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SIZING OF A STAND-ALONE PHOTOVOLTAIC SYSTEM BASED ON NEURAL NETWORKS AND GENETIC ALGORITHMS: APPLICATION FOR REMOTE AREAS

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ABSTRACT

In literature several methodologies based on artificial intelligence techniques (neural networks, genetic algorithms and fuzzy-logic) have been proposed as alternatives to conventional techniques to solve a wide range of problems in various domains. The purpose of this work is to use neural networks and genetic algorithms for the prediction of the optimal sizing coefficient of Stand-alone Photovoltaic (SAPV) systems in remote areas when the total solar radiation data are not available. A database of total solar radiation data for 40 sites corresponding to 40 locations in Algeria, have been used to determine the iso-reliability(sizing) curves of a SAPV system (C_A, C_S) for each site. Initially, the genetic algorithm (GA) is used for determining the optimal coefficient (C_{Aop}, C_{Sop}) for each site by minimizing the optimal cost (objective function). These coefficients allow the determination of the number of PV modules and the capacity of the battery. Subsequently, a feed-forward neural network (NN) is used for the prediction of the optimal coefficient in remote areas based only on geographical coordinates. For this, 36 pairs have been used for the training of the network and 4 pairs have been used for testing and validation of the network. The simulation results have been analyzed and compared with conventional methods in order to show the importance of the proposed methodology. This methodology has been applied for Algerian location, but it can be generalized in the World. The Matlab $^{(R)}$ Ver. 7 has been used for this simulation.

Keywords: *PV system sizing, optimal coefficient, genetic algorithm, artificial neural networks.*

1. INTRODUCTION

The optimal selection of the number of solar cell panels and the size of the storage battery to be used for a certain application at a particular site is an important economical problem. Besides being an economic waste, an oversized system also adversely affects further utilization of solar cells and the pollution-free photovoltaic energy. Undoubtedly, at the present stage of the development of photovoltaic (PV) technology, the major impediment to a wider market penetration, as noted by Haas [1], is the high investment costs of the PV systems. However, estimation of the sizing coefficients (PV-array area, useful capacity of battery) is very useful to conceive an optimal PV system as well as conceiving an optimal and economic stand-alone PV system particularly in isolated sites. In the last decade, several studies have been developed for sizing PV system by many scientists, including analytical solutions and numerical method approaches [2-10]. A suitable model for

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sizing PV system based on Energy generation simulation for various PVs and batteries is proposed in [11]. The selection of the numbers of PVs and batteries ensures that reliability indices such as the Loss of Load Hours (LOLH), in ref [12] the author have proposed a methodology of sizing PV system based on Markov chain for generating sequences of daily solar radiation values. In this approach the number of PVs and batteries are selected according to the desired System Performance Level (SPL) requirement. A review was given in [13] the proposed technique is based on the analytical [2] and numerical [3] approach to simulate the operation of a PV systems. The Loss of Load Probability (LLP) technique is often used for sizing PV system defined as the ratio between the energy deficit and the energy demand on the load. A Recent study is proposed in [14] this technique requires a long term of the observed time series of solar radiation data, is based on using a simple geometrical construction, the sizing curve is determined as a superposition of contributions from individual climatic cycles of low daily solar radiation, for sites with a good availability of daily solar radiation data, this approach over several advantages over the traditional LLP based methods [14]. A more recent study based on the using of the genetic algorithm for sizing hybrid PV system (PV-Wind generator) is presented in [15]. But it requires a long term of several meteorological parameters.

Generally, these methods need the availability of long term of the total daily solar radiation data, and other related methodological data (wind, temperature, humidity, etc.) for sizing PV or hybrid PV system. So, it is clear in the case where the actual or the synthesized solar radiation data are not available; this method cannot be applied for sizing and simulating the operation of a PV system. In order to solve this problem, other more recent methods based on Artificial Neural Network (ANN) and B-Spline function have been developed for sizing PV system in remote areas based on numerical approach [16-23]. In this paper we investigate the suitability of using the genetic algorithm for selection the optimal pair (C_{AOP}, C_{SOP}) of PV system corresponding to 40 locations, and then the ANN is used for prediction of the optimal sizing pair for isolated area in Algeria. Four experimental sites are used for validation and testing of the proposed method (GA-ANN) [24]. This paper is organized as follows: The next section presents a description of simplified stand-alone PV system. Section 3 presents the dataset of daily solar radiation used in this simulation. Section 4 gives an application of the both numerical and graphical approaches for developing the database for sizing PV system. A brief introduction of genetic algorithm and neural networks is presented in section 5. The proposed methodology is described in section 6, while section 7 provides the simulation and validation results.

2. STAND-ALONE PV SYSTEM

A stand-alone PV power supply system is established as a reliable and economical source of electricity in rural remote areas; especially in developing countries where the population is dispersed, with low income and a lack of power supply due to viability and financial contrariness. PVS are defined as autonomous systems that supplies electricity without being connected to the electricity grid. A schematic of the PVS systems is shown in figure 1.

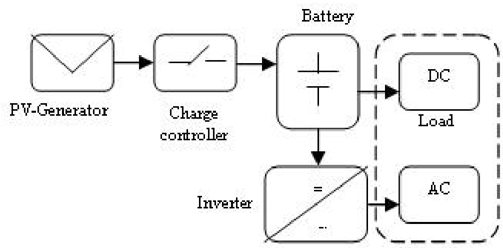

Fig.1 *Simplified schema of SAPV system*

3. DATASET OF SOLAR RADIATION DATA

The both databases of monthly total solar radiation corresponding to 40 sites and total daily solar radiation (during 10-years) have been collected from the National Office of Meteorological (NOM) in Algeria. Figure 2 shows the daily total solar radiation for 4-sites.

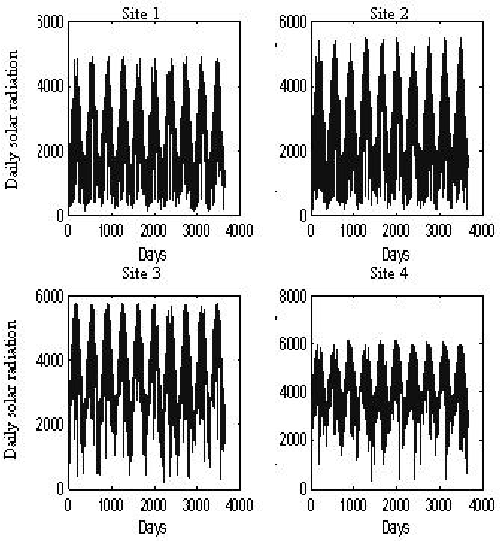

Fig.2 *Sequences of daily solar radiation data*

4. DEVELOPED SIZING DATABASE OF PV SYSTEM

The sizing of a PVS system is a general concept including the sizing of PV-array and the accumulator. A useful definition of such dimensions relates to the load. On a daily basis, the PV-array capacity, (C_A) is defined as the ratio between average PV-array energy production and the average load energy demand. The storage capacity, (C_S) is defined as the maximum energy that can be taken out from the accumulator divided by the average energy demand [13], so:

$$C_A = \frac{\eta_{PV} A_{PV} G}{L} \text{ and } C_S = \eta_B \frac{C_U}{L} \qquad (1)$$

Where A_{PV} is the PV-array area, η_{PV} is the PV-array efficiency, G is the average daily irradiation on the PV-array, L is the average daily energy consumption, C_S is the storage capacity and C_U is the useful accumulator capacity [13].

4. 1. Numerical Approach

The numeric method proposed by [3,13] is used for developing the database of optimal sizing coefficients of PV-system (C_A, C_S). The construction of a sizing curve based on LLP requires the modeling of PV system operation over substantial periods of time. Time series of solar radiation then cannot come directly from observation but need to be reproduced ''synthetically'' based on an algorithm which is faithful to the solar radiation statistics. The relationship between the LLP values and the perceived reliability requirements of the user are then indirect, although generally accepted correspondence exist for most standard applications [13]. The long term of total solar radiation data is required for implementing this technique, for this reason we have used the proposed approaches by [25, 26] for generating sequences of total daily solar radiation data (for 40-sites during 10-years), and then based on the numerical approach we have plotted the iso-reliability (sizing) curve for each sites used in this study, figure 3 show the iso-reliability curve for some Algerian sites, by using the analytical cost (see table 1), so, the first database of sizing coefficient of SAPV system is developed. For example table 2 illustrates these coefficients for some sites.

Table 1. *Data for cost analysis*

Battery				
Nominal capacity (Ah)	Voltage	Maximum, permissible depth of discharge (%)	Capital cost (€)	Maintenance cost (€/year)
220	12	80	260	2.5

PV -module						
V_{oc}(V)	I_{sc}(A)	V_{max}(V)	I_{max}(A)	P_{max}(V)	Capital cost(€)	Maintenance cost (€/year)
24	7	16.9	6.48	111	520	5.2

Inverter DC/AC			
Efficiency (%)	Power rating (W)	Capital cost (€)	Maintenance cost (€/year)
75	1400	190	19.2

Table 2. *Example of optimal coefficient of PV system calculated by numeric method*

Sites	Optimal sizing coefficient	
	Numerical method	
	C_{AOP}	C_{SOP}
1	1.22	1.15
2	1.20	0.97
3	0.79	0.85
4	0.70	0.81

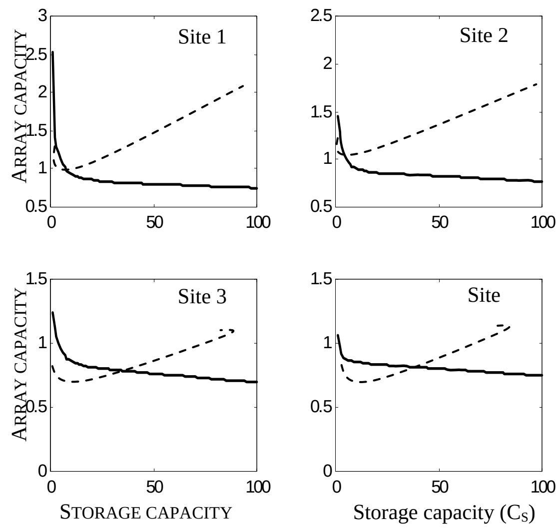

Fig. 3 *Iso-satisfaction curves (__) and cost curves (…) for LLP=1%*

4.2. Graphical Approach

The second used in this study is that proposed in [14], this technique is based on observed time series of solar radiation data for sizing PV system; which consists to determine of sizing coefficient by using a simple geometric constriction technique. We have used the actual time series of solar radiation data for 4-sites in order to determine the sizing coefficient for one interval time, for example figure 4(a) show the daily solar radiation data during a part of December. A quick estimate of the energy balance in a system designed for the average radiation (see Figure. 4(b)) indeed shows that there is a deficit in the energy supply for a considerable period of time, which has to be bridged over by the battery.

Assuming that the battery is fully charged at the beginning of this, the battery size is determined by the energy deficit at the end of the climatic cycle. Based on actual solar radiation data we have plotted the sizing curve (see figure 5).

The estimated coefficients by this technique for 4-sites are used for make a comparison between numerical methods. For example table 3 illustrates these coefficients for some sites

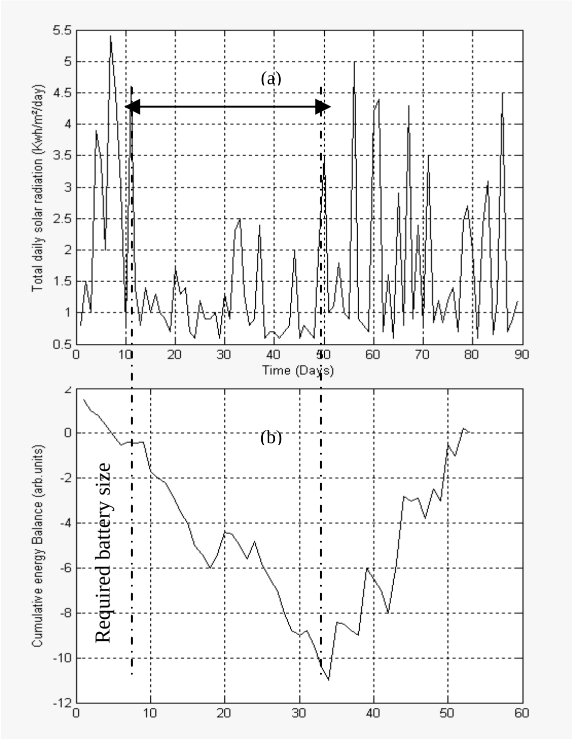

Fig.4 (a). *The daily solar radiation in Algiers during the winter of 2000–2001, showing the dominant climatic cycle extending from 11th November 2000 to 25th December 2001. The average daily radiation is the long mean value for December.* **(b)** The cumulative energy balance (energy taken out of the battery) for a system design based on the average daily

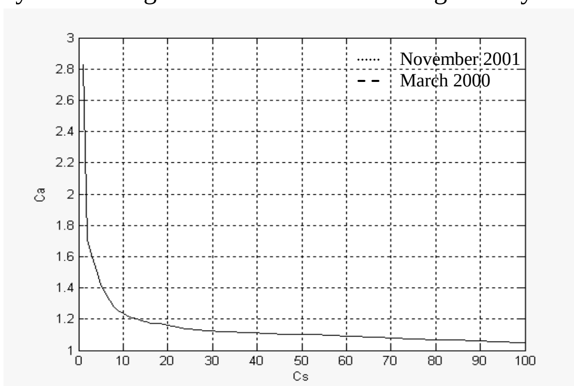

Fig.5 *the iso-reliability (sizing) curve*

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Table3. *Example of optimal coefficient of SAPV system calculated by graphical method*

Sites	Optimal sizing coefficient	
	Graphical method	
	C_{AOP}	C_{SOP}
1	1.23	1.01
2	1.15	0.95
3	0.75	0.64
4	0.68	0.58

5. GENETIC ALGORITHMS AND NEURAL NETWORKS

In this section, a brief description of the genetic algorithm and neural networks is presented.

5.1 Genetic Algorithm

The concept of Genetic Algorithms (GA) for solving optimization problems is based on the analogy to evolution theory in population genetics. Holland [27] adopted the idea of the survival of the fittest in a process of cooperation and competition among individuals to combinatorial optimization problems; the solutions of the problem are coded into chromosomes, i.e., a sequence of genes. A set of such chromosomes is called a population. Starting from initial population new chromosomes are generated by standard genetic reproduction operators, e.g. crossover and mutation and are evaluated with respect to a problem specific fitness function. Depending on their fitness values, some chromosomes survive and some die out leading to a new population. Through the repetition of this reproduction process, a sequence of populations is generated with the expectation to generate solutions of better quality during the course of this process. The GA-solution process can in general be structured into stages. In the first static stage a coding scheme and an appropriate fitness function capturing the main objective and constraints are defined for the given problem type. In addition, the static parameters of the GA-scheme are initialized e.g. population structure, size and communications scheme as well as the specification of operators and strategies to be applied in the dynamic stage. The dynamic stage is divided into four phases which are iteratively applied until a given termination criterion is reached to produce new populations and to simulate the natural evolution process.

1. **Selection phases:** in this phase a number of individuals of the current population are selected and paired for reproduction.
2. **Reproduction phase:** Applying the principal genetic reproduction operators like crossover and mutation new solutions are generated by sexual reproduction.
3. **Integration phase:** The new individuals are evaluated according to the defined fitness function. Then it is decided which of these offsprings will be integrated into the new population and which older individuals will be excluded from the actual population.
4. **Control phase:** In this phase, global metrics of the population are assed and the communication scheme is updated. The algorithm checks if the termination criterion holds.

5.2 Neural Networks

Artificial neural networks (ANN) have been successfully employed in solving complex problems in various fields of applications including pattern recognition, identification, classification, speech, vision, prediction and control systems [28]. Today ANNs can be trained to solve problems that are difficult for conventional computers or human beings. ANNs, overcome the limitations of the conventional approaches by extracting the desired information directly from the experimental (measured) data. The fundamental processing element of a neural-network is a neuron. Basically, a biological neuron receives inputs from other neurons, combines them in some way, performs a generally non-linear operation, and then outputs the final results. The network usually consists of an input layer, some hidden layers and an output layer [28, 29].

A simplified procedure for the learning process of an ANN is as follows:

- *Provide the network with training data consisting of patterns of input variables and target outputs.*
- *Assess how closely the network output matches the target outputs.*
- *Adapt the connection strength (i.e., weights) of the various neurons.*

- *Continue the process of adjusting the weights until the desired accuracy level is achieved.*

Usually a back-propagation learning algorithm is used. In this work we have used the Levenberg-Marquardt (LM) [30]. The LM algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated as $H = J^T J$ and the gradient can be computed as $g = J^T e$, where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard back-propagation technique (see [30]) that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \qquad (2)$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced for each iteration in the algorithm.

6. THE PROPOSED METHODOLOGY

The proposed method has been applied to the sizing of a stand-alone PV-system in order to power supply a domestic application (e.g. electrification; small water pumping system, etc.). The first step of the optimal sizing methodology consists of a system simulation procedure in order to examine whether a system configuration, comprising a certain number of system devices and installation details, fulfils the load power supply requirements during the year [15]. The total daily solar radiation data described above are used for this simulation study. However these data are transformed on inclined tilt equal to the altitude of the site by using Jordan model. The main objective of this methodology is to determine the optimal sizing coefficient by genetic algorithm for 40 sites and then use the optimum pair of coefficients for training the ANN in order to predict the optimal sizing coefficient for an isolated area. The block diagram of the proposed methodology is presented in figure 6, while figures. 7(a) and (b) show the GA process and the ANN model respectively,

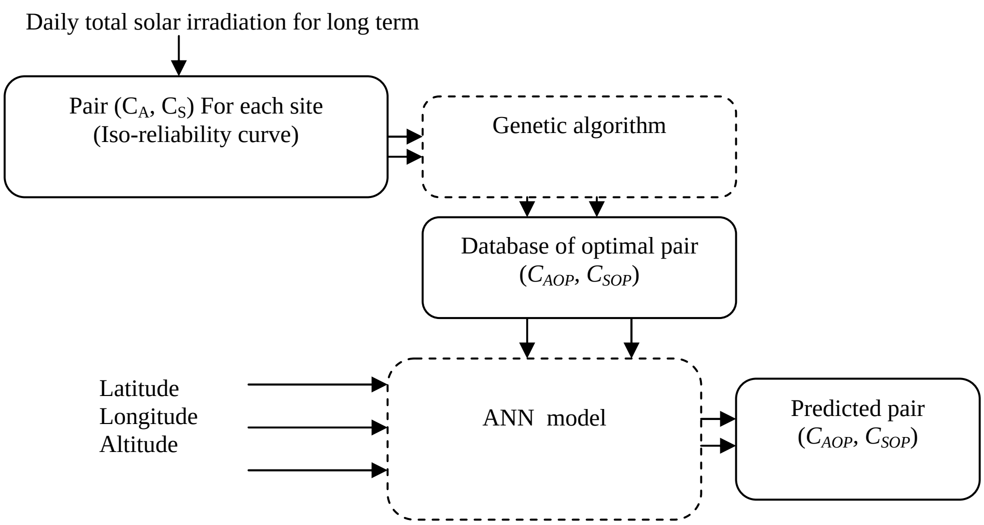


Fig. 6 *Diagram block of the proposed methodology*

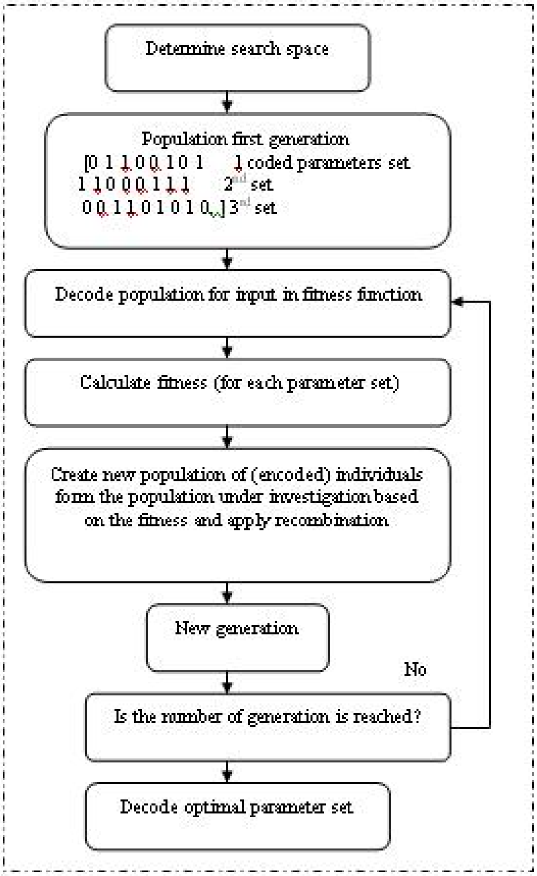


Fig. 7(a). *The GA process*

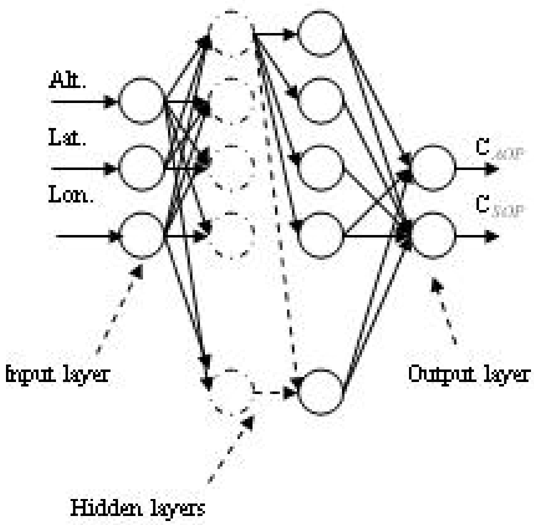


Fig. 7(b). *The ANN model used for predicting of the optimal sizing pair*

The cost function of the system is essentially based on the PV-array cost, battery cost and the cost of the maintenance around one year. The total cost of the system can be given by:

$$T_C(€)=C_{PV}+C_M+C_{BAT} \tag{3}$$

Where C_{PV} is the initial investment that represents the cost of the PV-array, and C_B is the price corresponding to the replacement numbers of the storage battery system during the considered period and C_M is the cost of the operation and maintenance.

The objective function that will be minimized by the GA is given by the following formula: .

$$\begin{cases} \min\{A_{PV}, C_U\} = \min\left\{\begin{aligned} &\left(\frac{A_{PV}}{M_{PV}}\right)(C_{PV} + MC_{PV}) + \\ &\left(\frac{C_U}{M_{BAT}}\right)(C_{BAT} + MC_{BAT}) \end{aligned}\right\} \\ C_A = \dfrac{\eta_{PV} A_{pv} H}{L} \\ C_S = \dfrac{C_U}{L} \end{cases} \tag{4}$$

Where M_{PV} is the PV module, M_{BAT} the battery capacity, MC_{BAT} and the MC_{PV} are the maintenance cost per year of the battery and PV respectively.

7. RESULTS AND VALIDATION

Based on a soft computing program prepared in Matlab (Ver. 7), we have selected the optimal coefficient of PV sizing for 40 sites. Figure 8 shows the fitness function for one site.

The obtained optimal sizing coefficient for some sites is shown in Table 4. These optimal pairs can be used for the determination of the PV-array area (A_{PV}) and the useful capacity of the battery (C_U) based on Eq.(1). In order to validate this approach we have selected 4 pairs from the database and the obtained pairs are compared against the experimental ones. Table 5 illustrates the relative error between the predicted optimal coefficients and actual coefficients. According to this table the mean relative error (MRE) is within 6% which is a good accuracy. Figure 9 shows the correlation coefficient between the actual and predicted ANN optimal coefficients. It should be noted that the R^2=0.98 which is satisfactory.

Table 4. *Optimal coefficient estimated by the GA-program*

Sites	Optimal sizing coefficient obtained from the Genetic algorithm method	
	C_{AOP}	C_{SOP}
1	1.12	0.98
2	1.05	0.93
3	0.72	0.59
4	0.65	0.54

Figure 10 presents the histogram curve of PV array area and useful capacity estimated by the numerical, graphical and the proposed methodology, it is clearly shown that the proposed approach have a less size of PV array and battery compared with the other method.

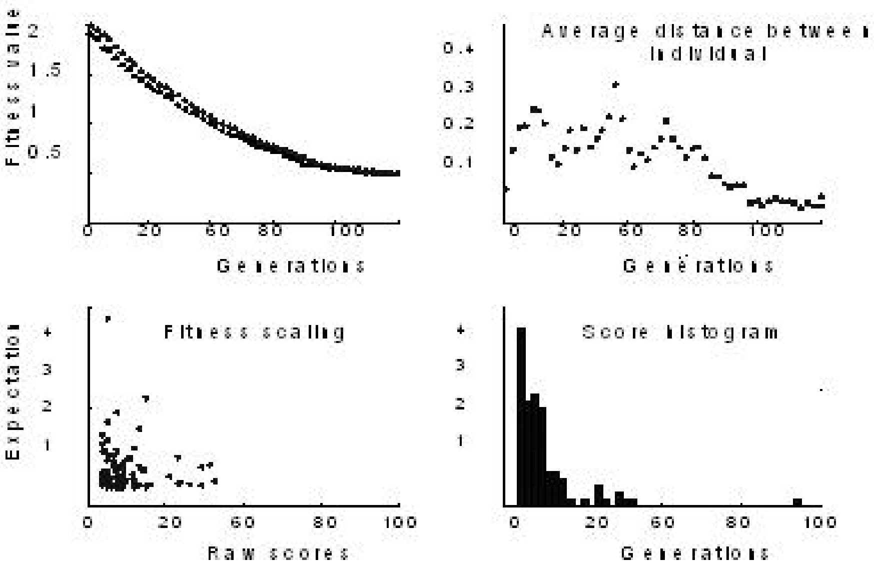


Fig.8. *Simulation results for 100 generations*

Table 5. *Comparison between experimental and actual optimal coefficients*

Site	Actual C_{AOP}	Predicted $\hat{C}_{AOP}$	*MRE (%)*	Actual C_{SOP}	Predicted $\hat{C}_{SOP}$	*MRE (%)*
1	1.12	1.155	2.45	0.98	0.955	4.5
2	1.05	1.032	1.95	0.93	0.965	3.8
3	0.72	0.753	2.15	0.59	0.634	6.3
4	0.65	0.685	1.65	0.54	0.513	5.5

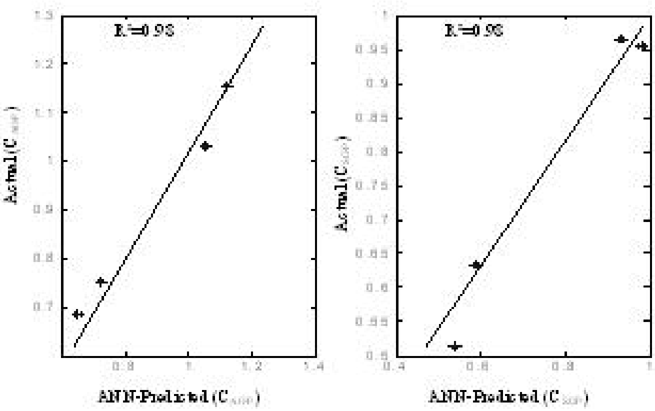
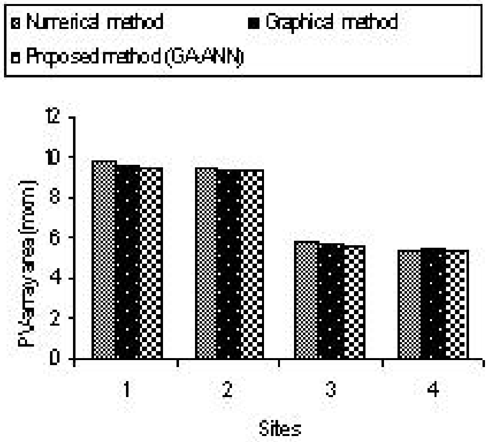


Fig 9. *The correlation coefficient between the actual and predicted ANN optimal coefficients*



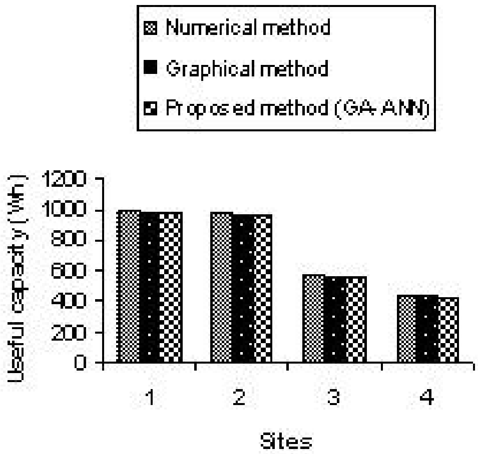


Fig.10. *Comparison between analytical, graphical approach and ANN*

8. CONCLUSIONS

In this paper, a genetic algorithm and an artificial neural network have been suggested in order to determine the optimal sizing of PV system, particularly, in isolated areas. The GA-ANN approach is considered as suitable for modeling the optimal sizing coefficients of SAPV system and it has been demonstrated. The GA has been used to determine the sizing pair (C_{AOP}, C_{SOP}) for 40 sites. From this database data from 36 sites have been used for training the network, and 4 sites for testing the networks. A correlation of 98% has been reached when complete unknown data coefficients were presented to the network. This is considered adequate and thus the neural network can be used efficiently for this type of modeling. The advantage of this model is that it can be used to estimate the PV-array area (A_{PV}) and the useful capacity of battery (C_U) from only geographical coordinates for any location and particularly in isolated sites where the global solar radiation data is not always available. The methodology has been applied and tested for Algerian location, but it can be generalized in any geographical area.

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