Quantum Evolutionary Algorithm Applied to Time Independent Transient Identification of a Nuclear Power Plant

Andressa dos Santos Nicolau, Roberto Schirru

Abstract — When transients occur during the operation of Nuclear Power Plants (NPPs), their identification is critically important for both operational and safety reasons. Thus, plant operators have to identify an event based upon the evaluation of several distinct process variables, which might difficult operators' actions and decisions. Transient identification systems have been proposed in order to support the analysis with the aim of achieving successful or effective courses of action, as well as to reduce the time interval for a decision and corrective actions. This article presents a system for accident and transient identification in a pressurized water nuclear reactor whose optimization step of the classification algorithm is based upon the paradigm of the Quantum Computing. In this case, the optimization metaheuristic Quantum Inspired Evolutionary Algorithm (QEA) was implemented and works like a data mining tool. The system is able to identify anomalous events, without the use of an initiating event (reactor scram, for instance) as the start point of a time dependence related to postulated transients. The results of the classification of transients are compared with other results in the literature.

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

I. INTRODUCTION

Both the efficiency and the safety in the operation of a Nuclear Power Plant (NPP) depend on the performance and conditions of the thousands of components that compose its several subsystems. Therefore the monitoring and control of several process variables related to them is inextricably associated with the operation of the NPP. On the other hand, faults in such components or subsystems favor the appearance of abnormal situations that might cause serious consequences. Thus, the correct diagnosis in an adequate interval of time is essential for the NPP operation and safety

The identification of acidentes, that are also seen as transients, is related with process variables and therefore yours classification is constrained by the information provided by the number of instruments. The recognition of patterns existent on the dynamics of the variation of the measurements can be used to support the prediction of possible behaviors of subsystems in a plant. In this way, decision support systems assist operators increasing the chances of proper courses of action, according to each different situation.

One of the major regulatory consequences after the Three Mile Islands accident was the proposal of normative documents by the United States Nuclear Regulatory Commission (1979) with the purpose of increasing the safety and the efficient operation of the NPP as well as the operator's responsiveness. Thus, the concept of the Critical Safety Functions [1] and the usage of computerized systems for the control and monitoring of information related to safety [2]-[3].

One of the first systems for the identification of nuclear accidents based on artificial intelligence techniques was proposed by [4]. Other transient identification systems based on Artificial Intelligence techniques that deal with the high complexity of the search space have been proposed [5]- [6]. Despite the problem difficulty of the diagnosis and identification of transients, such systems help the operator in the diagnosis of the operational conditions of the NPP.

Reference [2] proposed a new methodology for the identification of nuclear accidents, based upon the classification of anomalous events through direct measurements of Euclidean Distances, optimized by Genetic Algorithm GA [7]. Reference [6] applied the Particle Swarm Optimization [8] to this system.

The present article presents a transient identification system that uses the quantum-inspired algorithm Quantum Evolutionary Algorithm [9] as an optimizer, was used to find an optimal solution that regardless of time elapsed from the beginning of the transient, and consequently independ on the identification of the instant of the initiating event itself (reactor scram for instance). Within this perspective, this paper presents a novel aspect in relation to current literature, since most identification systems cited depend on detection of an event that can be used as an initiating of change over time, usually the reactor scram, to compare the patterns of accidents in time series.

The QEA is an optimization metaheuristic algorithm inspired on Evolutionary Computation, more specifically on GA. As the GA, 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.

Our results in the identification of transient and accidents are compared to other results in the literature, showing that the QEA achieved outstanding performance as the optimizer to find the ideal prototype vectors, which can be viewed as Voronoi Vectors [10], of classes to be identified. 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 description of the system proposed for the identification and classification of transients is in section IV, as well as the results obtained. The discussion of the results and the comparison with other techniques in section V. The conclusion is presented in the section VI.

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 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 [2] and [5]. Our system classifies an anomalous event in relation to the signatures of three design-basis accidents postulated by the FSAR [11] 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 [2]-[5] 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 [12]- [13], 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:

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

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:

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

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,

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

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 $\Delta\theta_{ij}$ and $S(\alpha_{ij}, \beta_{ij})$ are obtained in accordance with [14].

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 $\left|\alpha_{ij}'\right|^2 \leq \varepsilon \; e \; \left|\beta_{ij}'\right|^2 \leq 1-\varepsilon$ 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 $\left|\alpha_{ij}'\right|^2 \leq 1-\varepsilon \; e \; \left|\beta_{ij}'\right|^2 \leq \varepsilon$ 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 chances of stagnation of the algorithm into local minima during the evolution of the population. The numerical value of ε is defined according to the problem and 0 < ε < 1. The value of ε in used in this work was determined through experiments described in section VI.

IV. Implementation and Computational Experimental Results of the Transient Identification Sytem for a PWR Nuclear Power Plant.

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 [9].

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, parameter delta was Δ = 0.005* π, considered in our previous work [16], and the value of the Quantum Gate He, ε = 0.01. The choice of the value of ε = 0.01 was based on a series of tests presented in Table II.

TABLE II.
TEST FOR DIFFERENT VALUE OF PARAMETER ε

Value of ε	Convergence (generations)	Correct Classification
0.000	188	177
0.005	188	177
0.010	123	177
0.050	188	177
0.100	546	177
0.200	618	177

It is observed in Table II that values of ε <0.01 prevent premature convergence of the algorithm QEA and not make the search process slower, in other words do not require a greater number of generations to find the optimal solution.

The Table III show the results of the tests, for different values for the variable time, and presents the number of evaluations needed to find the optimal solution, 177 correct classifications.

TABLE III.
TEST FOR DIFFERENT VALUE OF TIME

Time	Convergence (evaluation)	Correct Classification
5	$2*10^3$	177
10	$2*10^3$	177
20	$2*10^3$	177
40	$2*10^3$	177
60	$2*10^3$	177

The graphic in Fig. 4 shows the position of prototypes vector of transients in two-dimensional plane of one possible solution. The first variable (y axis) of the Table I normalized in the interval [0-1], and time in seconds (x axis). The circle represents the prototype vector of LOCA, the cross of Blackout and the triangle represents of SGTR.

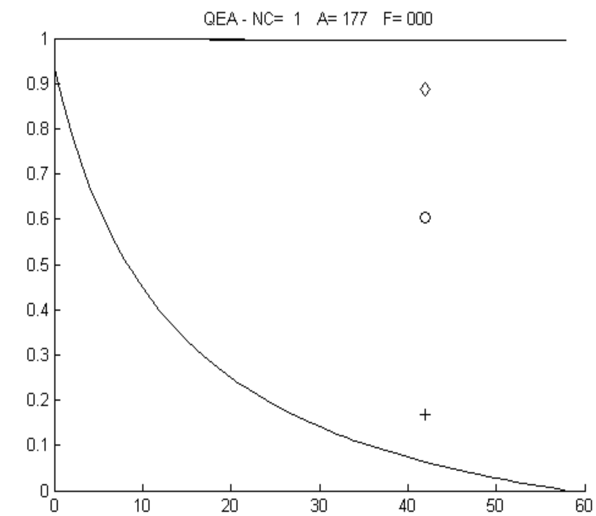

Fig. 4. Position of prototypes vector of transients in two-dimensional plane

Can be observed in the tests shown in this paper that there are several ideal solutions to diferents time instants, and other words, for each fixed time instant the system encountered a prototype vector (centroid) with the highest number of correct classification. This indicates that there must be an optimal solution invariant in the time, in the order words, the determination of the prototype vector of transients there are not time dependent.

This fact motivated us to make changes in our system for the identification of transient, in order to eliminate the time variable of the set of variables (Table I) considered necessary and sufficient for determining the centroid vectors for the transient.

Also in this case we use a 12 bits precision, each candidate solution of the new classical population P(t) is a vector represented by 51×12 = 612 bits (since there exist 17 variables for each one of the three postulated accidents, we have the total number of 51 variables in each individual without the time). In other words, inside a classical individual, each accident is represented by a group of 17×12 bits.

In order to verify the robustness of the ideal solution found by the system has included a Gaussian noise of zero mean and standard deviation of 1% (σ = 1%) in the signal event to be identified for each transient. The choice of the 1% noise in signal event is due to the fact that the percentage of error usually corresponds to the error found in the nuclear instrumentation.

The Table IV present the results for each accident and the level of noise introduced into the signal to be classified, where the maximum number of hits for each accident is 59 correct classifications.

TABLE IV
INSTANTANEOS CLASSIFICATION RESULTS

Transient	Noise (%)	Correct Classification
BLKOUT	0	100%
LOCA	0	100%
SGTR	0	100%
BLKOUT	1	100%
LOCA	1	100%
SGTR	1	100%
BLKOUT	2	100%
LOCA	2	100%
SGTR	2	93%

V. DISCUSSION

In order to compare the results obtained with previous techniques reported [5]–[6], the QEA was used to provide the prototype vector including the time variable, with maximum number of correct classifications is 177 (59 time points x 3 accident types). The comparison between the best result of the QEA, PSO and GA is presented in Table V. According to this Table, QEA proved more efficient and with less computational effort.

TABLE V.
COMPARISON OF GA, PSO AND QEA.

	Population Size	Convergence (evaluations)	Correct Classification
GA	2000	NA	98,0%
PSO	500	$2*10^6$	98,9%
QEA	100	$1*10^4$	100,0%

The results obtained with the QEA without the time variable are compatible to the techniques in the reference literature [2]-[5]-[6]-[16], for the transient identification problem, but were obtained with less computational effort (number of evaluations). This system allow a solution that approximates the ideal solution, the Voronoi Vectors for the classes of accidents with robustness.

The adjustments in the value of ε and Δ, used by the algorithm QEA was successfully applied in the solution of the transient identification problem of a PWR NPP and was efficient in the search of solutions in multimodal high dimensional spaces.

The graphic in Fig. 5 presents the fitness convergence of the QEA algorithm with 100 individuals, $\Delta = 0.005 * \pi$ and 220 generations ($2.2*10^4$ evaluations), and using the time as one data set variable. It was observed that the algorithm presents several stationary states, that is, it remains stuck

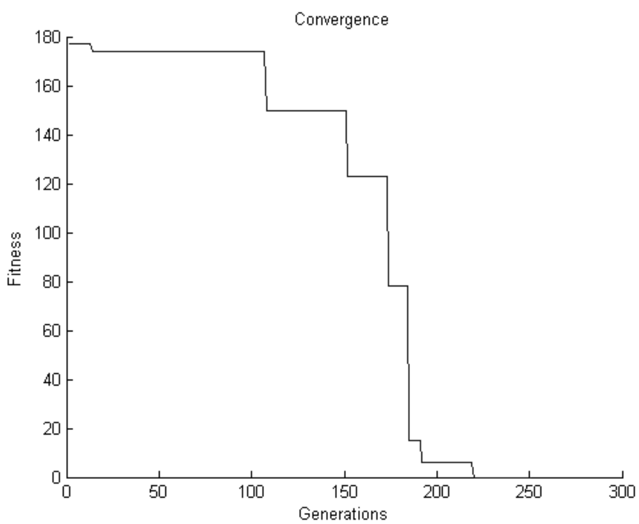

Fig. 5. Fitness Convergence

several generations without significant learning.

The results obtained by the system without the time variable, besides to classify the event independently of time and mainly without the need for detection or identification of an initiator event as the start point of t = 0, were obtained with less than $1.0*10^4$ evaluations. This represents a significantly less computational effort than the other works presented in literature.

VI. Conclusion

The present work shows the viability of the algorithm QEA as an optimization tool in discrete and continuous high-dimensional search spaces. Besides, to the best of our knowledge, this is the first application 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, the present article described the implementation and results of a new model of transient identification based on search of the Voronoi Vectors, with only one partition and independent of the existence of an event that can be used as a starting point for t = 0, which yielded a more efficient system compared to other models described in the literature. The QEA is a potential metaheuristic technique for optimization problems in Nuclear Engineering. Future work comprises the application of the model of the system for transient identification with QEA for a set containing more transient signatures and the determination of minimal sets of variables for the identification of transient

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