Application of Neural Networks and Genetic Algorithms for Predicting the Optimal Sizing Coefficient of Photovoltaic Supply (PVS) Systems

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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 Photovoltaic Supply (PVS) 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 curves of a PVS 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 couples of C_{Aop} and C_{Sop} have been used for the training of the network and 4 couples have been used for testing and validation of the model. The simulation results have been analyzed and compared with classical models in order to show the importance of this methodology. The Matlab (R) Ver. 7 has been used for this simulation.

Keywords: PV system sizing, optimal coefficient, genetic algorithm, Artificial neural network

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 parameters (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 this context, several studies were based on the concept of Loss of Load Probability (LLP), defined as the ratio between the energy deficit and the energy demand on the load [2-7]. This can be performed either with numerical [8] or graphic methods [9]. These methods need the availability of the total daily solar radiation data, for determining the optimal sizing coefficients of a PV system. Other more recent methods based on Artificial Neural Network (ANN) and B-Spline function [10-16] have been developed in order to select the optimal sizing PV system in remote areas. However, these models are based on a numerical approach. In this paper we investigate the suitability of using the genetic algorithm for selection the optimal couple of PV system corresponding to 40 locations in Algeria, and then the ANN is used for prediction of the optimal sizing coefficient for isolated area in Algeria. Five experimental sites are used for the validation of the model (GA-ANN). The next section presents a description of simplified stand-alone PV system sizing. Section 3 presents the genetic algorithm and neural networks. The proposed methodology of this work is described in section 4, while section 5 provides the simulation and validation results.

2. Sizing of the 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 Fig. 1.

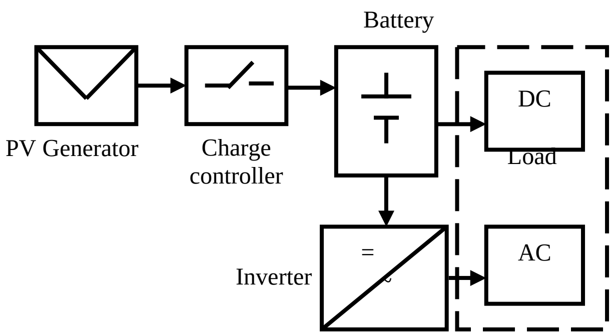

Fig. 1. Block Diagram of simplified stand-alone PV power system

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 [8], 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. It should be noted that C_A depends on the meteorological conditions of the location. This means that the same PV-array for the same load can be 'large' in one site and 'small' in another site with lower solar radiation. The task of sizing a PV-system consists of finding the best trade-off between cost and reliability. Very often, the reliability is an *a priori* requirement from the user, and the PV engineer problem is formulated as follows: which pair of C_A and C_S values leads to a given *LLP* value at the minimum cost?

All methods based on LLP concept require the knowledge of one of the components of solar radiation known as total solar radiation data measured by meteorological stations. However, these data are not always available because only a few weather stations are available in Algeria. Because of this fact, these data were collected by using the hybrid approach given in [17]. As an example, Fig. 2 shows the daily values of global solar radiation data for some sites.

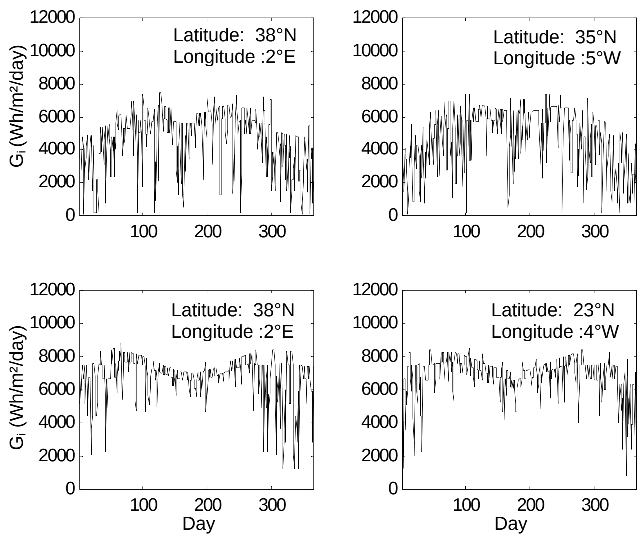

Fig. 2. Daily values of global solar radiation data received on inclined surface for samples sites.

3. Sizing data base of classical approach

In this section we show details of the numerical [8] and graphical approaches [9]. The collected total daily solar radiation data corresponding to 40 sites are used for plotting iso-reliability curves based on the LLP approach (see Fig. 3). We have used the graphical method to find the optimal couple (C_{aop}, C_{sop}) of PV system in order to form the first database, then based on analytical cost (see Table 1) we have formed the second database. For example, Table 2 shows the database for both the graphic and numeric methods.

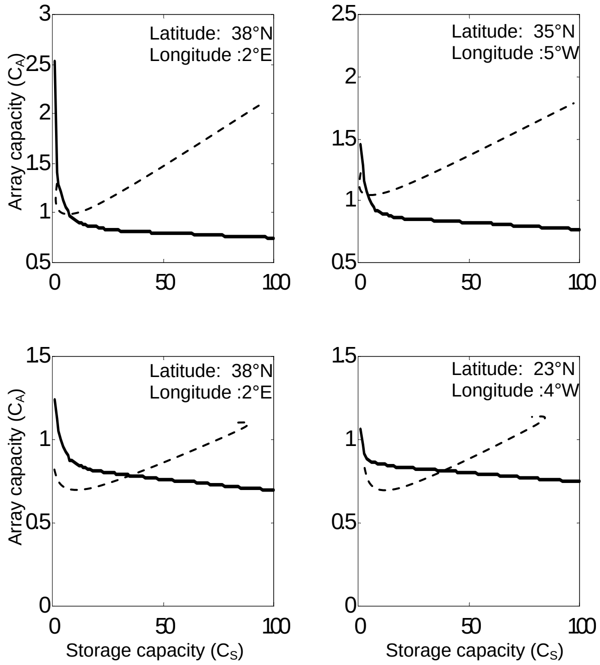

Fig. 3. Iso-satisfaction curves (__) and cost curves (…) for LLP=1%

Table 1. Data for cost analysis

PV array	Solarex 50W, 94x50x5 cm
Cost	30 US$ /PW
Maintenance cost	2 US$/year
Life time	8 years
Battery	18Ah, 51x22x22.5 Cm
Cost	522 US$/KWh
Maintenance cost	2 US$/year
Life cost	4 years

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

Sites	Optimal sizing coefficient			
	Graphical method		Numerical method	
	C_{aop}	C_{sop}	C_{aop}	C_{sop}
1	1.23	1.01	1.22	1.15
2	1.15	0.95	1.20	0.97
3	0.75	0.64	0.79	0.85
4	0.68	0.58	0.70	0.81

3. Genetic algorithms and neural networks

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

3.1 Genetic algorithm

The concept of Genetic Algorithms (GA) for solving optimization problems is based on the analogy to evolution theory in population genetics. Holland [18] 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 (see Fig. 4). 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.

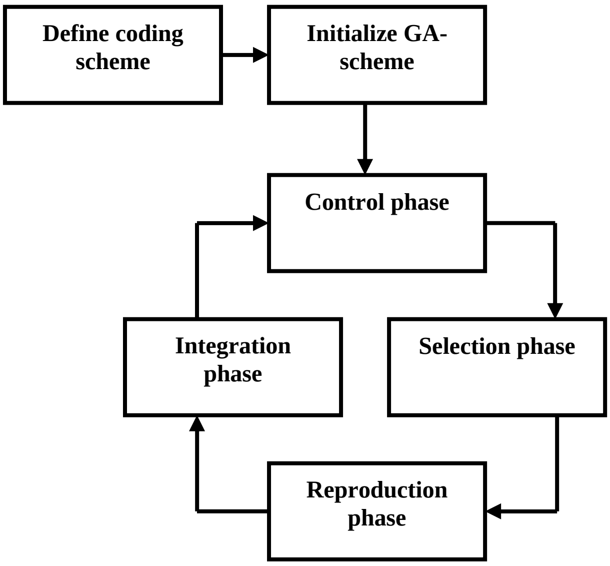

Fig. 4. GA- Scheme

3.2 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 [19]. 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 [19, 20]. Figure 5 shows the artificial neural network architecture employed in this study.

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 backpropagation learning algorithm is used.

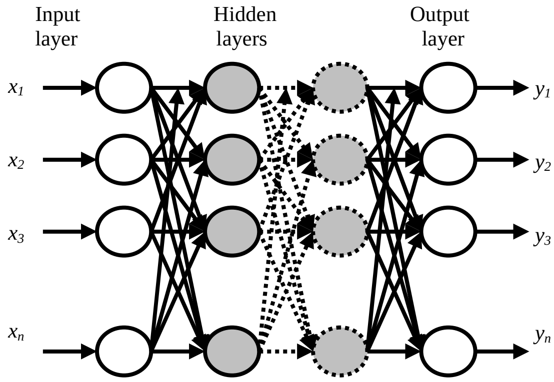

Fig. 5. The feedforward network

5. The proposed methodology

The objective of this work is to determine the optimal sizing coefficient by genetic algorithm (C_{Aop}, C_{Sop}) 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 developed model is presented in Fig. 6. The cost function of the system is essentially based on the PV-array cost, battery cost and the cost of the maintenance. The global cost of the system can be given by:

$$E_C=C_{PV}+C_M+C_R, \qquad (2)$$

Where C_{PV} is the initial investment that represents the cost of the PV-array and the battery system, C_M is the cost of the operation and maintenance and C_R is the price corresponding to the replacement numbers of the storage battery system during the considered period. The objective function that will be optimized by the GA, this function is given by:

$$F=(CA, CS)=>$$
$$j=((\eta_{PV}.Apv.H)/L,(\eta_B C_U)/L) \qquad (3)$$

So, C_{Aop}, and C_{Sop} correspond the optimal cost function.

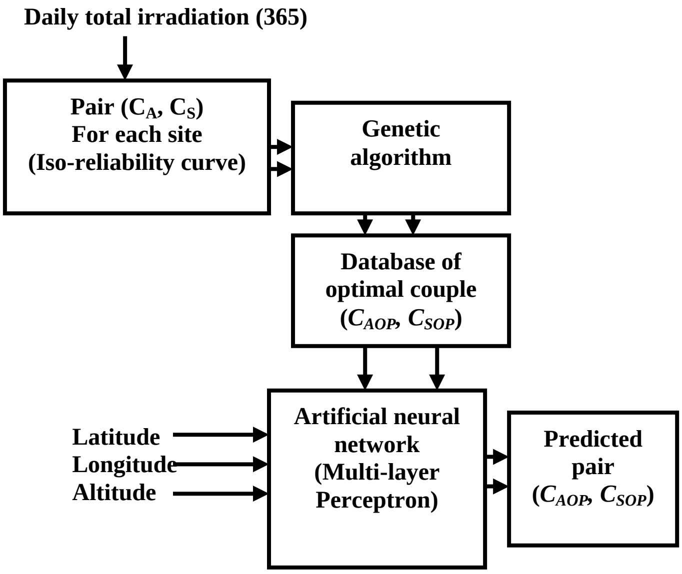

Fig. 6. Block diagram of the developed model

5. 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 7 shows the fitness function. Table 3 shows the obtained optimal sizing coefficient for some sites.

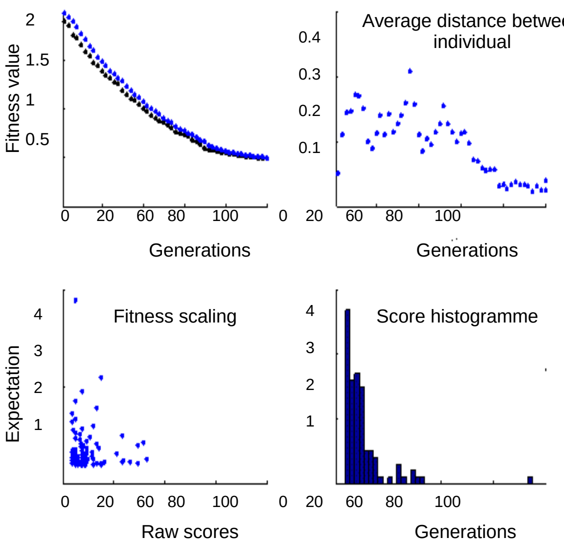

Fig. 7. Simulation results for 100 generations

Table 3. 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

These optimal couples can be used for the determination of the PV-array area (*Apv*) and the useful capacity of the battery (C_U) based on Eq. 1. In order to validate this approach we have selected 4 couples from the database and the obtained couples are compared against the experimental ones. Table 4 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 8 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 Comparison between experimental and actual optima 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

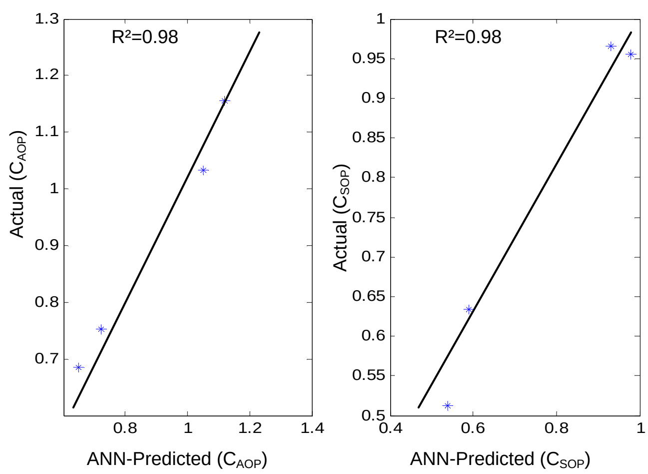

Fig. 8. Comparison between actual and ANN-predicted optimal coefficients

5. Conclusion

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 model is considered as suitable for modeling the optimal sizing parameters of PVS system. The GA has been used to determine the couple (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 parameters were presented to the model. 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 (*Apv*) 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.

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