Optimizing Parameters of Fuzzy Petri Net Based on Artificial Immune Algorithm

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***Abstract*—**Aiming at knowledge reasoning ability of fuzzy petri net depending on the parameter and the parameters usually obtained by specialist, an algorism based on artificial immune algorism for obtaining the optimum parameters was proposed. Firstly, the fuzzy petri net and generating rules were defined and described, and then the coding method of antibody, Affinity evaluation function and Simulated Annealing immune selection operator are designed to improve the classic artificial immune algorism. The specific algorism based on this improved artificial algorism was defined. The simulation experiment shows the method in this paper can accurately realize the parameters optimizing and has the litter square error, compared with the other methods, our method has the quick global convergence rate, optimizing ability and strong Versatility.

Keywords-component;Parameter optimizing; artificial immune; Petri Net; fuzzy

I. INTRODUCTION

Petri net has strict mathematical model, which can visually represent such series of behaviors as occurring order, concurrency, synchronization and asynchronization of the system in a graphical manner, and express and describe it with accurate and formalized language at the same time. So far, Petri net is widely used in the field of fault diagnosis, protocol scanning and analysis, automatic control and conflict detection [1-3].

Fuzzy Petri net is a kind of modeling tool, which is produced by fuzzy production rules and Petri net. It has not only the ability to express and describe Petri net but also the fuzzy reasoning power of fuzzy systems, which makes it the most suitable for representation and reasoning of knowledge. However, due to the lack of learning capability, its parameters like weight, threshold value and degree of confidence are dependent on human experience, too one-sided and influencing the precision of knowledge reasoning. Therefore, it is significant to solve and optimize each parameter of fuzzy Petri net.

Evolutionary algorithm has been applied in lots of papers to achieve learning and optimization of parameters [4-5]. In [5], it introduced Ant-Genetic Algorithm to achieve such a goal. Firstly, it used genetic algorithm to generate initial pheromones; then, with ant colony algorithm, those pheromones were optimized to get the best solution, which corresponded to parameter's optimized value. The paper [6] discussed the application of artificial fish swarm algorithm to optimize one parameter of fuzzy Petri net- degree of confidence. Through description of fish finding food, gathering, tailgating and random behaviors and mobile strategy, parameters were optimized. A hybrid intelligent algorithm of particle swarm optimization (PSO) and BP network algorithm was proposed in [7] and it was used to seek for the optimum of fuzzy Petri net. Next in [8], readers can see the demonstration of a two-phase method to optimize parameters of the net mentioned above. In it, genetic algorithm was used to obtain initial solutions during the first phase and then they were modified through BP network training.

All the above works mentioned different algorithms to achieve the optimization of parameters of fuzzy Petri net. They are meaningful to today's work. Yet, there are still shortcomings such as slow global convergence and easily falling into locally optimal solutions.

Artificial immune algorithm [9] is an optimized technique based on the theory of immunology and biological immune mechanism. It has strong global search ability, fast convergence and robustness.

Hence, it proposes a method for optimizing parameters of fuzzy Petri net based on improved artificial immune algorithm. The method can help realize optimization of such parameters as weight, threshold value and degree of confidence. This proposed method proves in the experiment that it can help optimize each parameter of the net, with good generality and high optimization precision.

II. FUZZY PETRI NET

A. Definition

Definition 1: Fuzzy Petri net can be defined as a 9-tuple model $\{P,T,I(p,t),O(t,p),M,Q,U,V,W\}$, where,

(1) $P=\{p_1,p_2,...,p_n\}$ is a finite set of fuzzy library;

(2) $T=\{t_1,t_2,...,t_m\}$ is a finite set of fuzzy transition, and $P\cap T=\Phi$, $P\cup T\neq\Phi$;

(3) $D=\{d_1,d_2,...,d_n\}$ is a finite set of proposition;

(4) $I(p,t)\subseteq(P\times T)$ is an input arc set of all fuzzy transitions;

(5) $O(t,p)\subseteq(T\times P)$ is an output arc set of all fuzzy transitions;

(6) M stands for the distribution of tokens in all fuzzy libraries;

(6) $Q:P\rightarrow D$ means one-one mapping of fuzzy library into proposition;

(7) $u\in U$ is degree of confidence and meets $0\leq u\leq 1$;

(8) $\lambda\in V$ is the threshold value of transition and suffices $0\leq\lambda\leq 1$;

(10) W is weight set, meaning the weight of input or output arc.

B. *Weighted fuzzy production rules*

Weighted fuzzy production rules are used to describe the fuzzy relationship of a proposition.

Definition 2: the basic rule *r* of such rules can be categorized into the three types:

Type one: IF d_{P1} THEN d_{R1} ($CF=u$, λ, w). The fuzzy Petri net of this type is shown in Figure 1.

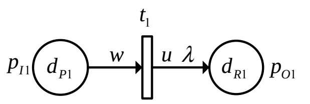

Fig. 1 Fuzzy Petri Net of Type One

Type two: IF d_{P1} AND d_{P2} AND…AND d_{Pn} THEN d_{R1} ($CF=u$, λ , $w_{P1}w_{P2},...,w_{Pn}$, $w_{P1}+w_{P2}+...+w_{Pn}=1$). The fuzzy Petri net of this type is shown in Figure 2.

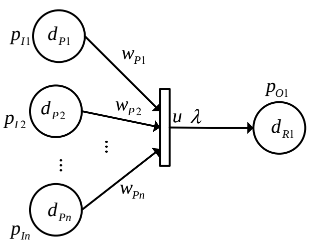

Fig. 2 Fuzzy Petri Net of Type Two

Type three: IF d_{P1} OR d_{P2} OR…OR d_{Pn} THEN d_{R1} ($CF=u_{P1}u_{P2},...,u_{Pn}$, $\lambda_{P1}\lambda_{P2},...,\lambda_{Pn}$, $w_{P1}w_{P2},...,w_{Pn}=1$). Figure 3 gives the fuzzy Petri net of the type.

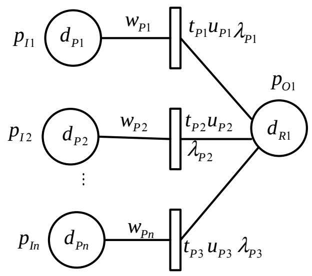

Fig. 3 Fuzzy Petri Net of Type Three

Of the above three fundamental types, $d_{P1}d_{P2},...,d_{Pn}$ is premise proposition, d_{R1} is conclusion proposition; d_i is proposition; $u_{P1}u_{P2},...,u_{Pn}$ is confident degree of rules; $\lambda_{P1}\lambda_{P2},...,\lambda_{Pn}$ is the threshold of activated proposition; $w_{P1}w_{P2},...,w_{Pn}$ is the weight of premise proposition influencing the conclusion.

A compound proposition can be formed by the three basic types with the use of logical connectors-AND and OR.

C. *Activation of fuzzy Petri net*

Definition 3: the condition for activating the transition of fuzzy Petri net is that: for $\forall p_{Ij}\in I(p,t_k)$, it suffices $\sum_{j=1}^{n}M(p_{Ij})\times w_{jk}\geq\tau(t_k)$, and whether the transition is activated or not is expressed by Sigmoid function.

Definition 4: when the transition of fuzzy Petri net is activated, tokens in the input library stay the same, while tokens in the output library can be obtained through the following equation:

$$\begin{aligned}\alpha(p_O)=\max\{&u_{P1}M(p_{I1})w_{P1},\\ &u_{P2}\alpha(p_{I2})w_{P2},...u_{Pn}\alpha(p_{In})w_{Pn}\}\end{aligned} \tag{1}$$

III. PARAMETER OPTIMIZATION BASED ON IMPROVED ARTIFICIAL IMMUNE ALGORITHM

Artificial immune algorithm makes analysis of problems to be solved. It regards pending problems as antigen and feasible solution as antibody. The adaptation of antigen to antibody (i.e. goodness or badness of solution) is evaluated by affinity function, and finally operations are carried out through immune operators on individuals to produce next generations.

A. *Antibody encoding*

Use real encoding mode to mean antibody and its length is the number n of to-be-optimized parameters of the fuzzy Petri net, so, antibody's code can be shown as:

$$w_{P1}w_{P2},...,w_{Pn}u_{P1},...,u_{Pn}\lambda_{P1},...,\lambda_{Pn} \quad (2)$$

B. Evaluation function of affinity

Affinity evaluation function is utilized to assess the capability of antibody matching with antigen. It can verify the superiority or inferiority of feasible solutions, as indicated as: $fit(x): S \to R$, in which, S is the solution space of a problem; R is the field of real numbers. Here they are represented by mean square error (MSE) which ends antibody outputs and the expected in the fuzzy library as to get the best antibody with minimum mean square errors (MMSE). Such function of evaluating affinity is shown as (3):

$$fit(x) = 1 / \frac{\sum_{i=1}^{M}\sum_{j=1}^{K}(M^i(p_{jo}) - \overline{M^i(p_{jo})})^2}{M-1} \quad (3)$$

where, M is total amount of antibodies; K is quantity of terminated fuzzy libraries; x is value of all parameters.

C. Parameters optimized by artificial immune algorithm

Use improved artificial immune algorithm to optimize fuzzy Petri net. Consider every single parameter which requires for optimization and has the least error as antigen and specific value of each as antibody. Simulated annealing algorithm is adopted to make immune selection so as to retain excellent individuals, just as shown as follows:

Method one: parameter optimization method based on improved artificial immunity

Initialization: population size M, iterations T, crossover probability p_c, mutation probability p_m, inoculation probability p_f, size of memory bank *q*;

Step one: use the expression (2) to encode antibodies, whose all gene-bits use random variables to generate real numbers between 0-1 till the population in M size is generated;

Ste p two: adopt formula (3) to calculate the fitness of antibodies in the population and find out individuals with the best affinity, then choose some of their genes as vaccine;

Step three: select the first *q* antibodies with the best fitness and save in memory bank;

Step four: perform respectively crossover and mutation operation on existing antibody population according to p_c and p_m. Suppose $fit_{\max}$ is the best affinity of the population, fit_{avg} the average fitness, fit_c and fit_m the affinity of crossover and mutation antibody respectively. Then, the adaptive adjustment of p_c and p_m can be expressed like formula (4) and (5). In them, c1, c2, c3, c4 are constants, adjustable to the actual needs;

$$p_c = \begin{cases} \frac{c_1(fit_{\max} - fit_c)}{fit_{\max} + fit_{avg} + 1} & fit_c \ge fit_{avg} \\ c2 & fit_c < fit_{avg} \end{cases} \quad (4)$$

$$p_m = \begin{cases} \frac{c_3(fit_{\max} - fit_m)}{fit_{\max} - fit_{avg} + 1} & fit_m \ge fit_{avg} \\ c4 & fit_m < fit_{avg} \end{cases} \quad (5)$$

Step five: vaccinate the current population and inspect the immunity of those vaccinal individuals;

If the affinity is not as high as their parents, then, they are replaced by those individuals in parental generation;

If the affinity of both offspring and antigens is better than their parents', use simulated annealing selection strategy to choose individuals based on p_f and add them into the parental population, like:

$$p_f(x_i) = \frac{e^{fit(x)/T_k}}{\sum_{i=1}^{n} e^{fit(x)/T_k}} \quad (6)$$

In (6), $fit(x_i)$ is the affinity of antibody x to antigen; $\{T_k\}$ is temperature control sequence close to 0.

Step six: compute again the affinity of all antibodies and extract according to the fitness degree the first *q* antibodies to update the memory bank and generate randomly 20% which are used to update antibodies whose affinity is in the last 20%.

Step seven: t=t+1 is applied to determine whether the current iteration t is the maximum. If yes, end it and export the best individuals; otherwise, turn back to **Step three** and reiterate the process.

IV. SIMULATION EXPERIMENT

Use Matlab simulation tool to demonstrate case simulation. The case model is shown in figure 4.

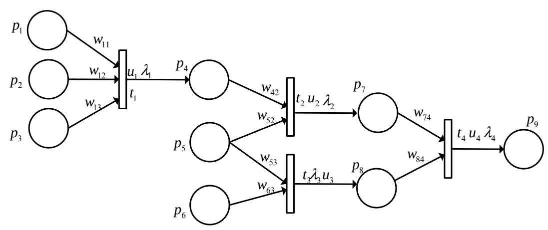

Fig. 4 Case Model of Fuzzy Petri Net

The expected values of parameters of fuzzy Petri net as shown in the above picture are:

w_{11}=0.31, w_{12}=0.42, w_{13}=0.37, w_{42}=0.53, w_{52}=0.47, w_{53}=0.38, w_{63}=0.62, w_{74}=0.51, w_{84}=0.49, u_1=0.89, u_2=0.81, u_3=0.91, u_4=0.79, λ_1=0.61, λ_2=0.72, λ_3=0.59, λ_4=0.63;

Antibodies can be encoded as per expression (2) into:

$$w_{11}w_{12}w_{13}w_{42}w_{52}w_{53}w_{63}w_{74}w_{84}u_1u_2u_3u_4\lambda_1\lambda_2\lambda_3\lambda_4 \quad (7)$$

When initializing, each gene bit is taken randomly from 0-1, while, the weight summation is set 1 for the identical transition on the input arc.

Parameters are set by artificial immune algorithm like: iterations T=100, antibody population size M =80, antibody length n =17, crossover probability p_c =0.63, mutation probability p_m =0.72, inoculation probability p_f =0.69, memory bank size q=10, c1=0.72, c2=0.68, c3=0.73, c4=0.59.

After 100 iterations, we get optimized results of each parameter:

w_{11}=0.298, w_{12}=0.423, w_{13}=0.279 , w_{42}=0.531 , w_{52}=0.469 , w_{53}=0.352 , w_{63}=0.648 , w_{74}=0.491 , w_{84}=0.509, u_1=0.915, u_2=0.815, u_3=0.896, u_4=0.765, λ_1=0.584 , λ_2=0.702 , λ_3=0.613 , λ_4=0.658. The aggregation of mean square errors of results of three types of parameters after optimization through the proposed method are respectively 10.35, 141.52 and 52.25.

Compare the proposed method with those in paper [7] and [8]. We can note how the affinity changes along with iteration as indicated by the curve in figure 5.

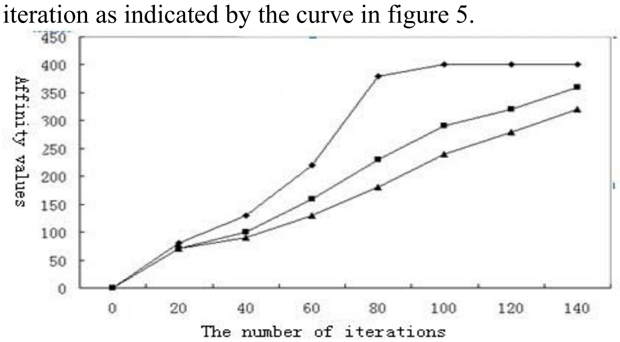

Fig. 5 Curve of Affinity Changing along with Iterations

As it shows obviously in the above graph, the affinity of the proposed method is higher than the other two methods during the running test, which converges when it reaches 100 iterations and is maximally 400. Comparatively, the affinity of the other two does not converge when it reaches the peak 140 iterations. The optimal values of their affinity are separately 320 and 360. The reason for such a big difference lies in the improved artificial immune algorithm using simulation annealing selection operator, which has stronger optimum-maintaining capability. What's more, adaptive crossover and mutation probabilities ensure the diversity of antibodies so that the method has more powerful global optimum ability and faster convergence rate.

V. CONCLUSION

Petri net is a kind of reasoning and modeling tool for discrete and dynamic system. It has rigorous mathematical model and simultaneously it can express and depict both the system and event in a formalized manner. Fuzzy Petri net is the outcome of fuzzy production rules and Petri net, preferably appropriate for the representation and reasoning of knowledge. Yet, when it does reasoning, necessary weight, threshold value and degree of confidence usually rely on experience. To overcome the problem, this paper introduces a parameter optimization method based on improved artificial immune algorithm. Through encoding parameters, designing affinity evaluation function and simulation annealing selection operator, it defines a new method for optimizing parameters of fuzzy Petri net, which is based on artificial immune algorithm. Simulation experiment reveals that the method can better optimize such parameters with smaller mean square errors. Compared with other methods, solutions obtained by the proposed one have higher affinity and stronger global convergence.

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