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Multicriteria Decision Mechanism CNSGA-AHP for the Automatic Test Task Scheduling Problem

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Abstract: Task scheduling problem is one of the key technologies for automatic test systems. This study proposes a novel and integrated multicriteria decision mechanism called the chaotic non-dominated sorting genetic algorithm plus analytic hierarchy process (CNSGA-AHP) for the automatic test task scheduling problem (ATSP). This mechanism contains two parts: the multiobjective optimisation algorithm CNSGA and the decision making method AHP. CNSGA hybrids chaotic sequences based on the logistic map and the non-dominated sorting genetic algorithm II (NSGA-II) to avoid becoming trapped in local optima. It is responsible for the search process and obtains a set of compromise solutions. However, getting this set does not completely solve the problem. A best compromise solution still must be chosen out of that set. Thereupon, AHP is used for the final decision making process and chooses a best schedule from the solutions obtained by CNSGA. The applied AHP can handle uncertainty, make the consistency check easily to pass and reduce the workload of decision-makers. A real-world ATSP abstracted from a missile system is applied to verify the effectiveness of CNSGA-AHP. Results show that CNSGA-AHP is very concise and suitable for the ATSP.

Key words: Automatic test task scheduling, multicriteria decision, NSGA-II, chaotic operator, analytic hierarchy process

INTRODUCTION

Automatic test technology has been used in aerospace systems to ensure safety and in some modern manufacturing processes to improve the production efficiency. One important feature of the Next Generation Automatic Test System (NGATS) is parallel testing (Curry *et al*., 2006). Parallel testing makes it possible to test more than one task at the same time. It can improve the throughput by taking full advantage of the test hardware. On the other hand, it increases the complexity of the system (Anderson, 2003). Therefore, an effective and efficient dispatching method for the Automatic Test Task Scheduling problem (ATSP) is significant. However, a concrete optimised algorithm has not been fully elucidated (Zhou *et al*., 2009). Hence, this study is motivated to perform.

The mean work of dispatching method for the ATSP is allocating a task onto the available instruments to improve the throughput, reduce the test time and optimise the resource allocation (Xia *et al*., 2007a). Many meta-heuristics methods and evolutionary algorithms have been proposed to solve the scheduling problems. The Simulated Annealing (SA), the Tabu Search (TS) and the Genetic Algorithm (GA) are generally used to deal with the single objective problems. For example, Liaw (2003) proposed a tabu search approach together with the optimal timing algorithm for solving the Open Shop Scheduling problem (OSSP). For the multiobjective problems, the Strength Pareto Evolutionary algorithm (SPEA), the Pareto Archived Evolutionary Strategy (PAES) and the non-dominated sorting genetic algorithm II (NSGA-II) (Deb *et al*., 2002) are widely used. For example, Moradi *et al*. (2011) used NSGA-II and Non-ranking Genetic Algorithm (NRGA) for solving the Flexible Job-shop Scheduling Problem (FJSP). Although, most of these multiobjective optimisation approaches have been successfully used in real-world problems, one aspect that is often disregarded in the current research is the decision making process (Fernandez *et al*., 2010). The multiobjective optimisation approaches always generate an approximation of the Pareto frontier, but getting this set does not completely solve the problem. A best compromise solution still must be chosen out of that set (Fernandez *et al*., 2011). That is to say, both the multiobjective optimisation algorithms (search process) and the decision maker's preferences (decision making process) should be considered to solve a multiobjective optimisation problem thoroughly. The combination of these two processes can be classified into three categories (Coello *et al*., 2007): the a priori, the progressive and the a posteriori decision.

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In the a priori decision, the decision-maker (DM) is consulted before starting the search process. The DM's preferences guide the search until the algorithm converges to a single point which may result in a half-baked search. The progressive decision is an interactive method. In the progressive decision, the DM participates in the course of an iterative optimisation process, gives information about the preferences to guide the search until the DM is satisfied with the current solution. In this process, the DM should always be present, which is not convenient. In the a posteriori decision, a multiobjective optimisation algorithm is usually used to obtain a set of compromise solutions. Then, the DM is asked to choose the final solution. The search process and the decision making process are separated and the alteration of one process will not influence the other process. The a posteriori decision is used in this paper because of its flexibility.

A multicriteria decision mechanism called the chaotic non-dominated sorting genetic algorithm plus analytic hierarchy process (CNSGA-AHP) is proposed to solve the ATSP. As mentioned above, the multicriteria decision mechanism CNSGA-AHP is made up of two parts: the multiobjective optimisation algorithm CNSGA and the decision making method AHP (Saaty, 1980). CNSGA incorporates chaotic sequences based on the logistic map into NSGA-II. NSGA-II is a typical representative of the multiobjective optimisation algorithms, which is effective and can maintain a better spread of solutions. Xu *et al*. (2006) used NSGA-II in the design of standalone hybrid wind/photovoltaic power systems. Chaos has some special characteristics such as the ergodic property and the stochastic and is highly sensitive to initial conditions. Because of these properties, optimisation algorithms based on chaos is presented to avoid becoming trapped in local optima (Li and Wang, 2011; Ren and Zhong, 2011). Thus, CNSGA can achieve better results. AHP is extensively adopted in multicriteria decision making (MCDM) and has successfully been applied to the ranking process of decision making problems (Saaty, 1996). Barker and Zabinsky (2011) used AHP for reverse logistics and Okeola and Sule (2012) applied AHP to study the urban water supply scheme. AHP has the following advantages (Duran and Aguilo, 2008), (1) it is the only known MCDM model that can measure the consistency in the decision maker's judgments, (2) it helps dissect the problem and structure it into a rational decision hierarchy, which makes the decision process easy to handle, (3) DMs can derive weights of criteria and scores of alternatives from comparison matrices by pairwise comparisons instead of quantify weights/scores directly, (4) it can hybridise with other techniques to handle more difficult problems, (5) it is easier to understand and can effectively handle both qualitative and quantitative data. However, in many practical situations, DMs may have some uncertain information and cannot assign exact numerical values to the comparison judgments. Then, some researches applied fuzzy AHP as an extension of conventional AHP to handle uncertainty. For example, Duran (2011) proposed a fuzzy-based AHP for comparative evaluation of a number of Computerised Maintenance Management Systems (CMMS) alternatives, Wang *et al*. (2011) presented an intuitionistic fuzzy AHP approach and Pan (2012) proposed an evaluation method for Smart Logistics based on benchmarking analysis and fuzzy AHP method.

Other researches considered the improvement of consistency check and the scale measurement. In CNSGA-AHP, the decision information can be quantified and the above issues are actually a matter of indifference. That is to say, the uncertainty can be handled, the consistency check can be passed easily and the scale measurement can be more exact. CNSGA-AHP is thus a suitable multicriteria decision mechanism for the ATSP.

PROBLEM FORMULATION

The ATSP is to assign the execution of n tasks on m instruments. In this problem, there are a set of tasks $T=\{t_j\}_{j=1}^{n}$ and a set of instruments $R=\{r_i\}_{i=1}^{m}$ (Xia *et al*., 2007b). The notifications P_j^i, S_j^i and C_j^i are used to present the test time, the test start time and the test completion time of task t_j tested on r_i, respectively. A variable O_j^i is defined to express whether the task t_j occupies the instrument r_i. Its definition is as follows:

$$O_j^i=\begin{cases}1 & \text{if } t_j \text{ occupies } r_i\\ 0 & \text{others}\end{cases} \tag{1}$$

Generally speaking, a task occupies more than one instrument.

In typical cases, some instruments could have redundancies, which make it possible for a task to choose the instruments. The alternative schemes for t_j is expressed as $W_j=\{w_j^k\}_{k=1}^{k_j}$ where k_j is the number of schemes of t_j. The numbers of schemes that correspond to every task can make up a set $K=\{k_j\}_{j=1}^{n}$. w_j^k is represented as $w_j^k=\{r_{jk}^u\}_{u=1}^{u_{jk}}$ and u_{jk} is the number of instruments for w_j^k. If $w_j^k \cap w_{j^*}^{k^*} \neq \varnothing$, t_j and t_{j^*} have resource conflicts. $P_j^k=\max_{r_i \in w_j^k} P_j^i$ is the test time of t_j for w_j^k.

In addition, hypotheses considered in this paper are the following (Xia *et al*., 2007b):

- All tasks and instruments are available at time 0
- At a given time, an instrument can execute only one task
- Each task must be completed without interruption once it starts
- Assume $P_j^i = P_j^k$ and $C_j^i = S_j^i + P_j^i$ to simplify the problem

In this study, there are two objectives should be minimised: the maximal test completion time (makespan) $f_1(x)$ and the mean workload of the instruments $f_2(x)$.

The definition of $f_1(x)$ is:

$$f_1(x) = \max_{\substack{1 \le k \le k_j \\ 1 \le j \le n}} C_j^k \quad (2)$$

where, C_j^k is the test completion time of t_j for w_j^k and meets the equation:

$$C_j^k = \max_{t_i \in w_j^k} C_j^i \quad (3)$$

The definition of $f_2(x)$ is:

$$f_2(x) = \frac{1}{Q} \sum_{j=1}^{n} \sum_{i=1}^{m} P_j^i O_j^i \quad (4)$$

where, Q is the parallel steps and its initial value is 1. Assign the instruments for all of the tasks, if $w_j^k \cap w_j^{k^*} \neq \varnothing$, Q = Q+1.

MULTICRITERIA DECISION MECHANISM CNSGA-AHP FOR THE ATSP

In CNSGA-AHP, multiobjective optimisation methods CNSGA can provide valuable trade-off information among the conflict objectives and multicriteria decision making approach AHP helps DMs choose the most desirable and satisfactory alternative. Before explaining the details of CNSGA-AHP, some concepts of Multiobjective Optimisation Problem (MOP) and multicriteria decision making should be introduced briefly.

Multiobjective optimisation problem: A multiobjective optimisation problem can be described, without loss of generality, as follows (Zhang and Li, 2007):

$$\begin{aligned} &\text{minimise } F(x) = (f_1(x), f_2(x), \cdots, f_M(x))^T \\ &\text{subject to } x \in \Omega \end{aligned} \quad (5)$$

where, Ω is the decision space and the function F means a mapping from Ω to R^M. R^M is the objective space, with M objective functions.

Multicriteria decision making: In MCDM, there are a number of options called alternatives and an ultimate goal. The DMs should choose from the alternatives to reach the goal according to some problem-based evaluation criteria. These criteria make different contribution to the goal and have different importance. DMs try to compare the effects of alternatives and achieve best quality of the final result.

CNSGA

Chaotic sequence: A chaotic sequence is generated by a chaotic map which is an evolution function that exhibits some sort of chaotic behaviour. The logistic map is a well-known one-dimensional chaotic map and its definition is as follows:

$$\lambda_{t+1} = \mu\lambda_t(1-\lambda_t), \lambda_t \in (0,1), t = 0,1,2,\cdots \quad (6)$$

where, λ_t is the value of the chaotic variable λ at the tth iteration and μ is the so-called bifurcation parameter of the system ($\mu \in [0, 4]$) (Hong *et al*., 2011). In this study, $\mu = 4$, then $\lambda_0 \notin \{0.25, 0.5, 0.75\}$.

Implementation of CNSGA: The main procedure of CNSGA is similar with NSGA-II, but some details are modified by chaos:

- The main loop of CNSGA begins with the combination of the current and previous populations and the calculation of the non-dominated fronts. Once all the Pareto fronts have been determined, the new population is obtained. Finally, using this population, individuals are selected, crossed and mutated to create a new population. This process is described in Fig. 1.
- Problem encoding is a representation in a chromosome, which is relative to the conditions of the problem being considered. Designing a suitable encoding approach for the ATSP is very important. In this study, a new encoding scheme, called the

```
While t<maxIterations
        Rt = Pt∪Qt
        V = fast-non-dominated-sort (Rt)
        Pt+1 = ∅ and i = 1
        until |Pt+1|+|Vi|≤N
                crowding-distance-assignment (Vi)
                Pt+1 = Pt+1∪Vi
                i = i+1
        sort(vi, <n)
        Pt+1 = Pt+1∪Vi[1:(N-|Pt+1|)]
        Qt+1 = make-new-pop (Pt+1)
        t = t+1
```

Fig. 1: Main loop of CNSGA

Integrated Encoding Scheme (IES), is proposed. This encoding scheme can use only one chromosome to contain the information about both the processing sequence of the tasks and the occupancy of the instruments for each task. The main concept of the IES is to use relationships between the decision variables to express the sequence of tasks and the values of the variables to represent the occupancy of the instruments for each task. Firstly, the decision variables are sorted in ascending order and the rank of every variable denotes a test task index in sequence. Then, the instrument assignment can also be obtained from the decision variables according to the equation $k = [x_{ij} \times 10] \bmod k_j + 1$. Where, x_{ij} represents the decision variable that corresponds to t_j and k_j is the number of schemes of t_j. The IES never generates a duplication of a certain task, can always get feasible instrument assignments, makes full use of decision variables and improves the encoding efficiency:

- The fitness function is used to measure the solutions. In this paper, the makespan and the mean workload of the instruments are the objectives. Their calculation is shown in Fig. 2.
- The Simulated Binary Crossover (SBX) operator is used in CNSGA. P_c is the crossover probability and η_c is the distribution index for the crossover operator.
- The polynomial mutation is applied with some modification. For a solution x_s, the polynomial mutation is described as follows:

$$x_s^* = x_s + (x_s^u - x_s^l) \times \delta_s \tag{7}$$

where, x_s^u and x_s^l are the upper and lower bound of x_s, respectively.

$$\delta_s = \begin{cases} (2u_s)^{\frac{1}{\eta_m+1}} - 1, & \text{if } u_i < 0.5 \\ 1 - (2 \times (1 - u_s))^{\frac{1}{\eta_m+1}}, & \text{others} \end{cases} \tag{8}$$

where, $u_s = \lambda_t^j$, p_m is the mutation probability and η_m is the distribution index for the mutation operator

AHP: It decomposes a complex issue into several levels, rigorously defines the manager priorities and computes weights associated to the alternatives. The output of AHP is a ranking indicating the overall preference for each decision alternative. The main steps of AHP include:

- **Step 1:** Define the problem and determine its goal. For the ATSP, this goal is to obtain a most satisfactory schedule

```
The task sequence is stored in an array S.
parallel_r is an array to record the instruments
that can work in parallel.
c_time is an array to record the completion time of
the tasks on their occupied instruments.
p_time is an array to record the work time of the
instruments.
    parallel_r = w^k_s[1]
    start = 1
    Q = 1
    for i = 2 to n
        if w^k_s[i] ∩ parallel_r = ∅
            parallel_r = parallel_r ∪ w^k_s[i]
        else
            Q++
            for j = start to i-1
                c_time[w^k_s[j]] = C^k_s[j]
                p_time [w^k_s[j]] = p_time[w^k_s[j]]+P^k_s[j]
            end for
            parallel_r =w^k_s[i]
            start = i
        end if
    end for
    Q++
    for j = start to i-1
        c_time[w^k_s[j]] = C^k_s[j]
        p_time[w^k_s[j]] = p_time[w^k_s[j]]+P^k_s[j]
    end for
    f1(x) = max(c_time)
    f2(x) = 1/Q sum(p_time)
```

Fig. 2: Calculation of the objective values

Table 1: Pairwise comparison scale for AHP preferences (Saaty, 1980)

Numerical rating	Verbal judgment of preferences
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate values between adjacent scale values
Reciprocals	a_{ij} indicates the importance of ith factor over jth, then a_{ji} can be calculated as the reciprocal of a_{ij}

- **Step 2:** Define the structure of the hierarchy of that problem from the top goal through intermediate levels of criteria, subcriteria and actors to the lowest level of alternatives. In this paper, the criteria (C) are the makespan (C_1) and the mean workload of the instruments (C_2) and the alternatives (A) are solutions obtained by CNSGA
- **Step 3:** Construct a set of pairwise comparison matrices for each lower level in a hierarchy and make all the pairwise comparisons by using the relative scale measurement shown in Table 1. In our work, f_{max} and f_{min} are the maximum and minimum of the fitness function, respectively. The comparisons can be quantified as follows:

Table 2: Average random consistency ratio (RI) (Saaty, 1980)

Size of matrix	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

$$a_{ij} = \begin{cases} \text{round}(\frac{f_j - f_i}{f_{max} - f_{min}} \times 8 + 1) & f_j - f_i \geq 0 \\ 1/\text{round}(\frac{f_i - f_j}{f_{max} - f_{min}} \times 8 + 1) & f_j - f_i < 0 \end{cases} \quad (9)$$

where, a_{ij} is an element of the pairwise comparison matrix, which indicates the importance of ith factor over jth. f_i and f_j are the fitness values of A_i and A_j.

- **Step 4:** Compute the consistency ratio (CR) for each pairwise comparison matrix to measure the consistency of the subjective ranking. Firstly, using the biggest eigenvalue λ_{max} of a pairwise comparison matrix to calculate the consistency index (CI) by CI = $(\lambda_{max}-n)/(n-1)$, where n is the matrix size. The CR is calculated by comparing the CI with a random index (RI), CR = CI/RI. RI is the consistency index of a randomly generated pairwise comparison matrix and its value depending on the matrix size is shown in Table 2. If CR$\leq$0.10, the judgment matrix is acceptable. Otherwise it is considered inconsistent and the matrix should be improved.
- **Step 5:** Calculate the relative weights and determine the ranking of the alternatives. The lambda max technique is commonly used, which defines a vector of weights as the normalised eigenvector w corresponding to the largest eigenvalue λ_{max}. If the combining vector of weights of the (k-1)th level $W^{(k-1)}$ and the vector of weights of the kth level w^k is obtained, the combining vector of weights of the kth level W^k can be calculated by $W^k = w^k W^{(k-1)}$, k>1.

RESULTS AND DISCUSSION

Experiments are designed to verify the effectiveness of CNSGA-AHP. The applied ATSP in Table 3 depends on a real-world instance that is abstracted from a missile system. There are 20 tasks to be tested and 8 instruments can be used. It was solved by CNSGA. The parameter settings of CNSGA are shown in Table 4 and the obtained compromise solutions are shown in Fig. 3. The objective values of these compromise solutions are [(39, 14.357), (34, 19.546), (45, 14.286), (52, 13.667), (38, 15.539), (32, 20.000), (33, 19.636), (35, 18.182), (59, 13.533), (65, 12.813)].

Then, AHP is applied to make the final decision. The structure of AHP is shown in Fig. 4.

Firstly, the pairwise comparison matrix for criteria with respect to goal was constructed in Table 5. Generally speaking, for the ATSP, makespan is more important than the mean workload of the instruments. Thus, the rating 5 was considered.

Table 3: A real-world ATSP with 20 tasks and 8 instruments

T	W_j	w^k_j	P^k_j	T	W_j	w^k_j	P^k_j
t_1	w^1_1	r_1 r_4	2	t_{11}	w^1_{11}	r_2 r_3	6
	w^2_1	r_3 r_5	5		w^2_{11}	r_2 r_5	8
	w^3_1	r_6 r_8	3		w^3_{11}	r_6 r_7	8
t_2	w^1_2	r_2	3	t_{12}	w^1_{12}	r_2	11
	w^2_2	r_4	4		w^2_{12}	r_5	13
	w^3_2	r_6	3		w^3_{12}	r_6	13
	w^4_2	r_7	4	t_{13}	w^1_{13}	r_2	4
t_3	w^1_3	r_3	5		w^2_{13}	r_6	5
	w^2_3	r_5	5		w^3_{13}	r_8	4
t_4	w^1_4	r_4	22	t_{14}	w^1_{14}	r_3	7
	w^2_4	r_8	20		w^2_{14}	r_5	8
t_5	w^1_5	r_7	23		w^3_{14}	r_7	8
t_6	w^1_6	r_1 r_4	7	t_{15}	w^1_{15}	r_8	2
	w^2_6	r_3 r_7	8	t_{16}	w^1_{16}	r_2	9
	w^3_6	r_6 r_8	8		w^2_{16}	r_5	7
t_7	w^1_7	r_1 r_2	2		w^3_{16}	r_8	6
	w^2_7	r_1 r_7	2	t_{17}	w^1_{17}	r_1 r_2	10
	w^3_7	r_3 r_8	3		w^2_{17}	r_5 r_7	12
t_8	w^1_8	r_1 r_3	5		w^3_{17}	r_5 r_8	11
	w^2_8	r_1 r_5	4	t_{18}	w^1_{18}	r_6	15
	w^3_8	r_4 r_7	2	t_{19}	w^1_{19}	r_2	8
t_9	w^1_9	r_1 r_4	11		w^2_{19}	r_4	7
	w^2_9	r_3 r_4	13		w^3_{19}	r_5	7
	w^3_9	r_7 r_8	12		w^4_{19}	r_8	6
t_{10}	w^1_{10}	r_1	9	t_{20}	w^1_{20}	r_3	4
	w^2_{10}	r_4	10		w^2_{20}	r_6	4
	w^3_{10}	r_8	10		w^3_{20}	r_8	5

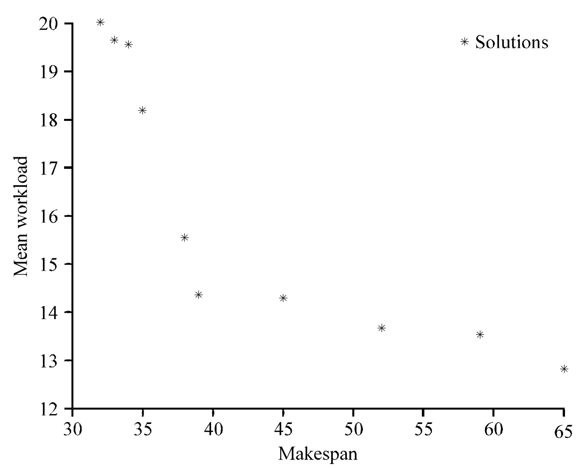

Fig. 3: Comparison solutions obtained by CNSGA

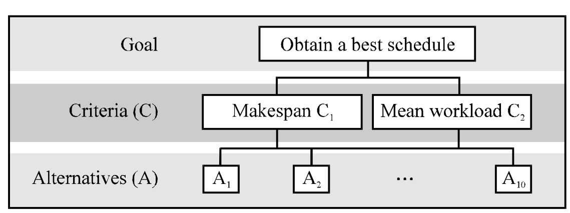

Fig. 4: Structure of the AHP

For matrix Goal-C, the biggest eigenvalue λ_{max} = 2 and the CI = 0. Therefore, the judgment matrix was acceptable. The vector of weights $W^2 = w^2 = (0.833, 0.167)^T$.

Table 4: The parameter settings of CNSGA

Population size N	Maximal generation gen	Crossover probability p_c	Mutation probability p_m	Distribution index (η_c, η_m)
200	250	0.9	1/n	(20,20)

Table 5: Pairwise comparison matrix Goal-C

Goal	C_1	C_2
C_1	1	5
C_2	1/5	1

Table 6: Pairwise comparison matrix C_1-A

C_1	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
A_1	1	1/2	2	4	1	1/3	1/2	1/2	6	7
A_2	2	1	4	5	2	1	1	1	7	9
A_3	1/2	1/4	1	3	1/3	1/4	1/4	1/3	4	6
A_4	1/4	1/5	1/3	1	1/4	1/6	1/6	1/5	3	4
A_5	1	1/2	3	4	1	1/2	1/2	1/2	6	8
A_6	3	1	4	6	2	1	1	2	8	9
A_7	2	1	4	6	2	1	1	1	7	9
A_8	2	1	3	5	2	1/2	1	1	7	8
A_9	1/6	1/7	1/4	1/3	1/6	1/8	1/7	1/7	1	2
A_{10}	1/7	1/9	1/6	1/4	1/8	1/9	1/9	1/8	1/2	1

Table 7: Pairwise comparison matrix C_2-A

C_2	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
A_1	1	7	1	1/2	2	7	7	5	1/2	1/3
A_2	1/7	1	1/7	1/8	1/5	2	1	1/3	1/8	1/8
A_3	1	7	1	1/2	2	7	7	5	1/2	1/3
A_4	2	8	2	1	3	8	8	6	1	1/2
A_5	1/2	5	1/2	1/3	1	6	6	4	1/3	1/4
A_6	1/7	1/2	1/7	1/8	1/6	1	1	1/3	1/8	1/9
A_7	1/7	1	1/7	1/8	1/6	1	1	1/3	1/8	1/9
A_8	1/5	3	5	1/6	1/4	3	3	1	1/6	1/7
A_9	2	8	2	1	3	8	8	6	1	1/2
A_{10}	3	8	3	2	4	9	9	7	2	1

Secondly, the pairwise comparison matrix for alternatives with respect to the criterion was created according to the Eq. 9. Both the makespan (C_1) and the mean workload of the instruments (C_2) are considered and the pairwise comparison matrices are shown in Table 6 and 7.

For matrix C_1-A, the biggest eigenvalue $\lambda_{max} = 10.338$, the CI = 0.038 and CR = 0.025<0.10. Therefore, the judgment matrix was acceptable. The vector of weights corresponding to C_1 was:

$$w_1^3 = (0.093, 0.167, 0.056, 0.033, 0.103, 0.195, 0.170, 0.150, 0.019, 0.014)^T$$

For matrix C_2-A, the biggest eigenvalue $\lambda_{max} = 10.404$, the CI = 0.045 and CR = 0.030<0.10. Therefore, the judgment matrix was acceptable. The vector of weights corresponding to C_2 was:

$$w_2^3 = (0.115, 0.020, 0.115, 0.174, 0.078, 0.017, 0.018, 0.034, 0.174, 0.256)^T$$

Thus, the vector of weights of the third level was:

$$w^3 = (0.093, 0.167, 0.056, 0.033, 0.103, 0.195, 0.170, 0.150, 0.019, 0.014; 0.115, 0.020, 0.115, 0.174, 0.078, 0.017, 0.018, 0.034, 0.174, 0.256)^T$$

The combining vector of weights was:

$$W^3 = w^3 W^2 = (0.097, 0.142, 0.066, 0.056, 0.099, 0.166, 0.144, 0.131, 0.045, 0.054)^T$$

The ranking of all the alternatives were 6, 3, 7, 8, 5, 1, 2, 4, 10 and 9. Therefore, the most satisfactory solution was (32, 20.000). Because the makespan is more important, the ranking of the alternatives is almost corresponding to the ranking of the makespan. Only the solution (65, 12.813) was reverse due to its lowest mean workload.

The above experiments show that CNSGA-AHP is very effective and suitable for the ATSP. It can generate a set of compromise solutions and then choose a most satisfactory solution from them scientifically.

CONCLUSIONS

This study proposes a multicriteria decision mechanism CNSGA-AHP for the automatic test task scheduling problem. In CNSGA-AHP, the multiobjective optimisation algorithm CNSGA is used to generate a set of compromise solutions. It incorporates chaotic sequences based on the logistic map into NSGA-II to avoid becoming trapped in local optima and thus achieve better solutions. On the other hand, the widely applied decision making method AHP is used to choose a most satisfactory schedule from the solutions obtained by CNSGA. CNSGA-AHP is a novel and integrated method combined the search process and the decision making process flexible. It can handle uncertainty, make the consistency check easily to pass and reduce the workload of DMs. Experiment results show that CNSGA-AHP is very concise and suitable for the ATSP.

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