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Full Length Research Paper

The genetic algorithm to management measures of information security systems

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A novel genetic algorithm is proposed to improve the effectiveness of management measures of information security systems. In this work, the information security management measure is evaluated via simulation systems. The genetic algorithm is used to adjust the information security management measure, and obtains the satisfied information security management measure. The experimental results suggest that this proposed approach is feasible, correct and valid.

Key words: Simulation optimization, genetic algorithms, orthogonal design.

INTRODUCTION

As a result of the rapid development of computer network, the whole society has become more and more dependent on information system. At the same time, the vulnerability of information system will impose direct threat to national critical infrastructure (Pereira et al., 2010). As for the current situation of electric system information security, Liu has introduced measures for solving power information system in the aspects of technology and management. The technological measures include physical isolation, intrusion detection, hidden danger scan, virus scanning and anti-virus, data encryption, data backup while management measures emphasis contents like information security education, personnel, password, technology and data, and illustrate implementation points of power information security. Cheng proposes information security management measures from two aspects:

Measures complementary to IT technology security and measures inter-support with IT technology security. It is therefore not difficult to see that the present researches for information security management are basically some experienced measures or identification methods. To improve the effectiveness of management measure for the information security, the parallel control approach is employed to the simulation, evaluation and optimization of information security management measure. From these existing references (Ozkan and Karabacak, 2010), the present researches to information security management are some experienced measures or qualitative methods. To improve the effectiveness of management measure of information security systems, the genetic algorithm is employed to optimization of information security management measures.

In order to improve the performance of genetic algorithms, many researchers have studied applications of the interaction between evolution and learning (Xing et al., 2008, 2010). These methods keep useful features of previous individuals to improve the performance of current individuals (Xing et al., 2006, 2007). Such approaches outperform the traditional evolutionary algorithms on several benchmarks (e.g., flexible job shop scheduling problem, traveling salesman problem, and capacitated arc routing problem) (Ho et al., 2007; Louis and McDonnell, 2004).

PROBLEM FORMULATION

This work studies the optimization of management measures of information security systems. In this work, if the definitional domain of variables is continuous, then we call it as the continuous variables; if the definitional domain of variables is discrete, then we call it as the discrete variables; if the definitional domain of variables is Boolean, then we call it as the Boolean variables. This problem can

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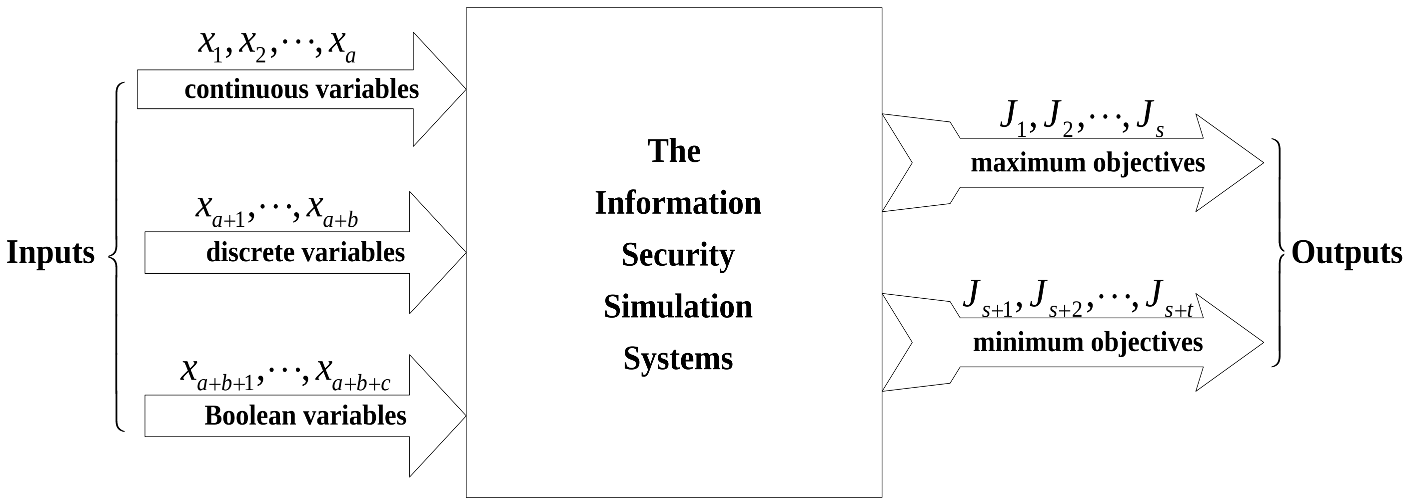


Figure 1. The framework of information security systems.

be formulated as Figure 1. The purpose of this paper is optimizing management measures of information security systems. For this reason, we should characterize the features using some parameters. The parameters can be the continuous variables, discrete variables and Boolean variables. The inputs of this problem can be displayed as

$$X = x_1, x_2, \cdots, x_a, x_{a+1}, \cdots, x_{a+b}, x_{a+b+1}, \cdots, x_{a+b+c}$$

Suppose l_i and u_i denote the minimum value and the maximum value of variable x_i, then the constraints of this problem can be summarized as:

$$\begin{cases} l_i \le x_i \le u_i & \forall i = 1, 2, \cdots, a \\ x_i \in Z, l_i \le x_i \le u_i & \forall i = a+1, a+2, \cdots, a+b \\ x_i \in \ 0,1 & \forall i = a+b+1, a+b+2, \cdots, a+b+3 \end{cases}$$

In the optimization of management measures of information security systems, there are two kinds of objectives: The maximum objective and minimum objective. Therefore, the objectives of this optimization problem can be summarized as:

$$\begin{cases} \max \ J_1, J_2, \cdots, J_s \\ \min \ J_{s+1}, J_{s+2}, \cdots, J_{s+t} \end{cases}$$

THE IMPROVED GENETIC ALGORITHM

Here, our improved genetic algorithm is proposed to improve the effectiveness of management measures of information security systems. This approach, called improved genetic algorithm (IGA) can be briefly sketched as follows: It gained the initial population through sampling by orthogonal design and quantization technology; evolved the current population through crossover and mutation operations. The computational flow of IGA is displayed in Figure 2.

Population Initialization

In the proposed IGA, the floating point array is employed to represent one chromosome. The length of chromosome is the number of variables. In the population initialization phase, it is desirable that chromosomes should be scattered uniformly over the feasible space. Therefore, it gained the initial population through sampling using orthogonal design and quantization technology. The process of population initialization is displayed in steps.

Step 1

Divide the feasible space L, U into B subspaces by Formula (1):

$$u_k - l_k = \max_{1 \le i \le n} \ u_i - l_i$$
$$\begin{cases} L_i = L + \ i-1 \ \left[\ u_k - l_k \ /B \right] 1_k \\ U_i = U + \ B-i \ \left[\ u_k - l_k \ /B \right] 1_k \end{cases}, i = 1, 2, \cdots, B \tag{1}$$

Here, $L = \ l_1, l_2, \cdots, l_n \ ^T$ and $U = \ u_1, u_2, \cdots, u_n \ ^T$ are the lower and upper bound respectively and B is the design variable.

Step 2

Divide each variable into Q_1 levels in each subspace. Suppose the

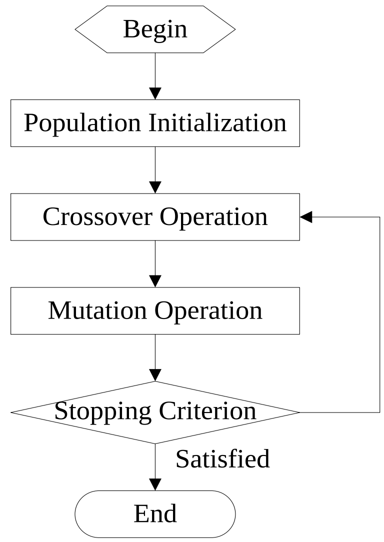


Figure 2. Optimization framework of our IGA.

Table 1. The corresponding relationship to discrete variables

Levels	1	2	$\cdots$	μ	$\mu+1$	$\cdots$
Values	1	2	$\cdots$	μ	1	$\cdots$

Table 2. The corresponding relationship to discrete variables (another case)

Levels	1	2	$\cdots$	Q_1
Values	1 or 2	3 or 4	$\cdots$	$\mu-1$ or μ

feasible space of variable x_i is l_i, u_i, and variable x_i can be divided into Q_1 levels according Formula (2):

$$a_{ij} = \begin{cases} l_i & j=1 \\ l_i + (j-1)\left[(u_i - l_i)/(Q_1 - 1)\right] & 1<j<Q_1 \\ u_i & j=Q_1 \end{cases} \qquad (2)$$

Step 3

Select M_1 chromosomes from each subspace. Construct the orthogonal table $\left[a_{ij}\right]_{M_1 \times N}$, and apply M_1 combinations to get M_1 chromosomes.

Step 4

Select the best G chromosomes from $M_1 B$ chromosomes. To continuous variables $x_1, x_2, \cdots, x_a$, these Q_1 levels are $a_{i1}, a_{i2}, \cdots, a_{iQ_1}$, they are float numbers, and there is no conversion to these variables.

To discrete variables $x_{a+1}, x_{a+2}, \cdots, x_{a+b}$, Q_1 levels are also $a_{i1}, a_{i2}, \cdots, a_{iQ_1}$, and there should exist one conversion to these variables. Suppose the feasible value of discrete variable x_k is $1, 2, \cdots, \mu$, if $\mu \le Q_1$, then variable x_k will be assigned as follows as shown in Table 1.

If $\mu > Q_1$, then variable x_k will be assigned as shown in Table 2. To these Boolean riables $x_{a+b+1}, x_{a+b+2}, \cdots, x_{a+b+c}$, Q_1 levels are also $a_{i1}, a_{i2}, \cdots, a_{iQ_1}$, and there is need of one conversion to these variables. To the Boolean variable x_k, it will be assigned as shown in Table 3.

Table 3. The corresponding relationship to Boolean variables.

Levels	1	2	3	4	$\cdots$	Q_1
Values	1	0	1	0	$\cdots$	1

Table 4. Parameter settings of the study IGA.

Parameter	**Signification**	**Setting**
Q_1	Number of quantization levels	5
B	Number of subspaces	1
G	Population size	20
Q_2	Number of quantization levels	3
F	Number of factors	4
P_c	Crossover probability	0.60
P_m	Mutation probability	0.10
$MaxGen$	Maximum iterative	100

Table 5. Experiment results produced by different methods.

Different method	**Objective**	**The number of fitness evaluation**
Improved genetic-annealing algorithm	986.05	1219
Genetic algorithm-simplexes	952.79	1308
New immune GAs	944.26	1257
OGA/Q	955.68	1198
The proposed approach	910.29	983

Crossover and mutation operations

The crossover recombines the gene-codes of two parents and produces offspring such that the children inherit a set of building blocks from each parent. In the crossover operation, it is very pivotal to select a small, but representative sample of points as the potential offspring. For this purpose, the orthogonal crossover with quantization (Leung and Wang, 2001) was applied as the crossover operator of IGA.

Mutation takes place on some newly formed children in order to prevent all solutions from converging to their particular local optima.

To the continuous variables X_i, it randomly generates a real number $Z \in l_i, u_i$, and then replaces X_i by Z to get a new chromosome.

To the discrete variables X_j, it randomly generates an integer number $z \in \left[l_j, u_j \right]$, and then replaces X_j by Z to get a new chromosome.

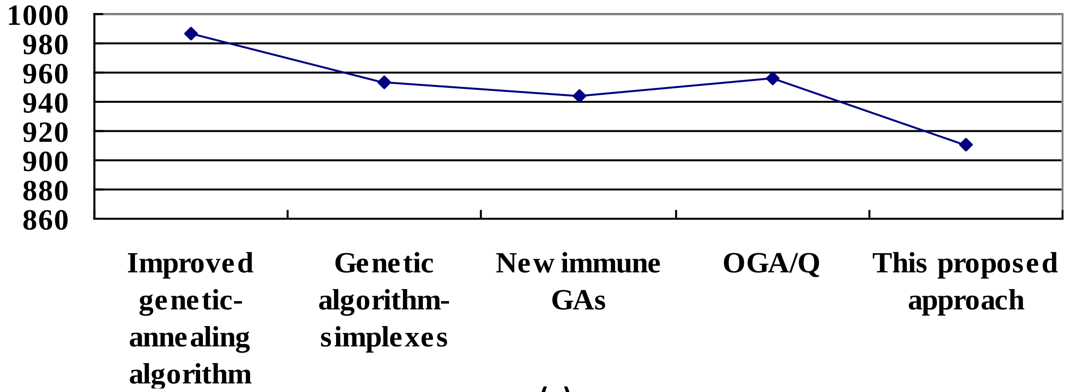
To the continuous variables X_k, if it is 0, then replaces X_k by 1 to get a new chromosome; if it is 1, then replaces X_k by 0 to get a new chromosome.

EXPERIMENTAL RESULTS

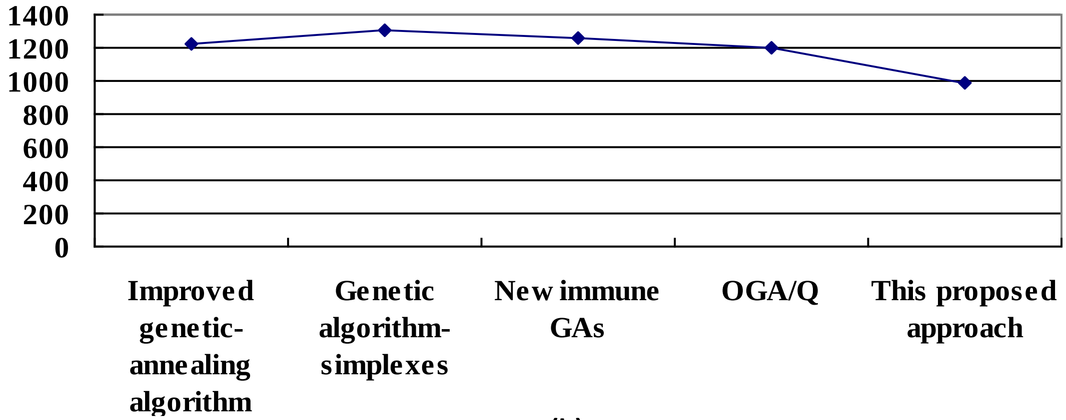
The IGA is demonstrated by an experiment. The experiment was performed on a Pentium IV 2 GHz personal computer with a single processor and 1 G RAM. Each experiment was run 50 times. The parameter settings to the IGA used in this paper are listed in Table 4.

In order to demonstrate the efficiency, improved genetic-annealing algorithm (Lan et al., 2002), genetic algorithm-simplexes (Han and Liao, 2001), new immune GAs (Zhang and Yang, 2005), and OGA/Q (Leung and Wang, 2001) were applied to compare with our IGA. The experiment results produced by five different methods are listed as Table 5 and Figure 3.

These results show that this IGA is clearly superior to the other four approaches. The results show drastic reductions in the number of fitness evaluations by the IGA and that it outperforms the other. The IGA can obtain the satisfied information security management measure.



(a)



(b)

Figure 3. (a) The objective produced by different methods. (b) The number of fitness evaluations of different methods.

Conclusions

The contribution of this paper: A novel genetic algorithm is proposed to improve the effectiveness of management measures of information security systems. The experimental results suggest that this proposed approach is feasible, correct and valid.

The future research directions can be summarized as follows: (1) Improve the performance of this approach largely, and (2) Apply this approach to solve other complex simulation problems.

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