between 1/7 and 1/4.

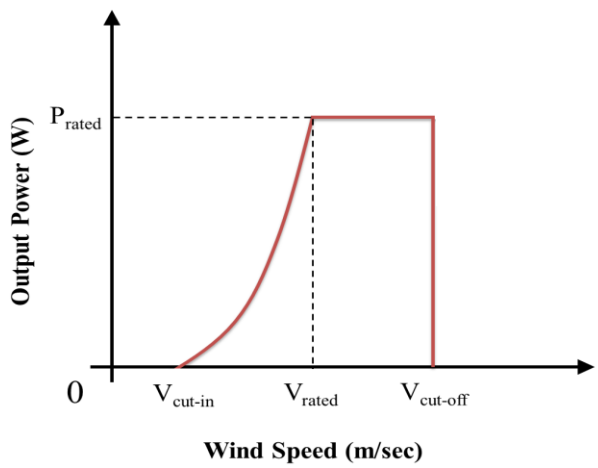

Fig 3. WG power versus wind speed characteristic

2.4. Battery Bank

With respect to battery banks, the bank which is used in this model can only be discharged only 80 percent. This amount is related to discharge depth which is determined by system designer. Minimum allowable battery capacity in the discharging process can be formulated as:

$$C_{\min} = (1 - DOD).C_n \quad (10)$$

In which C_{min} is the minimum allowable battery capacity, *DOD* is the maximum discharge depth and C_n is nominal battery capacity. The amount of battery capacity is proportional to time and changes in the research period as:

$$C^{i}(t) = C^{i}(t-1) + n_B.\frac{P_B^{i}(t)}{V_{BUS}}.\Delta t \quad (11)$$

$$C^{i}(24) = C^{i+1}(0) \quad (12)$$

In which $C^i(t)$ and $C^i(t-1)$ are available battery capacity (ah) at tth and t-1th day respectively, n_B is battery efficiency , $P_B^{i}(t)$ is battery input/output power , V_{BUS} is bus bar voltage (dc) and Δt is the simulation time step. The number of serial batteries can be calculated as:

$$n_B^{S} = \frac{V_{BUS}}{V_B} \quad (13)$$

In which n_B^{S} is the number of serial batteries and V_B is the nominal voltage of each battery.

2.4. Complete Model

The total amount of transferred power from solar cells and wind units can be calculated as:

$$P_{re}^{i}(t) = N_{PV}.P_{PV}^{i}(t) + N_{WG}.P_{WG}^{i}(t) \quad 1 \le i \le 365 \;,\; 1 \le t \le 24 \quad (14)$$

In which N_{PV} is the total number of solar cells and N_{WG} is the total number of wind units. Also the input power to dc/ac convertor can be calculated as:

$$P_L^{i}(t) = \frac{P_{Load}^{i}(t)}{n_i} \quad (15)$$

In which $P_L^{i}(t)$ is the input power to convertor, n_i is the convertor efficiency and $P_{Load}^{i}(t)$ is the estimated load demand in t_{th} interval and I_{th} day. Battery capacity can be calculated with this process:

If *$p^i_{re}(t)=p^I_l(t)$* ***then*** *battery capacity would not change.*
If *$p^i_{re}(t)>p^I_l(t)$,* ***then*** *additional power amount which is $p^i_b(t)=p^i_{re}(t)–p^I_l(t)$ is used for battery charging.*
If *$p^i_{re}(t)<p^i_l(t)$,* ***then*** *the lack of power or $p^i_b(t)=p^i_{re}(t)–p^i_l(t)$ can be compensated with the battery itself.*

All above-mentioned equations and the resulting model with respect to its constraints run in hourly and yearly running intervals. The flowchart of our algorithms is show in Fig. 4.

2.5. GSA Algorithm

GSA is an algorithm which is related to collective intelligence and of course it is memory less. This

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optimization algorithm is designed based on gravitational rules and object movements in an artificial system at discrete times in which system space is the problem definition space. With respect to gravity rule, any object (with mass) understands the location and position of other objects by gravitational rule. So we can use this force as a tool for information exchange [10]. In this algorithm object masses are determined with respect to objective function. In a system with n objects, the position of each object is a point in the space that is a solution for our problem. X_i is the position of the object in d^{th} dimension and can be shown as:

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^n) \quad \text{for } i = 1, 2, ..., N \qquad (16)$$

In which, n is the dimension of the problem and N is the number of objects. In this system a force with the amount of $F_{ij}^d(t)$ is applied to I_{th} object from j_{th} object at the time of t and in the direction of d. The amount of this force can be formulated as:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}(x_j^d(t) - x_i^d(t)) \qquad (17)$$

In which $M_{Pi}(t)$ is the active gravitational mass of j and $M_{\alpha j}(t)$ is the inactive gravitational mass of I, and in our algorithm we assume that both of them are equal to M. Also each object has an acceleration and speed which are respectively shown by a_I (t) and V_I (t). With respect to the second law of Newton each object in the d_{th} dimension has an acceleration which is proportional to the applied force (in that dimension) divided by inertial mass and this is shown in (18). Moreover the speed of each object in time can be calculated by (19):

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \qquad (18)$$

$$v_i^d(t+1) = rand_j \times v_i^d(t) + a_i^d(t) \qquad (19)$$

After the calculation of speed and acceleration, we can use (20) in order to calculate the new position of I_{th} object in d_{th} dimension.

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (20)$$

In our method, new position is considered as the location of new objects in search space and we can normalize the mass of the new objects by (21) and (22):

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - Worst(t)} \qquad (21)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \qquad (22)$$

In which $fit_i(t)$ represents the amount of fitness of the I_{th} object at t and worst(t) and best(t) are respectively the fitness amounts of the worst and the best objects in the total population at t and we can calculate their amounts by these equations:

$$best(t) = \min\{fit_i(t)\} \qquad (23)$$

$$worst(t) = \max\{fit_i(t)\} \qquad (24)$$

2.6. PSO Algorithm

PSO algorithm is inspired from nature and is based on social behaviour of birds of fishes in the food finding processes. Movement rules and searching rules in this algorithm are simple and meaningful and are developed for NLP programs with continues variables but also we can use them for NLP problems with discreet variables too. In this algorithm the location of each particle changes by its speed vector. Direction and amount of each speed vector is also influenced by previous speed vector in the direction of the best previous personal and group experience. The mathematical representation of this thing is shown in eq. (25).

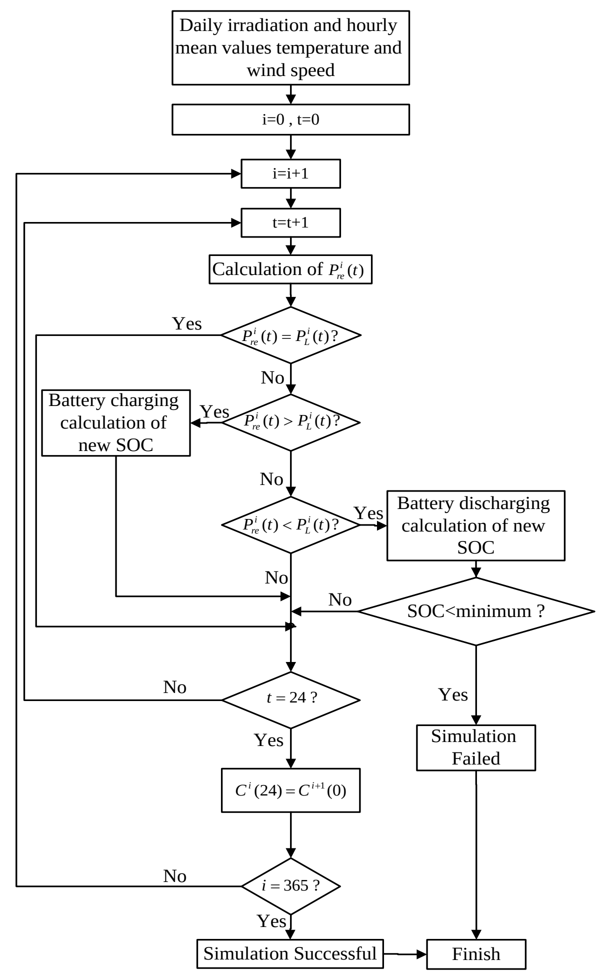

Fig 4. Flowchart of the proposed optimization algorithm for the simulated model

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As we can see, the previous speed vector is combined with distance vector to the best personal result and distance vector to the best group result and so the new speed vector direction is determined:

$$V_i^{k+1} = w \times V_i^k + C_1 \times rand_1 \times (P_{best\,i} - s_i^k) + C_2 \times rand_2 \times (g_{best} - S_i^k) \quad (25)$$

In which V_i^{k+1} is the corrected speed vector for i_{th} particle in $K+1_{th}$ iteration, V_i^k is the speed vector for i_{th} particle in K_{th} iteration, S_i^k is the location coordinate of i_{th} particle in k_{th} iteration, $rand_{1,2}$ is a random number between 0 and 1, P_{Best} is the location vector of the best personal experience (for i_{th} particle), g_{Best} is the location vector of the best group experience, w is the weight factor for each particle, and C_1 and C_2 are learning coefficients which are fixed on 2. With eq. (25) for each particle we can calculate a special speed and in the next iteration we can rewrite particle location as:

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (26)$$

W or weight function can be determined by eq. (27). Regularly the amount of this weight factor in each iteration, decreases linearly so it can be guaranteed that the direction is toward the best personal and group experience:

$$w = w_{max} - \frac{(w_{max} - w_{min})}{iter_{max}} \times iter \quad (27)$$

In which W_{max} is the initial weight, W_{min} is the final weight; $iter_{max}$ is the maximum allowable iteration and iter is the number of iteration.

3. Results and Discussion

3.1. Test System 1

In this test system, the proposed model have been simulated in MATLAB 7.1 and IEEE-30 bus reliability test system (IEEE-RTS30) with 1 kW maximum peak load or load demand has been used as a load profile. Other assumptions like PV modules installation tilt angle and simplification in simulation time-intervals are obtained from [2]. The average daily vertical and horizontal solar irradiation during 52 weeks of a year is shown in Fig. 5 (left). Also, Wind speed at the WG installation height is shown in Fig. 5 (right). In addition, information of load profile is presented in Fig. 6 (left). Simulation of the proposed model was lasted 5 seconds.

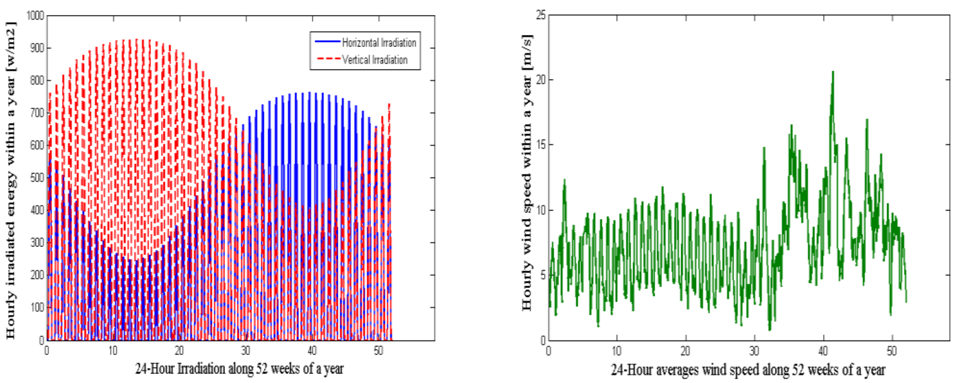

Fig 5. 24-hour average irradiation during 52 weeks of a year (left figure) and 24-hour average wind speed during 52 weeks of a year (right figure)

The algorithm results or optimum combination is presented in Table 1. It should be mentioned that information about the types of equipment and their costs is obtained from [1] and [2]. Due to the continuous essence of GSA and the discontinuity of this problem results, value of objective function is determining as the nearest value to the discontinuous result of each variable in each iteration. As a matter of fact, answers will be rounded. Fig. 6 (right) shows the battery charge of the optimum combination during the case study. Also, Fig. 7 shows the convergence procedure of GSA in solving duration for PV/WG sizing problem.

3.2. Test system 2

In this test system, the proposed model have been simulated in MATLAB 7.1 and IEEE-30 bus reliability test system (IEEE-RTS30) with 10 kW maximum peak load or load demand has been used as a load profile.

Table 1. Optimum combination of the hybrid PV/WG system according to the proposed model

System Type	Number of PV modules	Number of WG	Number of Batteries	Total Cost (Euro)
Hybrid PV/WG System	1	3	4	26129.09

Other assumptions like PV modules installation tilt angle and simplification in simulation time-intervals are similar to the test system 1 [2]. The average daily vertical and horizontal solar irradiation during 52 weeks of a year and Wind speed at the WG installation height are similar to the test system 1 too. In addition, information of load profile is presented in Fig. 8 (left). Simulation of the proposed model was lasted 112 seconds. The algorithm results or optimum combination is presented in Table 2. Fig. 8 (right) shows the convergence procedure of GSA for PV/WG sizing problem. Fig. 9 shows the convergence procedure of PSO algorithm for PV/WG sizing problem.

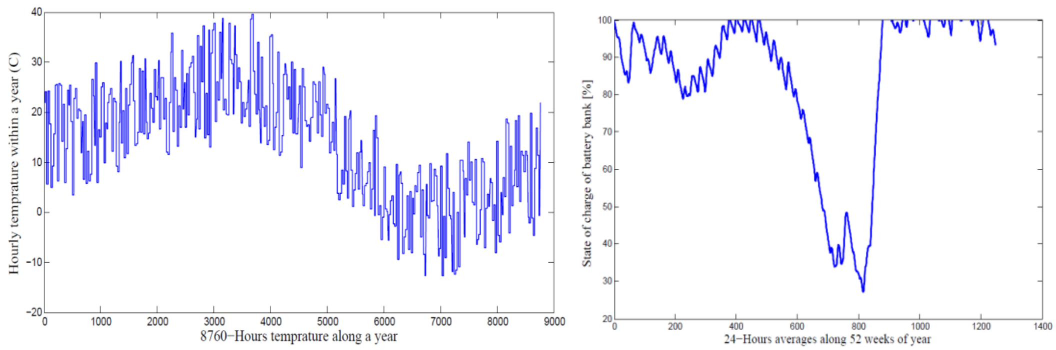

Fig 6. 24-hour load demand during 52 weeks of a year of the test system 1(left) and the battery charge of the optimum combination during the case study (right).

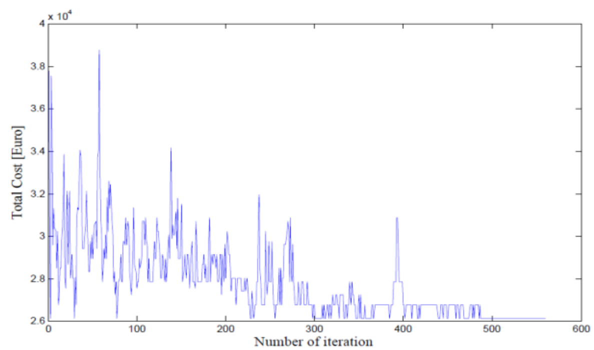

Fig 7. Convergence procedure of the proposed algorithm

Table 2. Optimum combination of the hybrid PV/WG system according to the proposed model

System Type	Number of PV modules	Number of WG	Number of Batteries	Total Cost (Euro)
Hybrid PV/WG System	2	30	41	214356.85

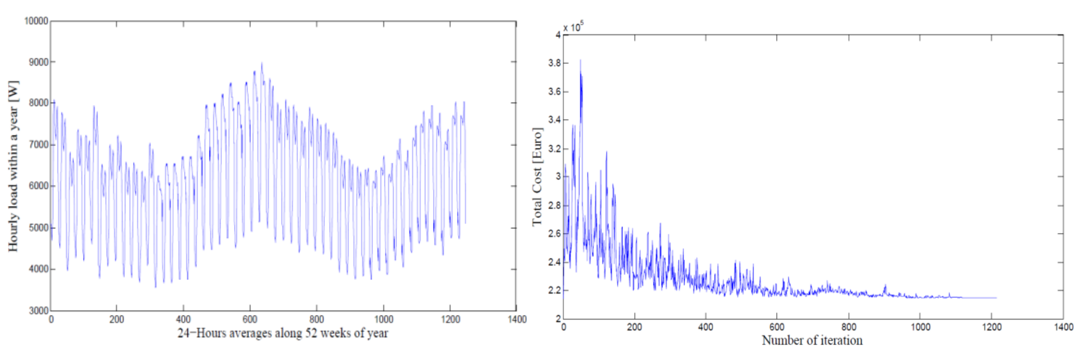

Fig. 8. 24-hour load demand during 52 weeks of a year of the test system 2 (left) and Convergence procedure of the GSA algorithm in test system 2 (right)

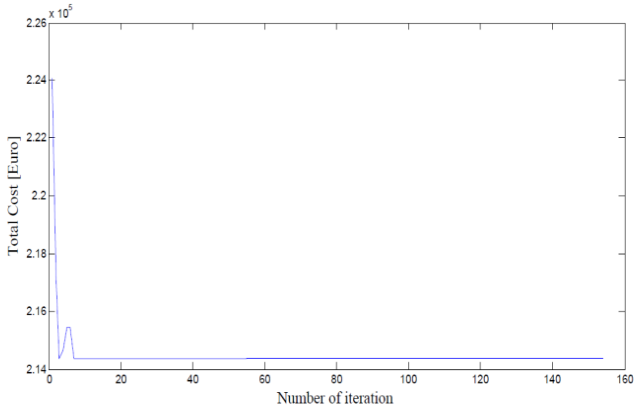

Fig 9. Convergence procedure of the PSO algorithm in test system 2

4. Conclusion

Application of renewable energy sources as a distributed generation will reduce the emission of greenhouse gases and also, will save a lot of investment that lost in fossil energy fields. There are a lot of potentials to use renewable energy sources in Iran. This paper presents the optimum sizing of a hybrid PV/WG system for three test systems, using gravitational search algorithm (GSA). The results show the algorithm ability to solve optimization problems in power systems in a fast and accurate manner and also, without any computational burden.

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