Study of the Quantum Evolutionary Algorithm Parameters Applied to Transient Identification

Andressa dos Santos Nicolau, Roberto Schirru

Abstract – In this work we present a study on the behavior of the Transient Identification System, proposed in our previous work, when modified the main parameters of the optimization tool. The optimization tool used for this study was the Quantum Evolutionary Algorithm (QEA). Besides verifying the influence of the QEA main parameters separately, we propose the modification of these parameters, fixed in canonical form, as a decreasing function in time. Our results for the Transient Identification System are comparable with those present in the current literature, moreover, shown as that these parameters guide the behavior of the algorithm.

Keywords — Nuclear Power Plant, Quantum Computer Transient Identification, Artificial Intelligence, Diagnosis Systems.

I. Introduction

Quantum computing [1] is a new a research area that includes concepts like quantum mechanical computers and quantum algorithms. So far, many efforts on quantum computer have progress actively due to its superiority to classical computer on various specialized problems. There are well-known quantum algorithms such as Grover's database search algorithms, and Shor's quantum factoring algorithm [2]. During the past two decades, evolutionary algorithms have gained much attention and wide applications, which are essentially stochastic search methods based on the principles of natural evolution [3]. Since later 1990, research on merging evolutionary computing and quantum computing has been started and gained attention in physics, mathematics and computer science fields. Quantum-inspired evolutionary computing are characterized by certain principles of quantum mechanisms implemented in a classic computer [2].

The memory of a classic computer is comprised of information bits that can hold a "1" or "0" information. On the other hand, in a quantum computer calculations are done making direct use of quantum mechanic properties such as superposition and interference between states. In this way, a quantum computer maintains a set of Q-bits that can hold a "1", a "0" or a superposition of these values, or in other words, it may contain a "1" or a "0" at the same instant.

Combining the concepts of Quantum Computation and Evolutionary Computation, arise the quantum inspired evolutionary algorithms. These algorithms are classics but, based on the main paradigms of quantum theory, such as superposition and interference of states. One of the main metaheuristic optimization which combine elements of quantum computing and evolutionary computing is the Quantum Evolutionary Algorithm (QEA) proposed by [4]-[5] QEA is based on the most important concepts of quantum computing, the quantum bit (Q-bit) and superposition of quantum states. As the Genetic Algorithm (GA) [3]-[6], the QEA is based on a population and each individual is characterized as a chromosome. Notwithstanding, instead of a conventional binary representation, chromosome in the QEA is formed by Q-bits and unlike GA, which uses for instance the operators mutation and crossover, the population evolves based upon a variation operator known as Q-gate.

The QEA has shown to be an efficient, robust and simple optimization algorithm, and has been successfully applied to many different kinds of problems, particularly for complex problems as the Transient Identification of a Nuclear Power Plant [7]-[8]. But a thorough study of the influence of its main parameters in the convergence of the algorithm, it is still a field to be explored. In this work we present a study on the influence of the Delta (Δ) and the Eps (ε) of the QEA, in the behavior of Transient Identification System proposed by [7]. Besides verifying the influence of the main parameters separately from the QEA, we propose the modification of these parameters, fixed in canonical form, as a decreasing function in time (generations).

The Δ parameter is critical for the performance of QEA, as beside being responsible for learning of the algorithm, which balance global and local exploration ability of the quantum population.On the other hand the ε parameter introduced by [7]-[8] in the original model of the QEA, has a role of delaying the premature convergence of the algorithm, and reduce the probability of the algorithm stagnation in a local optimum.

For the optimization algorithms in general, it is interesting to have a greater capacity to exploit the search space early in its evolution, so you can find promising regions of good fitness and a more refined search at the end of its evolution.

Thus, in order to improve the balance global and local exploration abilities of the quantum population, at the beginning and end of process, with the goal of ensuring a fast converge of the algorithm, we modification the parameter Δ as a decreasing function in time. This approach has been used for the parameter w of Particle Swarm Optimization (PSO) [9]-

[10]. Conversely, in order to slow the convergence of the algorithm, we modification the ε parameter in a decreasing function in time.

Our results for the Transient Identification System are comparable with those present in the current literature, moreover, show that the Δ and ε parameters guide the behavior of the algorithm. The remainder of the paper is organized as follows. The problem of transient and accident identification is described in section II. The section III describes the QEA. The study of influence the Δ and ε parameter of QEA in the Transient Identification System are shown in section IV. The conclusion is presented in the section V.

II. Transient Diagnosis System

The identification of a transient is considered a complex task, since it comprises the monitoring of several state variables such as pressure, temperature, flow etc. When a Nuclear Power Plant (NPP) is projected, transients that might occur during its operation are postulated. Such transients relative to the design-basis accidents present well defined curves which represent the temporal evolution of several state variables. Thus, a system for the diagnosis of transients is supposed to classify an anomalous event occurring during the operation of the NPP, associating it to one of those design-basis accidents in order to support the operators' decision.

The diagnosis system proposed in the present work is based upon Euclidean Distance such as in the systems proposed by [7], [11] and [12]. Our system classifies an anomalous event in relation to the signatures of three design-basis accidents postulated by the FSAR [13] for Angra 2 NPP, located in the Southeast of Brazil.

The system compares the distances between vector composed by the set of variables of the anomalous event, in a given time t, and the centroid, represented by prototype vector, of the design-basis transient variables. The less distance will indicate the class of the transient which the anomalous event belong to. Thus, the QEA was used to find the best position of the centroid of each class of the selected transients, which maximize the number of the correct classifications. In other words, the QEA was used for finding the ideal prototype vector (centroid) for each class to be identified and can be viewed as the Voronoi Vectors that represent the best solution to the problem, with the highest number of correct classifications.

Notwithstanding, the work reported herein is different from the system proposed by [11]-[12] in the sense that, in such works, the optimization is also related to the smallest number partitions for the classification. In this case, we proposed a novel method of identification of transient based on only one partition, different from the models aforementioned, and independent of the event detection that can be used as the initial mark (t=0) of the time series of the transient to be identified.

The three accidents chosen for comparison with the existing works were the Blackout (BLKOUT), the Lost of Coolant Accident (LOCA) and the Steam Generator Tube Rupture (SGTR). Each transient was represented by the temporal evolution of the variables described in the Table I.

TABLE I.
STATE VARIABLES USED IN THE REPRESENTATION OF THE SIGNATURES OF THE DESING-BASIS ACCIDENTS.

Variable	Description	Unit
V01	Time	s
V02	Reactor water flow	%
V03	Hot leg temperature	ºC
V04	Cold leg temperature	ºC
V05	Primary water flow	kg/s
V06	Steam generator water level – large range	%
V07	Steam generator water level – narrow range	%
V08	Steam generator pressure	MPa
V09	Feed water flow	kg/s
V10	Steam flow	kg/s
V11	Flow in the rupture	kg/s
V12	Primary system flow	kg/s
V13	Primary system pressure	MPa
V14	Thermal power	%
V15	Nuclear power	%
V16	Subcooling power	ºC
V17	Pressurizer water level	%
V18	Primary mean temperature	ºC

III. Quantum Evolutionary Algorithm

A. Fundamentals of the Quantum Evolutionary Algorithm.

Quantum Computation is based upon the principal concepts of the Quantum Theory [1], [13] and [14], the superposition and interference of quantum states, which make possible the execution of parallel operations.

In classical computers, the information is encoded as a sequence of bits. Unlike classical computers, quantum computers process the information using a set of quantum bits (Q-bits). A generic Q-bit $|\psi\rangle$ might be represented not by an exact representation, but by a linear combination of the vectors

$|0\rangle$ and $|1\rangle$, given by :

$$|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \text{ and } |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (1)$$

in such way that

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (2)$$

where α and β are complex numbers that satisfy

$$|\alpha|^2 + |\beta|^2 = 1 \quad (3)$$

In Quantum Mechanics, the vector $|\psi\rangle$ is also called *state*. Thus, the physical interpretation of the Q-bit (eq. 1) is that he assumes simultaneously the states $|0\rangle$ and $|1\rangle$. In Quantum Mechanics, this ability of being simultaneously in two or more states is known as quantum states superposition. In other words, the information stored in $|\psi\rangle$ is a combination of all the possible states of $|0\rangle$ and $|1\rangle$.

In order to make the information in $|\psi\rangle$ accessible in a classical way, it is necessary to make an observation, that is, a measurement. This measurement has as a probabilistic outcome, a unique value contained in the superposition. Thus, although there exist a superposition of states, when a Q-bit is observed, it is observed in a single state. Thus, when $|\psi\rangle$ is measured, it is possible to find the state $|0\rangle$ with a probability $|\alpha|^2$ or the state $|1\rangle$ with a probability $|\beta|^2$.

A set of N Q-bits may be put in a superposition of 2^N states, and each one of these states corresponds to certain Q-bits in the state $|0\rangle$ and others in the state $|1\rangle$, such as (000...0), (100...0), (010...0), (111...0), ..., (111...1). These states encode all the possible numbers represented by N bits. This allows the application of a physical operation that corresponds to a computational calculation simultaneously to all the possible values, with a consequent parallel computation.

Although the Quantum Computing is promising in terms of processing, two issues prevent that its scale of utilization becomes larger: difficulties of implementation of a quantum computer and algorithms that can explore the ability of parallel processing of such computers. Notwithstanding, the development of quantum-inspired algorithms such as the QEA, and their procedures based on superposition and interference of quantum states, represent a promising possibility for the field of Optimization Metaheuristics for application to engineering problems.

B. *The canonic algorithm of the Quantum Evolutionary Algorithm.*

The main idea in the QEA is that the operations related to the search will be performed on quantum individuals of a population $Q(t)$, whose collapse into classical information will provide, at each generation t, a classical population $P(t)$ formed by classical candidate solutions. The quantum population $Q(t)$ of n quantum individuals, or quantum chromosomes in terms used for the description of GAs, is represented by the set $Q(t) = \{q_1(t), q_2(t), ..., q_n(t)\}$. For a search space where the candidate solutions are represented by m bits, the quantum chromosome $q_i(t)$ is given by:

$$q_i(t) = \begin{bmatrix} \alpha_{i1}(t) & \alpha_{i2}(t) & ... & \alpha_{im}(t) \\ \beta_{i1}(t) & \beta_{i2}(t) & ... & \beta_{im}(t) \end{bmatrix} \quad (4)$$

where, $|\alpha_{ij}(t)|^2 + |\beta_{ij}(t)|^2 = 1$ according to eq. (3). The index $i = 1,2,..., n$, corresponds to the quantum individual $q_i(t)$ whereas the index $j = 1,2,..., m$ corresponds to the number of a specific Q-bit of an individual i. $Q(t)$ is initialized as $Q(t) = \{q_1(0), q_2(0), ..., q_n(0)\}$ in such a way that $\alpha_{ij}(0) = \beta_{ij}(0) = \frac{\sqrt{2}}{2}$ $\forall$ $i = 1,2,..., n$ and $j = 1,2,..., m$.

As a consequence, $|\alpha_{ij}|^2 = |\beta_{ij}|^2 = \frac{1}{2}$, which means that the Q-bits have the same probability of being in the states $|0\rangle$ or $|1\rangle$ in the initialization.

The classical population P(t) of n classical individuals is represented by the set $P(t) = \{X_1(t), X_2(t), ..., X_n(t)\}$. The candidate solutions $X_i(t)$ with m bits, which will be evaluated by the fitness function $f(X_i(t))$, are represented by:

$$X_i(t) = [x_{i1}(t) \; x_{i2}(t) \; ... \; x_{im}(t)] \quad (6)$$

where $x_{ij}(t)$ is the observed bit. According to our model of QEA, the best candidate solution of P(t) at each iteration t is stored in B(t), that is,

$$B(t) = [b_i(t) \; b_2(t) \; ... \; b_m(t)] \quad (7)$$

where $b_j(t)$ represent the bits of the best solution. The algorithm of the QEA is described in Fig. 1.

1. t ← 0
2. Initialize $Q(t)$
3. Repeat until a stopping criterion is satisfied
  3.1. Generate $P(t)$ observing the states of $Q(t)$
  3.2. For i = 1 to n evaluate $f(X_i(t))$
  3.3. Store the best solution of $P(t)$ in $B(t)$
  3.4. Update $Q(t)$ using Q-gate U
  3.5. t ← t + 1

Fig. 1. Algorithm of the QEA.

The bits $x_{ij}(t)$ obtained in the item 3.1 of Fig. 1 are outcomes for the observation of the states of the individuals of *Q(t)*. The algorithm for the production of P(t) is described in Fig. 2. The probabilities $|\alpha_{ij}|^2$ and $|\beta_{ij}|^2$ play a fundamental role during the observation of a quantum individual $q_i(t)$: if the value of the random parameter is greater than $|\alpha_{ij}|^2$, then $|x_{i1}(t)| = 1$, otherwise $|x_{i1}(t)| = 0$.

Begin
 $i = 0$
  while (i < n) **do**
   $i = i + 1$
   $j = 0$
    while (j < m) **do**
     $j = j + 1$
      if random $[0,1] > |\alpha_{ij}|^2$
       then $|x_{ij}| = 1$
       else $|x_{ij}| = 0$
      end if
    end
  end

Fig. 2. Pseudo-code for update of the Q-bit.

The complex numbers α_{ij} and β_{ij}, and therefore *Q(t)*, are updated according to the Quantum Gate operator, which will be described hereafter.

C. *The Quantum Gate Operator*

The updating of the population in the QEA is done by the Quantum Gate operator, defined by the rotation matrix $U(\Delta\theta_{ij})$, which will be applied to each one of the columns of the each individual's Q-bits. In practice, each pair of values α_{ij} and β_{ij} is treated as a bi-dimensional vector and rotated using $U(\Delta\theta_{ij})$ in such a way that

$$\begin{bmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{bmatrix} = U(\Delta\theta_{ij})\begin{bmatrix}\alpha_{ij}(t)\\ \beta_{ij}(t)\end{bmatrix} \tag{8}$$

The operator $U(\Delta\theta_{ij})$ is given by:

$$U(\Delta\theta_{ij}) = \begin{vmatrix}\cos(\xi(\Delta\theta_{ij})) & -sen(\xi(\Delta\theta_{ij}))\\ sen(\xi(\Delta\theta_{ij})) & \cos(\xi(\Delta\theta_{ij}))\end{vmatrix} \tag{9}$$

with

$$\xi(\Delta\theta_{ij}) = S(\alpha_{ij}, \beta_{ij}) \times \Delta\theta_{ij} \tag{10}$$

where the sign function $S(\alpha_{ij}, \beta_{ij})$ represents the direction of rotation and the pass $\Delta\theta_{ij}$ represents the angle of rotation. Fig. 3 exhibits the procedure for application of the operator $U(\Delta\theta_{ij})$.

Begin
 $i = 0$
  while (i < n) **do**
   $i = i + 1$
   $j = 0$
    while (j < m) **do**
     $j = j + 1$
     Determine $\Delta\theta_{ij}$ **with the lookup**
     Obtain $\begin{vmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{vmatrix}$ **as:**
     $\begin{vmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{vmatrix} = U(\Delta\theta_{ij})\begin{vmatrix}\alpha_{ij}(t)\\ \beta_{ij}(t)\end{vmatrix}$
    end
  end

Fig. 3. Pseudo-code for update of the Q-bit.

Both and $S(\alpha_{ij}, \beta_{ij})$ are obtained in accordance with Table II. Their values depend basically on the possible combinations for $x_{ij}(t), b_j(t)$ and the expression $f(X_i(t)) > f(B(t))$, for a maximization problem (1st, 2nd and 3rd columns, respectively). In this way, $\Delta\theta_{ij}$ (in the 4th column) may assume either the Δ value, defined empirically for each problem, or zero. On the other hand, the value of $S(\alpha_{ij},\beta_{ij})$ is obtained according to the values of the 5th, 6th, 7th or 8th column.

For example, in a maximization problem, when $b_j(t)=1$ and $x_{ij}(t)=0$, if $f(B(t)) > f(X_i(t))$, it might be interesting for the candidate solution to have an increase in this bit's probability of assuming the value 1, since this bit of the best solution is 1. Therefore, the probability $|\beta_{ij}|^2$ should be increased. Thus, for a better visualization and considering a particular case where α_{ij} and β_{ij} are real numbers, considering the representation of a circle with radius 1 with the representation of the states $|0\rangle$ and $|1\rangle$ (Fig. 4, based on [4]), for α_{ij} and β_{ij} in the first quadrant, the direction of rotation will be counter-clockwise, that is, increasing the probability of the state $|1\rangle$; on the other hand, if α_{ij} and β_{ij} in the second quadrant, the direction of rotation will be clockwise.

TABLE II.
A MODIFIED ROTATION GATE.

x_i	b_i	$f(X)>f(B)$	$\Delta\theta_{ij}$	$S(\alpha_{ij},\beta_{ij})$ $\alpha_{ij}\beta_{ij}>0$	$\alpha_{ij}\beta_{ij}<0$	$\alpha_{ij}=0$	$\beta_{ij}=0$
0	0	False	0	0	0	0	0
0	0	True	0	0	0	0	0
0	1	False	1	1	-1	0	±1
0	1	True	1	-1	1	±1	0
1	0	False	0	-1	1	±1	0
1	0	True	0	1	-1	0	±1
1	1	False	1	0	0	0	0
1	1	True	1	0	0	0	0

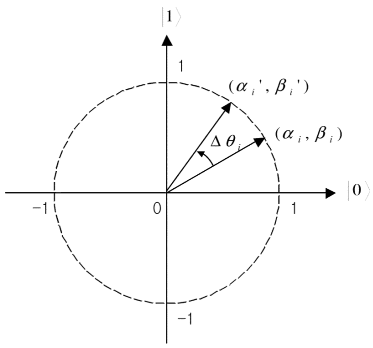

Fig. 4 Rotation of the quantum gate.

D. The Quantum Gate H_ε

QEA model applied to the transient identification model adopted corresponds basically to the model described above. In order to avoid the premature convergence of the Q-bit, [15] proposed the Quantum Gate H_ε defined by

$$\begin{bmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{bmatrix} = H_\varepsilon(\alpha_{ij}(t),\beta_{ij}(t),\Delta\theta_{ij}) \tag{11}$$

During the application of the Quantum Gate H_ε, the rotation

$$\begin{bmatrix}\alpha_{ij}'\\ \beta_{ij}'\end{bmatrix} = U(\Delta\theta_{ij})\begin{bmatrix}\alpha_{ij}(t)\\ \beta_{ij}(t)\end{bmatrix} \tag{12}$$

is calculated as an intermediate step and the final updating depends on the value of the constant ε, in such a way that

if $|\alpha_{ij}'|^2 \le \varepsilon \; e \; |\beta_{ij}'|^2 \le 1-\varepsilon$ then

$$\begin{bmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{bmatrix} = \begin{bmatrix}\sqrt{\varepsilon}\\ \sqrt{1-\varepsilon}\end{bmatrix} \tag{13}$$

if $|\alpha_{ij}'|^2 \le 1-\varepsilon \; e \; |\beta_{ij}'|^2 \le \varepsilon$ then

$$\begin{bmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{bmatrix} = \begin{bmatrix}\sqrt{1-\varepsilon}\\ \sqrt{\varepsilon}\end{bmatrix} \tag{14}$$

otherwise, $\begin{bmatrix}\alpha_{ij}(t+1)\\ \beta_{ij}(t+1)\end{bmatrix} = \begin{bmatrix}\alpha_{ij}'\\ \beta_{ij}'\end{bmatrix}$. (15)

This gate was introduced in this model has the objective of reducing the probability of the algorithm stagnation in a local optimum during the evolution of the population. The numerical value of ε is defined according to the problem and its values in the interval 0 < ε < 1. The value of ε used in this work was determined through experiments described in section IV.

IV. Study of Influences the Δ and ε Parameters of the Transient Identification System.

In our transient identification system, the time axis was partitioned into 60 seconds after the beginning of the transient

(t=0), reactor scram at 100% of nuclear power, which yields 61 time values. Therefore, the maximum number of correct classifications for the three postulated accidents is 177 (59 time values x 3 accidents types), since the two first seconds represent the plant operating at normal condition.

During the data analysis of accidents to be identified, as well as a process of data miming, the system needs to identify the most characteristic and representative set of values for the 18 process variables (Table I) that correspond to the identification of each one of the three postulated accidents (LOCA, BLKOUT, SGTR). It should be noted that initially the variable time was considered as one of 18 state variables in the accident data set.

Using a 12 bits precision, each candidate solution of the classical population $P(t)$ is a vector represented by 54×12 = 648 bits (since there exist 18 variables for each one of the three postulated accidents, we have the total number of 54 variables in each individual). The choice to use 12 bits of precision in this work aimed to compare the results from validation tests of our implementation the QEA with the results found in the original work [4].

In other words, inside a classical individual, each accident is represented by a group of 18×12 bits. In the QEA implemented, the number of individuals was n = 100, and the values assigned to the Δ and ε parameters are shown this section.

A. Parameter Δ

The Δ parameter is critical for the performance of QEA, as beside being responsible for learning of the algorithm, which balance global and local exploration ability of the quantum population, as the inertia weight, w, of the PSO.

In order to observe the influence the parameter Δ of QEA in the performance the Transient Identification System was set ε = 0.01 in according to [7], and were assigned different values for the Δ, so that they could represent a significant change in the behavior of the algorithm. For each value of Δ were simulated 10 runs with different seeds. Table III shows the average generation in which the global optimum (177) was found.

TABLE III.
TEST FOR DIFFERENT VALUE OF DELTA PARAMETER

Δ	ε	Average Convergence	Correct Classification
0.0005*π	0.01	1269	177
0.005*π	0.01	183	177
0.1*π	0.01	82	177

It is observed in Table III a large Δ facilitates exploration of the search space and decrease the convergence time of the algorithm, but can make the algorithm to converge prematurely to local optimum, as already demonstrated in previous work (). Conversely, a small Δ values makes the algorithm takes longer to converge and can sometimes achieve the optimal overall, but with more computational effort.

Thus, in order to improve the balance global and local exploration abilities of the quantum population, at the beginning and end of process, with the goal of ensuring a fast converge of the algorithm, we modification the parameter Δ as a decreasing function in time.

In table IV, set again ε = 0.01 and were attributed different ranges to the linear decay of Δ. For each simulated range of Δ were performed 10 runs with different seeds. Table IV shows the average generation in which the global optimum (177) was found.

TABLE IV.
TEST FOR PARAMETER Δ IN A DECREASING FUNCTION IN TIME

Δ	ε	Average Convergence	Correct Classifications
0.1*π →0.0005*π	0.01	104.9	177
0.1*π → 0.03*π	0.01	105,7	177
0.1*π → 0.05*π	0.01	125.6	177

Comparing the results in Table IV with the results of table III, it is observed that used the Δ parameter as a function decreasing in time causes the algorithm presents a better robustness in the process, and even a significant improvement in their performance with regard to the number of generations needed to find best result.

B. Parameter ε

The ε parameter introduced by [7]-[8] in the original model of the QEA, has a role of delaying the premature convergence of the algorithm, and reduce the probability of the algorithm stagnation in a local optimum.

In order to observe the influence the parameter ε of QEA in the performance the Transient Identification System was set Δ=0.005*π in according to [7]-[8], and were assigned different values for the ε, so that they could represent a significant change in the behavior of the algorithm. For each value of ε were simulated 10 runs with different seeds. Table V shows the average generation in which the global optimum (177) was found.

TABLE V.
TEST FOR DIFFERENT VALUE OF PARAMETER Eps

ε	Δ	Average Convergence	Correct Classification
0.005	0.005*π	390	177
0.05	0.005*π	1156	177
0.1	0.005*π	1156	177

It is observed in the Table V a large ε avoid premature convergence of the algorithm doing the convergence slower, in consequence requires more evaluations to find the best result, and small ε makes fast converge.

According the findings of the study above, and in order to slow the convergence of the algorithm, we propose the implementation of a ε parameter in a decreasing function in time, so that at the beginning of the process the algorithm has a lower probability of convergence than the end of the process. The result is shown in table VI, where set again Δ= 0.005*π and were attributed different ranges to the linear decay of ε.

TABLE VI.
TEST FOR PARAMETER ε IN A DECREASING FUNCTION IN TIME

ε	Δ	Average Convergence	Correct Classifications
0.08 →0.05	0.005*π	104.9	177
0.1 → 0.02	0.005*π	953	177
1.0 → 0.03	0.005*π	125.6	177

Comparing the Table VI with Table V it is observed that ε decreases linearly it result in increase to the convengence time, but we can observed that depending on the range chosen for the decay of ε the computational effort of solving the problem increases overly, it is like this technique unattractive.

V. Discussion

The results of section IV, present in Tables III and IV shown that the use of the Δ parameter as a function of decreasing the time it made the algorithm to present more robust behavior, and independent of the chosen range give the expected result with a less computational effort on average. Yet the use of the Δ parameter as a constant became the algorithm more dependent on the value chosen it was presented a premature convergence as a slow evolution, with great computational effort.

The results in Tables V and VI of section IV, show that use the ε parameter as a decreasing function in time it made the algorithm present a slow convergence, and increase the computational effort. This technique can be applied to problems that present a premature convergence, where the process slow convergence of the algorithm can be used as an interesting alternative to finding the best results.

VI. Conclusion

The present work shows the viability to modification the Δ and ε parameters of the QEA, fixed in form canonical, in functions decreasing in time. Besides, to the best of our knowledge, this is the first study of the influence the main parameters of the QEA in multimodal and complex problem in Nuclear Engineering such as the transient identification in a PWR NPP operating at 100% power.

In this way, describes the implementation and results of modification of the main parameters of the QEA as functions decreasing in time, presenting an alternative way to control the behavior of the algorithm.

According to the results found in this work, the use of the Δ parameter as a decreasing function in time and the ε parameter as a constant showed better behavior of the QEA algorithm as optimization tool of Transient Identification System.

Acknowledgment

The authors R. S. and A. S. N. acknowledge CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) and FAPERJ (Fundação de Amparo à Pesquisa do Estado do Rio de Janeiro).

References

[1] Deutsch, D., 1985. “Quantum Theory, the Church-Turing Principle and the Universal Quantum Computer”. Proceedings of the Royal Society vol. 400, pp. 97-117.

[2] Nielsen, M. A., Chuang, I. L., 2000. “Quantum Computation and Quantum Information”. United Kingdom, Cambridge University Press.

[3] Goldberg D. E., 1989. *Genetic Algorithms in Search Optimization and Machine Learning*. (Bookstyle), Addison-Wesley Publishing Company, Massachusetts.

[4] Han, K.-H., Kim, J.-H., 2002. “Quantum-Inspired Evolutionary Algorithm for a Class of Combinatorial Optimization”. *IEEE Transactions on Evolutionary Computation* vol. 6, pp. 580–593.

[5] Porto, D., Martinez, A., Scimone, S., Sciagura, E., “Quantum Evolutionary Algorithms: A SW-HW approach”. (Published Conference Proceedings style),” in *Proc. 5th WSEAS Int. Conf. on Computational Intelligence, Man-Machine System And Cybernetics*, Venice, Italy, 2006, pp. 20–22.

[6] Jimenez, J. F., Cuevas, F. J., Carpio, J. M.., Sciagura, E., “Genetic Algorithm Applied to Clustering Problem and Data Mining”. (Published Conference Proceedings style),” in *Proc. 7th WSEAS Int. Conf. on Simulation, Modelling and Optimization,* Beijing, China, 2007, pp. 15–17.

[7] Nicolau, A. S., Schirru, R., “Quantum Evolutionary Algorithm Applied to Time Independent Transient Identification of a Nuclear Power Plant”. (Published Conference Proceedings style),” in *IEEEAM Int. Conf. on, Applied Computer Science (ACS),* Greece, Malta, 2010.

[8] Nicolau, A. S., Schirru, R., Medeiros, A., "Quantum Evolutionary Algorithm Applied to Transient Identification of a Nuclear Power Plant" , Progress in Nuclear Energy, submitted for publication.

[9] Kennedy, J., Eberhart, R.C., 2001. "Swarm Intelligence". Morgan Kaufmann Publishers, San Francisco, CA.

[10] Changsheng, G., Juan, H., Liang, Z., "A New Quantum Evolutionary Algorithm and its Applications ". (Published Conference Proceedings style)," in *Proc. 5th WSEAS Int. Conf. on Mathematical Biology and Ecology (MABE'9)*

[11] Pereira, C.M.N.A., Schirru, R., Martinez, A.S., 1998, "Learning an Optimized Classification System From a Data Base of time Series Patterns Using Genetic Algorithm". In: Ebecken, N.F.F. (ed.), Data Mining, Computation Mechanics Publications, WIT Press, England

[12] Almeida, J. C. S., Schirru, R., Pereira, C.M.N.A., 2003. "A Possibilistic Approach for Transient Identification with "Don't Know" Response Capability Optimized by Genetic Algorithm". In: Ruan, D., Fantoni, P. F. (eds.), Power Plant Surveillance and Diagnostics, Springer-Verlag, USA

[13] United States Nuclear Regulatory Commission, 1979. TMI2 Lessons Learned Task Force Final Report - NUREG 0585.

[14] Fang, L., Chen, P., Liu, S., "Particle Swarm Optimization with Simulated Annealing for TSP". (Published Conference Proceedings style)," in *Proc. 6th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases, Corfu Island,* Greece, Malta 2007, pp. 16–19.

[15] Han, K.-H., Kim, J.-H., 2004. "Quantum-Inspired Evolutionary Algorithms with a New Termination Criterion, H_ε Gate, and Two-Phase Scheme." *IEEE Transactions on Evolutionary Computation* vol.8, pp. 156–169.

[16] Nicolau, A.S., Schirru, R., Medeiros, J.A.C.C, 2009, "Quantum computation and Swarm Intelligence Applied in the Optimization of Indentifications Accidents in a PWR Nuclear Power Plant", COPPE/UFRJ, INAC.

Andressa dos Santos Nicolau - graduated in Physics from the State University of Rio de Janeiro (2007), Masters in Nuclear Engineering from Universidade Federal do Rio de Janeiro (2010), and currently a doctoral student in Nuclear Engineering from Universidade Federal do Rio de Janeiro (2010). She has experience in Computer Science with emphasis in Artificial Intelligence.

Roberto Schirru - Fellow of the CNPq Research Productivity - Level 1B. He graduated BA in physics from the Federal University of Rio de Janeiro (1976), specializing in Real Time Processing by Digital Computer Equipaments (1977), specialization in Artificial Intelligence Expertise by the European Centre for Nuclear Research (1993), Master of Engineering Nuclear Federal University of Rio de Janeiro (1980) and Ph.D. in Nuclear Engineering from Universidade Federal do Rio de Janeiro (1991) and postdoctoral Institute Della Molle Di Studi Di Inteligenzia Artificialle, Switzerland (1994). He is currently Associate Professor at Federal University of Rio de Janeiro. He has experience in Artificial Intelligence with emphasis in Computer Systems. Acting on the following topics: Knowledge Representation, Operation of Nuclear Plants, Safety of Nuclear Plants.