Conductivity Polynomial Model Parameters identification based on Particle Swarm Optimization

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Abstract: This paper presents a new approach of parameters identification using Particle Swarm Optimization (PSO). This new technique is applied to a nonlinear system which is the conductivity of a low pressure discharge lamp. The latter is considered as the most important component of a plasma reactor used for water ultraviolet disinfection. PSO, an intelligent meta-heuristic for hard optimization, is shown to be a very efficient tool for parameters identification of complicated nonlinear physical systems. A comparison between experimental and simulation results proves the efficiency of the proposed method.

Keywords: Discharge Lamp, Conductivity Model, Particle Swarm Optimization, Parameter Identification.

1. INTRODUCTION

The mathematical modelling is used for a better understanding of real physical systems. Generally, the model identification is based on local convergence methods. However, the performance of these classical approaches are only limited for linear convex models. In the case of no convex optimization problems which are encountered in a lot of practical physical and engineering applications, heuristic approach may emerge as valuable solution.

In reality, there is no common approach to nonlinear systems identification and some methods are available for specific systems classes.

In literature, we find many global optimization research methods such as the simulated annealing and the genetic algorithms, but these techniques need many parameters to set and can have problems with time convergence (Prez et al., 2007; Yin et al., 2010).

Since, Genetic Algorithm (GA) has the global searching ability in complex space, it has been widely used in nonlinear system identification, and however it has the shortage of slow convergence speed and pre-maturation. The Simulated Annealing (SA) is an attractive alternative to traditional local search method as it is quite easy to implement.

The most negative aspect of these two stochastic methods is their lack of memory, which limits the search and convergence ability of the algorithms. However, Particle Swarm optimization (PSO) emerges as a powerful stochastic optimization method which overcomes this problem (Clerc, 1999; Eberhart et al., 1998).

Particle swarm optimization (PSO) has attracted much attention in the last ten years in the stochastic search algorithm. So many complex problems have been solved using this new technique such as parameters identification problems for nonlinear systems.

The discharge lamp, which represents the most important component of a plasma reactor, is the typical example of the physical systems modelling. But physical models, based on the full equation of plasma, are very complex and need lamp data as pressure or gas filling composition that are not usually available, and a large calculation time is necessary. The work of Zissis and Damelincour describe a discharge lamp conductance by a differential equation, named G-model, using coefficients considered as unknown parameters (Zissis et al., 2002; Zissis, 2005). Such parameters were identified from input-output measurements with different classical local techniques (Blanco et al., 2007; Blanco et al., 2011; Billing et al., 1982).

In this paper we present a new method to conductivity parameters extraction using the PSO algorithm as an identification tool. The effectiveness of PSO is demonstrated to show its convergence properties.

The paper is organized as follows. Section 2 states the conductivity model of a discharge lamp. Section 3 presents the PSO method. Section 4, describes the steps to identify the low pressure discharge lamp conductivity model with PSO algorithm. Section 5 gives results showing the effectiveness of the proposed method.

2. THE CONDUCTIVITY MODEL OF DISCHARGE LAMP

In view of the importance of water in the human life, its treatment and conservation are essential in an urgent way on most of planet and particularly on the Mediterranean circumference. Research in this field presents a major priority. In the above mentioned areas, the requirements of water in the rural zones are important and generally more difficult to satisfy because of dispersion of the habitat and the limited energy installations.

All resources must thus be mobilized including on the level of the habitat individual, recovery, storage of rain water, exploitation of the urban tablecloths by well, the water used by station of purification. However these resources can be factor of diseases transmission when their exploitations are badly led and the water treatment is badly adapted or inadequate.

The water disinfection by ultraviolet radiations was developed in North America these last twenty years. This disinfection technique proceeds without any addition of chemicals and none under chemical is formed. Also, this disinfection is reliable and reveals a simple use with a great profitability and a high effectiveness.

For the user, handling does not present a danger. In fact, the lamps are protected and the system is in safety. The process of water disinfection by ultraviolet radiations is a cylindrical stainless reactor. It is equipped with mercury low pressure discharge lamps, emitting with the germ-destroying wave length of 254 nanometres.

The radiant energy flux emitted by a discharge lamp as the arc voltage is a complex function of the current and time. They depend on the geometrical characteristics of the lamp, the nature of rare gas, the pressure and the temperature. The variations are very complicated and have a behaviour which depends on internal dynamics whose equations are not exactly given, what makes difficult the determination of a general model, which characterizes the emitted flows variation or the arc voltage according to the arc current and thereafter according to time.

For simplicity reason, we are going to concentrate our study on the low pressure discharge, considered as the most important component of the plasma reactor.

Aiming to study the interaction between discharge lamps and electric source circuits, it's necessary to have a model of the lamp which is neither simplest nor of a high complexity. The polynomial approximation of the discharge lamp conductance time variation which is derived from a physical complex model, had been recognized to be efficient in simulation of high complexity degree circuits.

Many authors tried to present mathematical models for the arc conductance aiming to provide significant representation of the system behaviour. Unfortunately, all these models are restricted by approximations and experimental reasons.

To obtain models for discharge lamps is not easy due to the negative impedance of discharge lamps and the complexity of physical phenomena that occur inside the discharge tube. Moreover, discharge lamps can be operated at different frequencies with electromagnetic or electronic ballasts. These different operating conditions can affect lamp behavior. For instance, it is well known that the I-V discharge lamp characteristic changes with frequency, so lamp models should be able to reproduce and predict lamp behavior under different operating conditions.

A discharge lamp inserted in an alternative source circuit (Fig. 1) is a nonlinear element; this nonlinearity is due to the exponential nature of the conductivity dependence on the internal energy of the lamp. The study of a complex system consisting on an electronic power supply and a highly non-linear element needs a competence combination from several disciplines.

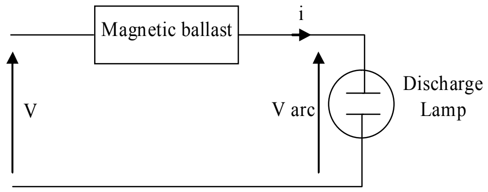

Fig. 1. A discharge lamp inserted in an alternative circuit.

Discharge lamps need some electric circuits for their correct operation. It is realized through ballasts, which can be constructed from classical passive components only (magnetic ballast) or from semiconductors and passive components (electronic ballast). But majority of discharge lamps are powered by magnetic ballast. Such circuits have to ensure three general functions which are start of a discharge lamp, a lamp relighting each half cycle and control of current through a discharge lamp.

Looking at the existing literature, we noticed that very complex physical models have been developed for almost any type of discharge lamp. But in many cases the lamp models developed by the specialists are incompatible with the software used by the other community. Thus, electrical engineers tried to create some simple lamp models based essentially on experimental I-V characteristic of the lamp. In this work, experimental data have been obtained from a 70W discharge lamp operating at 50Hz inserted in an alternative circuit (Fig. 1) and 2500 measurements (input-output) are considered.

Fig. 2 and Fig. 3 show the real lamp voltage and current waveforms. Fig. 4 shows the lamp I -V characteristic at 50Hz.

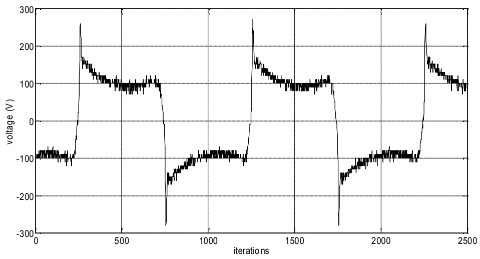

Fig. 2. Measured voltage waveforms.

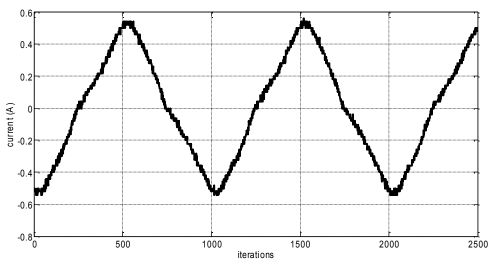

Fig. 3. Measured current waveforms.

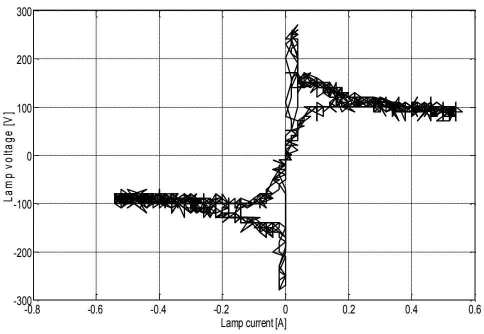

Fig. 4. Real lamp I - V characteristic.

Experimental results show that the discharge lamp is a very complex nonlinear system.

The lamp conductivity is deducted from voltage v(V) and current i(A) of the lamp in the following equation:

$$g\left(\Omega^{-1}\right)=\frac{i(A)}{v(V)} \tag{1}$$

Fig. 5 shows the lamp conductance waveforms deducted from experimental measurements and equation (1).

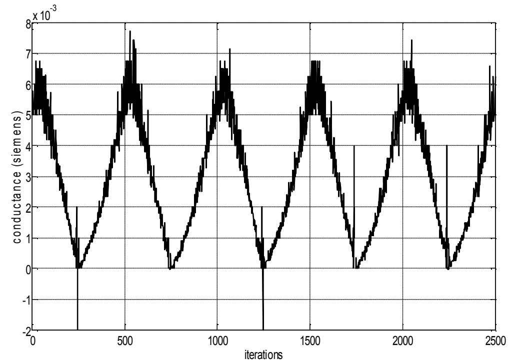

Fig. 5. Measured conductance waveforms.

The polynomial approximation of the discharge lamp conductance time variation, which is derived from a physical complex model, had been recognized to be efficient in simulation of high complexity degree circuits. Many authors tried to present mathematical models for the arc conductance aiming to provide significant representation of the system behaviour; unfortunately all these models are restricted by approximations and experimental reasons.

The mathematical modelling is used for the better understanding of real physical systems. The description of the system is realized by the number of mathematical equations. They try to characterize the objective reality more or less complex. The creation of a model is based on these general steps: a task analysis and formulation, a mathematical model construction, an identification of model parameters, a mathematical model solving, a verification of the model and finally results interpretation (Kopernicky, 2008.

The modelling of discharge lamp is the typical example of the physical systems modelling. We present in the following the most known models.

2.1. Mayr's nonlinear model

$$\frac{1}{g}\frac{\partial g}{\partial t}=\frac{hE}{w_0}i-\frac{1}{\theta} \tag{2}$$

Where h, E, g, i, w0 and Θ are respectively the arc length, the electrical field in the arc, the arc conductance, the arc current, the time constant of the arc and the dissipated energy at the time origin.

The equation (2) can be written as:

$$\frac{\partial g}{\partial t}=\delta i^2-\beta g \tag{3}$$

Where δ=1/w0 and β=1/θ

In fact, the parameters β and δ cannot be considered as constant values if all physical phenomena in the lamp such as the temperatures profiles and other parameters of the plasma are considered.

2.2. Herrick's nonlinear model

Based on equation (3), Herrick proposed a general nonlinear polynomial model (equation 4) justified by experimental reasons only (Herrick 1980).

$$\frac{\partial g}{\partial t}=a_4 i^4+a_3 i^3+a_2 i^2+a_1 i-b_4 g^4-b_3 g^3-b_2 g^2-b_1 g \tag{4}$$

a_i and b_i are constant parameters to be estimated using parameters identification algorithms.

In fact the number of terms in this model depends on the physical characteristics of the lamp.

References describe a discharge lamp conductance by a differential equation named G-model. The parameters of the lamp conductance "g(t)" are given by means of a single differential equation of the type:

$$\frac{dg}{dt}=a_2 i^2(t)-b_1 g(t)-b_2 g^2(t) \tag{5}$$

Where i(t) and g(t) are the lamp current and conductivity.

The work of Stambouli (Sambouli M., 1984), describe a discharge lamp conductance by a differential equation of the first order with the same form of equation (5). In this work, coefficients a and bi can be determined experimentally from the voltage-current characteristics or from physical evaluation and have physical meaning.

a_2, b_1 and b_2 are parameters to be identified, a_2 means input energy to the plasma, b_2 means radiation losses, b_1 means thermal losses and the number of elastic collisions.

Noting that there are many forms of discharge lamp conductivity model, but our work is based on the model of equation (5) which is linear with respect to parameters but nonlinear with respect to measure.

3. PARAMETER IDENTIFICATION USING PARTICLE SWARM OPTIMIZATION

3.1. Overview of particle swarm optimization

A fundamental part of engineering applications in systems simulation and control relates to system models, and considerable effort has been devoted towards developing methods to identify precise models together with accurate estimation of system parameters. To date a wide range of analytical techniques have been introduced to meet these demands. However, for non-linear systems, limited progress has been made using analytical methods. In responding to ever-increasing demands, nonlinear optimization techniques have been an alternative approach to cope with the need to adapt the system identification and parameter estimation methodology in response to inherent changes occurring in dynamic systems. Computational intelligence (which attempts to biologically emulate the adaptive evolutionary nature of living beings like reasoning, decision-making, learning, and optimization via a series of techniques) is one suitable technique for system identification and parameter estimation.

The initial ideas on particle swarms of Kennedy (Kennedy et al., 1995) (a social psychologist) and Eberhart (Eberhart et al., 1998) (an electrical engineer) were essentially aimed at producing computational intelligence by exploiting simple analogues of social interaction, rather than purely individual cognitive abilities. So, Kennedy and Eberhart have originally proposed PSO algorithm. This algorithm works by initializing a flock of birds randomly over the problem space, where every bird is called as a “particle”. The particles remember the best solution found by itself and by the whole swarm along the search trajectory, than they update their velocity and position.

Particle swarm optimization (PSO) is a stochastic search algorithm for nonlinear functions based on the reproduction of a social behavior. It was first introduced in 1995. Since then, it has been widely used to solve a large range of optimization problems. The algorithm was presented as simulating animal’s activities (Clerc M., 1999; Eberhart et al., 1998).

PSO is based on an individual set arranged in uncertain way called particles which move in the research space and represents a potential solution. Each particle has a memory concerning its better visited solution as well as the capacity to communicate with its setting constituent particles. Based on this information, particle is going to follow a tendency; first, of its motivation to return toward its optimal solution, and second, of the relation to solutions found in its neighborhood.

From local and empiric optima, the whole of particles goes, normally, to converge toward the global optimal solution of the treated problem.

Based on the stated information of which it arranges, a particle must decide its next movement that is to decide its new velocity.

It combines three information linearly:

- The present position
- The better performance
- The best performance of its neighbors.

In this paper, we haven’t explained the neighbors topology because it haven’t an large importance, but authors interested can see the work of Maurice Clerc (Clerc M., 1999).

Recent implementations of the PSO have made use of dynamically changing inertia values. The weight factor usually starts with a large value, which decrease over time.

The next figure show the particle evolution through work space, and explain how to move from a position to another, with references to the neighbors, and taking information about the better position of a particle in the swarm.

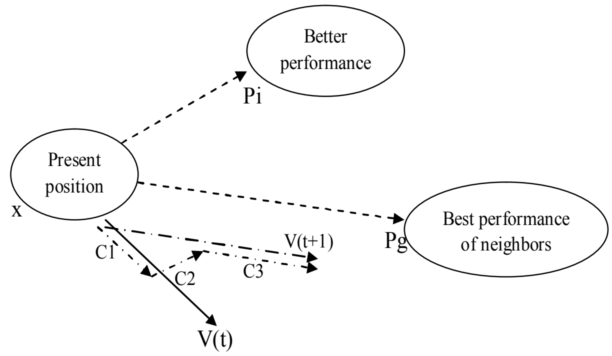

Fig. 6. Vector diagram of a particle movement.

Three fundamental elements for the calculation of the next displacement of particle: according to its own velocity, towards its best performance and the best performance of its best informant.

The simplest way to calculate the true displacement starting from these three basic vectors is to make a linear weighting of it, thanks to confidence coefficients.

As a deduction from the vector diagram of a particle movement (Fig. 6), the equations of a particle movement can be written as:

$$\begin{cases} v(t+1) = c1.v(t) + c2.(Pi - x(t)) + c3.(Pg - x(t)) \\ x(t+1) = x(t) + v(t+1) \end{cases} \tag{6}$$

Where ci are confidence coefficients defined as:

c1 is constant (confidence in its own movement) and must have an absolute value less than 1 (recommended 0.7 to 0.8); c2 and c3 (respectively confidence in its best performance and that of its best informant) are randomly selected with each step of time according to a uniform distribution so that c2+c3<4 (Clerc, 1999).

Recent work done by Clerc (Clerc, 1999) indicates that use of a constriction factor may be necessary to insure convergence of the particle swarm algorithm but PSO algorithm with the constriction factor can be considered as a special case of the algorithm with inertia weight.

The new velocity is calculated from a linear combination of three elements, and then applied to the current position to give the new position.

The implementation procedure of the PSO algorithm can be illustrated in the flowing chart in Fig. 7. Then, in the next part of this paper, we explain how to implement this chart step by step. All these algorigramme steps are detailed with references to our work parameters.

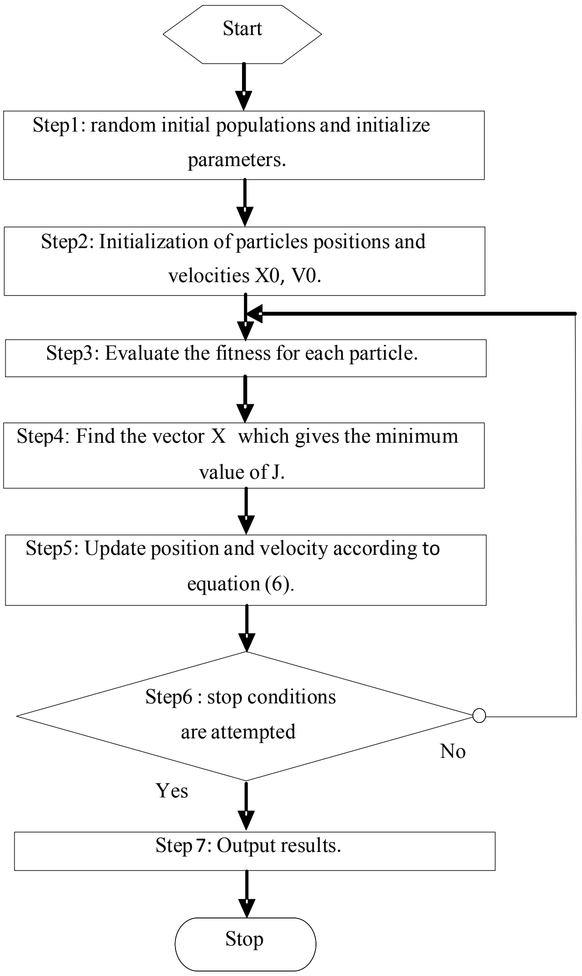

Fig. 7. Flowchart of PSO.

Let's consider X=[a2 b2 b1] the parameters vector to be identified (particles of the PSO algorithm). These three parameters are coefficients of the polynomial conductance model given in eqaution 5.

This vector must minimize an error function called fitness function J(X). Steps of this algorithm are the follows:

Step1: Generate randomly the initial population and set the initialized parameters, c1=0.79/MaxIter, where MaxIter is number of iteration and c2+c3<4.

Step2: Randomly initialization of particles position and velocity X0 and V0.

Step3: Evaluate the fitness for each particle, the global best particle is chosen to be the particle with the best fitness. Substitute Xi vectors in J(X).

Step4: Find the vector X which gives the minimum value of J: this is the initial global minimum.

Step5: Update position and velocity according to equation (6).Make sure that the updated velocity and position particles are not out of their limits, if it's the case the over-limit elements are set to the corresponding limits.

Step6: Go back to step3 until the stop conditions are attempted (number of iteration reaching the maximum or sufficient optimization error find).

Step7: The best solution obtained during the optimization process is output in this step.

In this paper, PSO is proposed for solving parameters identification problem of nonlinear physical system (a low pressure discharge lamp). Practical application of PSO leads us to allege that PSO is indeed more accurate, reliable and efficient at locating global optima than the local alternatives which can't give good results.

3.2. Application of the PSO for conductivity parameters identification

Conductivity parameter identification problem is to estimate with PSO the parameters a2, b1 and b2 of equation (5) by using experimental data obtained from well-defined standard conditions (Liu A. et al., 2009; Liu L. et al., 2007).

The fitness function is defined as a measure of how well the model output fits the measured system output (Kennedy et al., 1995; Alrashidi et al., 2010) . The system's dynamics can be described using a differential equation such us:

$$\frac{dg(t)}{dt} = f(p, g(t), i(t)) \tag{7}$$

Where g(t) is the lamp conductivity defined as its output and i(t) is the current which represent the lamp input. p is the vector of the three unknown parameters (p=[a2 b2 b1]) and f is a nonlinear function.

To formulate the optimization problem, equation (7) can be written with the next form:

$$\dot{g} = f(p, g, i) \tag{8}$$

To identify p, the system model is introduced as:

$$\dot{\hat{g}} = f(\hat{p}, \hat{g}, i) \tag{9}$$

From equation (8) and (9), the same input "i" is applied to the system and its model having the same structure of the real system. To evaluate the parameters to be identified, the real system output "g" is compared with that of the model.

Hence, the optimization problem can be formulated as to minimize the fitness function defined by:

$$J(\hat{p}) = \sum_{i=1}^{N} \left[g(ti, p) - gi \right]^2 \tag{10}$$

Where g(ti,p) and gi are, respectively, the numerical solution of the mathematical model and experimental data point for the i-th data point. N is the total experimental data number.

The next figure illustrate how to implement the identification procedure and prove that system identification is equivalent to a particle swarm optimization problem.

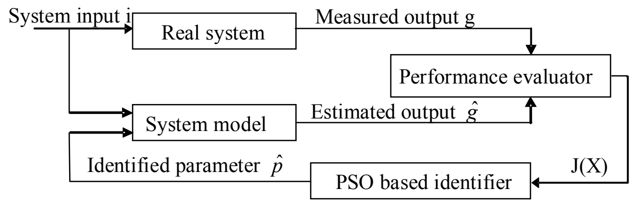

Fig . 8. Diagram block of the PSO identification approach.

First, the same input is presented both to the real system and its model. Then, measured and estimated outputs are used to calculate the fitness function with a performance evaluator. Based on the calculated function, the PSO identification algorithm performs the unknown parameter vector.

As described in Section 2, low pressure discharge lamp conductivity model identification is an identification problem with nonlinear model structure. In the next section, we identify the conductivity parameters of the lamp from its measured current and voltage, and then we compare these parameters with the simulation results.

4. EXPERIMENTAL RESULTS

The identification was held for a low pressure discharge lamp inserted in an alternative circuit (fig. 1) with the characteristics mentioned in the table 1.

Table. 1. Characteristics of the low pressure discharge lamp.

Diameter	Length	Power	Nominal current
15 mm	400 mm	70 W	0.65 A

The PSO identification tool was coded in Matlab R2008b, and the developed algorithm was run on an Intel Core 2 Duo CPU 2.67 GHz with 4 GB memory capacity.

With a digital scope, we have taken 2500 measured input-output data. In this experiment we use only 1250 samples to find the parameters vector p. The rest of data (1250 samples) are used in the lamp conductivity model verification procedure which is performed by simulation with MATLAB software.

The lamp conductivity was given from experimental measurements using the equation (1), so for every measured current and voltage point, we have to complete the calculated conductivity, and then we make a table containing voltage, current and conductivity.

The illustration of real and estimated conductivity of the low pressure discharge lamp is shown in the Fig. 9. This curve shows that the proposed PSO approach converges very quickly and gives very good results. In fact, there is no error between the experimental and the calculated conductivity of the lamp.

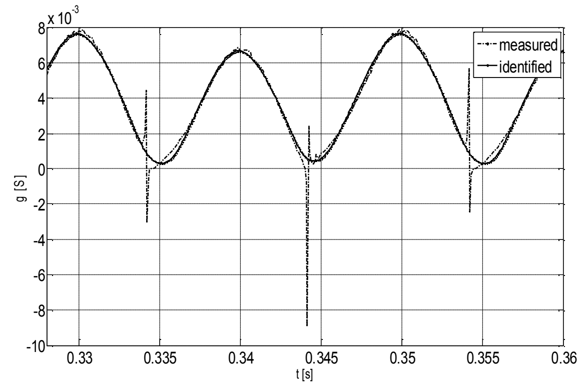

Fig. 9. Measured and identified conductivity waveforms.

The waveform of lamp conductivity is exactly the needed form, so we can deduce that particle swarm optimization, makes as an intelligent optimization technique, is a very good method to identify nonlinear system parameters.

The fitness function is given by the following figure (Fig. 10). We deduce that after a little number of iterations, the fitness function, which represents the error between lamp and its model, becomes minimal.

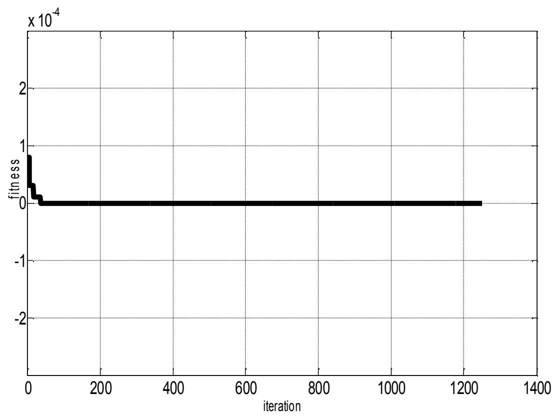

Fig. 10. Fitness function.

Table 2 gives model parameters identified with PSO method.

Table. 2. Identified parameters.

a2	b2	b1
93.33	582036.5	994.7

After finding the parameter vector p (see Table. 2.), we use the obtained values to simulate the conductivity model of the discharge lamp.

Using Matlab/Simulink, we make the conductivity model of the lamp, and then we use the find values to simulate this model. This part of work is just used to verify the obtained results, and then to justify the efficiency of the used method in parameters identification.

The diagram bloc of the model simulation is given by the figure 11:

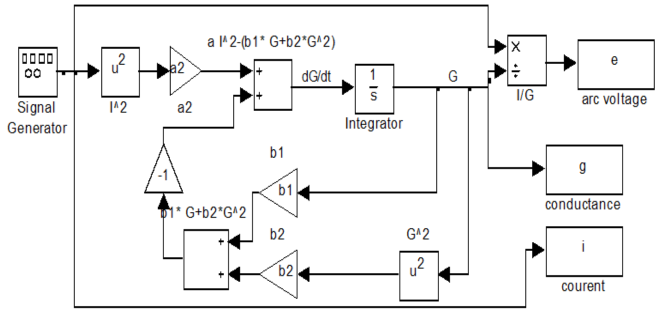

Fig. 11. The Matlab Simulink conductance model.

The waveforms of the lamp voltage and current are given by Fig. 12 and Fig. 13.

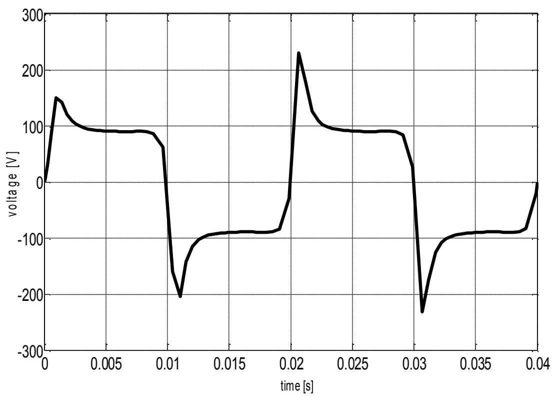

Fig. 12. Simulated voltage waveforms.

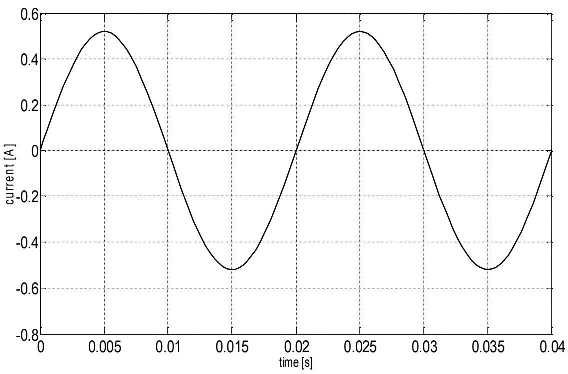

Fig. 13. Simulated current waveforms.

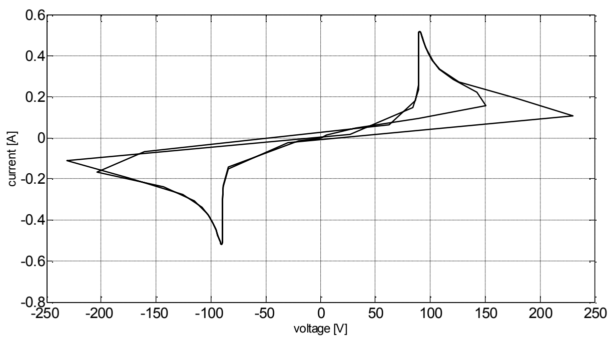

Fig. 14. Real lamp V-I characteristic at 50Hz.

Comparing experimental waveforms of voltage and current (Fig.2 and Fig.3) with simulated PSO based ones (Fig.12 and Fig.13), we can see clearly the concordance of the obtained results and the efficiency of the proposed identification approach.

The comparison in figures 12 and 13 confirms that the nonlinear continuous time conductance model (equation 5) associated with the identified coefficients (table 2), represents very well the input-output behaviour of the discharge lamp. In fact, the application of the identification procedure using the particle swarm optimization based procedure showed a great concordance between the real behaviour and the estimated model.

As an intelligent computational method based on stochastic search, PSO is shown to be a versatile and efficient tool for this complicated engineering problem.

In this work, it was shown that parameters identification of physical complex systems can be solved using heuristic optimization methods like particle swarm optimization and the efficiency of the method was approved so we can use it to have parameters of many others nonlinear systems in our laboratory.

The method is generally applicable to other types of complex systems, and as well as other dynamic systems with nonlinear model structure.

5. CONCLUSION

In this paper, we have presented the nonlinear conductivity model of a low pressure discharge lamp considered as a physical complex nonlinear system. Parameters of this nonlinear system were identified using Particle Swarm Optimization (PSO) approach. The paper gives a view of this new optimization method, and explains how to implement it for extracting parameters of nonlinear complex systems. Both simulation and experimental results are provided to demonstrate the effectiveness and the efficiency of this identification method. It is shown that the PSO algorithm is able of tracking time-varying parameters with good accuracy. However, applied to low pressure discharge lamp, this PSO base identification method is generally applicable to other systems, in our research unit, like permanent magnet synchronous motors or stepper motors.

It was shown that the modelling of discharge lamps is not a simple task, mainly due to the fact that the discharge is a complex phenomenon which involves electrical, chemical, thermal and optical characteristics. But, we have proven that PSO can solve the difficult part in this problem which is the parameters identification.

REFERENCES

Alrashidi MR, Alhajri MF, Alothman AK, Elnaggar KM (2010). Particle Swarm Optimization and Its Applications in Power Systems. *Computational Intelligence in Power Engineering. SCI*(302):295–324.

Ben-Yaakov S, Shvartsas M, Glozman S. Statics and dynamics of fluorescent lamps operating at high frequency: modeling and simulation. *IEEE Trans. Applicat*. Ind., 38: 1486-1492, Nov/Dec 2002.

Billing SA, Fakhouri SY (1982). Identification of Systems Containing Linear Dynamic and Static Nonlinear Elements. *Automatica*. 18(1):15-26.

Blanco C, Anton JC, Robles A, Ferrero FJ, Campo JC, Ganzalez M, Zissis G (2007). A Discharge Lamp Model Based on Lamp Dynamic Conductance. *IEEE Transaction On Power Electronics*. 22(3):727-734.

Blanco C, Anton JC, Robles A, Ferrero FJ, Viera JC, Bhosle S, Zissis G (2011).Comparison Between Different Discharge Lamp Models Based on Lamp Dynamic Conductance. *IEEE Transaction On industrial Applications*. 47(4): 1983–1991.

Clerc M (1999). The Swarm and the Queen: Towards a Deterministic and Adaptive Particle Swarm Optimization. *In Proceeding of Congress on Evolutionary Computation*. CEC99(3):1951-1957.

Eberhart R, Shi Y (1998). Comparison between Genetic Algorithms and Particle Swarm Optimization. In *Proceedings of the Seventh Annual Conference on Evolutionary Programming. Springer-Verlag*. 611-619.

Erenturk K (2008). Dynamic Characterization of a UV Fluorescent Lamp. *IEEE transaction on plasma science*. 36(2) :519-523.

Fukuyama Y, Yoshida H (2001). A Particle Swarm Optimization for Reactive Power and Voltage Control in Electric Power Systems. *In Proceedings of the IEEE Congress on Evolutionary Computation*. CEC2001(1). 87-93.

Herrick PR (1980). Mathematical models for high-intensity discharge lamps. *IEEE Transaction on Industry Applications*. IA16(5):648-654.

Jiaxiang Z, Kanellakopoulos I (2002). Active identification for discrete-time nonlinear control-Part II: Strict-feedback systems. *IEEE Transaction on Automatic Control*. 47(2): 225-240.

Kaelo P, Ali MM (2006). A numerical study of some modified differential evolution. *Europ. J. of Operat. Research*. 169 (3):1176-1184.

Kennedy J, Eberhart R (1995). Particle Swarm Optimization. In *Proceedings of IEEE International Conference on Neural Networks*. 4:1942-1948.

Kopernicky J. Electric conductivity model of discharge lamps. *PhD thesis*, l'Université Toulouse III- *Paul Sabatier et l'Université Technique de Liberec*, 2008.

Lin W, Zhang H, Liu PX (2006). A New Identification Method for Hammerstein Model Based on PSO. *Proceeding of the 2006 IEEE international Conference on Mechatronics and Automation*. 2184-2188.

Lister GG (1992). Low-pressure gas discharge modeling. *J. of Physics D: Applied physics*. 25(12): 1649-1680.

Liu A, Zahara E (2009). Parameter identification problem using particle swarm optimization. *Fifth International Conference on Natural Computation.* ICNC'09:275-278.

Liu Li, Liu W, Cartes DA (2008). Particle swarm optimization-based parameter identification applied to PMSM. *Proceedings of the 2007 American Control Conference*.ACC'07:2955-2960.

Messai Tlili, Abdeljelil Chammam and Anis Sellami, "Modeling and control of a low pressure discharge lamp used for ultraviolet radiations water disinfection", *The 4th International Renewable Energy Congress IREC'2012,* December 20 - 22, 2012, Sousse – Tunisia.

Messai Tlili, Abdeljelil Chammam and Anis Sellami, "Parameters identification of a low pressure discharge lamp based on PSO", *16th IEEE Mediterrnean Electrotechnical Conference MELECON 2012*, March 25-28, 2012 - Hammamet, Tunisia.

Panda G, Mohanty D, Majhi B, Sahoo G (2007). Identification of Nonlinear Systems using Particle Swarm Optimization Technique. *IEEE Congress on Evolutionary Computation:* 3253-3257.

Perez JR, Basterrechea J (2007). Comparison of Different Heuristic Optimization Methods for Near-Field Antenna Measurements. *IEEE Transactions on Antennas and Propagation.* 55(3):549-555.

Schwaab M, Biscaia EC, Monteiro JL, Pinto JC (2008). Nonlinear parameter estimation through particle swarm optimization. *Chemical Engineering Science*. 63(6):1542-1552.

Stambouli M. Modélisation d'une décharge de Mercure Haute Pression: Application a l'analyse des circuits électroniques comportant des lampes a décharge. *PhD thesis, ENSIT,* Tunisia 1984.

Yin JJ, Tang W, Man KF (2010). A Comparison of Optimization Algorithms for Biological Neural Network Identification. *IEEE Transactions on Industrial Electronics*. 57(3):1127-1131 .

Zissis G (2005). Light Sources: what evolution for the future? *In Proceeding ECMS 2005. Electronic, Control, Modelling, Measure and Signal*. University Paul Sabatier, Toulouse.

Zissis G, Damelincourt JJ (2002). Modelling discharge lamps for electronic circuit designers: a review of the existing methods. *In the 29th IEEE Inteernational Conference on Plasma Sciences* (ICOPS 2002).318.