Tabu-model-based Estimation of Distribution Algorithm Framework for Permutation Optimization Problems

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The estimation of distribution algorithm (EDA) is a common and effective method to solve the permutation optimization problems. EDA describes the distribution of the superior samples by establishing a probability model and samples the model to find better solutions in search space. Although EDA has a strong ability for global search, it lacks a mechanism to jump out of the local optima. In this paper, a tabu probability model is designed to depict the distribution of the solutions which needs to be taboo. A similarity between a solution and the tabu model is defined to judge whether the solution should be taboo. A local search operator is conducted for the taboo solutions to improve the sample diversity, and a modification strategy of sampling model is proposed to regain the sample diversity. Based on the above concepts and operators, a tabu-model-based EDA framework is proposed. In this paper, two calssic permutation optimization problems, quadratic assignment problem (QAP) and travelling salesman problem (TSP), are selected to test the proposed EDA framework. The node histogram model (NHM) and the edge histogram model (EHM) are used to design the tabu-model-based EDAs, *T-EHM* and *T-NHM*, to customize for the two problems. Finally, compared with the traditional EDAs, *T-NHM* and *T-EHM* have much stronger abilities to relieve the premature convergence, and can find the better solutions for QAP and TSP respectively.

Keywords: Estimation of distribution algorithm, tabu probability model, quadratic assignment problem, travelling salesman problem

1. Introduction

As a classic evolutionary algorithm in intelligent computing, the estimation of distribution algorithm (EDA) is based on probability model (sampling model) from statistics. EDA has been applied extensively to layout optimization, resource allocation and production scheduling [1]. The evolution of the population in EDA is guided by the sampling model which describes the distribution information of the dominant individuals in solution space. The characteristic based on statistics makes EDA be qualified for many complex optimization problems.

The EDA performs poorly on jumping out of the local optima, in spite of a strong ability for global search. In the early stage of the algorithm, different areas of solution space are sampled to estimate the probability of the occurrence of the optimal solution. And in the late stage of algorithm, the sampling model will gradually converge and focus on the most likely area where the optimal solution is located. It is obvious that if the sampling model converges, all the individuals will gather in a small search space. Meanwhile, traditional EDAs are lacks of the strategy for jumping out of this small space to prevent premature convergence.

In order to make up the shortcoming of EDA, many scholars have carried out extensive research. Jing-hui Zhong presented an enhanced continuous EDA with multiple probabilistic models (MP-EDA) [2]. In the MP-EDA, the population was divided into two subpopulations which are used respectively to roughly capture the global optima and find highly accurate solutions. Q. Yang proposed a multimodal EDA employing niching technology when solving multimodal optimization [3]. The dynamic cluster sizing afforded a potential balance between exploration and exploitation, and reduced the sensitivity to the cluster size in the niching methods. T. Weise also presented a general framework for multi-model EDAs in which clustering was used to divided selected individuals into different groups to build separate models to prevent premature convergence [4].

The solution to many optimization problems can be represented as a permutation and these problems can be called permutation optimization problems such as travelling salesman problem (TSP), quadratic assignment problem (QAP) and job shop problem (JSP). W. Chmiel introduced the conditional expectation value for QAP, and presented a set of the effective pseudo-genetic operators based on conditional expectation [5-6]. S. M. Chen presented a new method called the genetic simulated annealing ant colony system with particle swarm optimization techniques for solving the TSP [7]. J. W. Gu proposed a novel competitive co-evolutionary quantum genetic algorithm for a stochastic job shop scheduling problem. Two new strategies named as competitive hunter and cooperative surviving are developed in population growth process [8]. F. Hafiz designed a new probability-based approach for the learning in particle swarm optimization (PSO) and the comparative study revealed that the technique was more effective [9]. H. Zhang proposed a hybrid algorithm (EGATS) that combines an elite genetic algorithm and tabu search (TS) to solve the QAP, and the competitive performance of EGATS was verified [10].

From the above brief summary, tabu search technique has been combined with others algorithms to solve permutation problems. Among the heuristic algorithms, tabu search has a strong ability to prevent repeated search and jump out of the local optimal solution [10-12]. Therefore, referring to mechanism of tabu search, this paper concentrates on studying the tabu model which describes the distribution of the taboo solutions. The concept of similarity between solution and tabu model is defined and the following set of operators to improve traditional EDA are presented, which include the mutation operator based on similarity and the updating strategy of the sampling model based on the tabu model. Then, two EDAs which employ edge histogram model (EHM) and node histogram model (NHM) respectively are customized for solving the benchmarks of QAP and TSP [1].

The rest of this paper is organized as follows. Section II presents the problem formulation and theory about EDA including EHM and NHM. Section III gives the design details of tabu-model-based EDAs. In Section IV, the computational experiments are carried out. Finally, conclusions are summarized in Section V.

2. Problem description and basic EDA

2.1. Model of QAP and TSP

the solutions to QAP and TSP can be coded handily as a set of permutation. The solution space can be denoted as:

$$\Omega = \{x = (x_1, x_2, \cdots, x_n) \mid x_i \in \{1, 2, \cdots, n\}, \quad x_i \neq x_j, \forall i \neq j\}. \tag{1}$$

where x_i is the ith element in x.

In QAP, n facilities need to be allocated to n different locations. And the allocation for each facility will cause a cost which is related with the distance and flow between facilities.

The flow and distance matrix can be denoted as:

$$D = [d(i,j)]_{n\times n} \tag{2}$$

$$H = [h(k,l)]_{n\times n} \tag{3}$$

where d_{ij} is the distance between location i and j, and h_{kl} means the flow between facility k and l.

The objective is to minimize the total cost to allocate all facilities to different location, whose mathematical model is as follows:

$$F_{QAP}(x) = \sum_{i=1}^{n}\sum_{j=1}^{n} d(x_i, x_j) h(i,j) \tag{4}$$

In TSP, n cities which are located in different locations are given, and the salesman needs to visit each city without repetition and return to the starting city. The optimization objective is to minimize the length of the Hamiltonian graph composed of all cities.

Given the distance matrix $Dis = [dis(i,j)]_{n\times n}$ and $i, j \in \{1, 2, ..., n\}$, the objective function F can be defined as the sum of the distance from x_i to x_{i+1}, which can be denoted as follows:

$$F_{TSP}(x) = \sum_{i=2}^{n} dis(x_{i-1}, x_i) + dis(x_n, x_1) \tag{5}$$

2.2. Estimation of distribution algorithm

Estimation of distribution algorithm was introduced first in 1996. EDA collects the relationship between components in dominant individuals to establish statistical model [13]. The statistical model contains the evaluation about the area where the optimal solution is located. Through sampling strategy new solutions are generated from this statistical model, and the new solutions will be nearer by the best solution. Therefore, one of the differences between EDA and the other algorithms is the statistical model, which learns the information about dominant individuals and dynamically adjusts search weight in different area through macroscopic probability value [14].

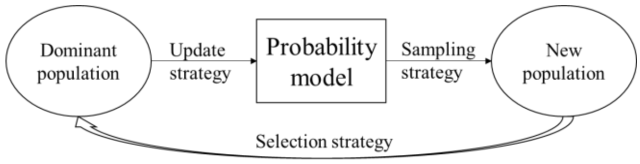

Fig 1. The procedure of EDA

Different probability models will reflect different features of solutions and can be classified as PBIL, UMDA, MIMIC, COMMIT and so on. The basic steps of EDAs are always as follows:

Step 1: Initialize key parameters of EDA, including the iterations $Iter_{max}$ and population scale p;

Step 2: Generate the initial population whose scale is p;

Step 3: Calculate the fitness of each individual;

Step 4: **Select** better individuals into dominant group whose scale is $\eta \cdot p$;

Step 5: **Update** probability model according to dominant group;

Step 6: **Sample** probability model to generate new population;

Step 7: Judge the termination criterion. If satisfied, jump out and output optimal solution; if not, jump to Step 3.

Among all kinds of EDAs, the EDAs which employ NHM and EHM are classic methods to solve permutation optimization problems. These models will be introduced simply in the following sections.

2.3. Node histogram model

The NHM focus on collecting the absolute address information of each element and can be presented as a matrix:

$$G_{NHM} = [g_{nhm}(i, x_i)]_{n\times n} \tag{6}$$

where $g_{nhm}(i,x_i)$ means the probability that the ith element of the optimal permutation is x_i .

The sampling method of NHM to obtain a permutation is as follows:

Step 1: Set i=1;

Step 2: Select task point k according to the elements in the line i of G_{NHM} by the roulette wheel. Let $\mathbf{z}(i) = k$;

Step 3: Set all the elements of the column k in G_{NHM} to zero;

Step 4: Let $i = i+1$ and repeat Steps 2 and 3 until all of the element are selected.

The formula for updating NHM can be denoted as follows:

$$G_{NHM} = (1-\mu_n)\cdot G_{NHM} + \mu_n \cdot G'_{NHM} \tag{7}$$

where $\mu_n \in (0,1)$ is the learning rate and G'_{NHM} is the new probability matrix extracted from the dominant population.

2.4. Edge histogram model

The EHM focus on collecting the relative address information of two adjacent elements and can be presented as the following matrix:

$$G_{EHM} = [g_{ehm}(x_i, x_{i+1})]_{n\times n} \tag{8}$$

where $g_{ehm}(x_i,x_{i+1})$ means the probability that the next element of x_i in permutation is x_{i+1}.

The sampling method of NHM to obtain a permutation is as follows:

Step 1: Set i=1;

Step 2: Select task point k according to the elements in the line i of G_{EHM} by the roulette. Let $\mathbf{z}(i) = k$;

Step 3: Set all the elements of the column k in G_{EHM} to zero;

Step 4: Let $i = k$ and repeat Step 2 and 3 until all of the elements are selected.

The formula for updating NHM can be denoted as follows:

$$G_{EHM} = (1-\mu_e)\cdot G_{EHM} + \mu_e \cdot G'_{EHM} \tag{9}$$

where $\mu_e \in (0,1)$ is the learning rate and G'_{EHM} is the new probability matrix extracted from the dominant population.

3. Design of EDAs employing tabu models

Tabu Search (TS) uses a dynamic tabu list or tabu table and has a strong ability to jump out of local optimal solution. If a solution was in tabu list, it will no longer be searched. This way can avoid repeated search and guarantee that algorithm continues to search toward to different areas. Referring to this characteristic, this paper uses tabu probability model to collect the information of the taboo solutions and design a set of operators to prevent premature convergence.

3.1. Tabu probability model

Although tabu model has a similar updating formulate and form with EHM and NHM, the purpose of tabu model is different from them. EHM and NHM describing the space of the best solution are used to be sampled to generated new individuals, but tabu model storing the distribution of the taboo solutions is for judging whether an individual needs to be abandoned.

Although tabu model has a similar purpose with tabu list, they are different essentially. Tabu list just stores the taboo solutions one by one from the perspective of individual. However, from the perspective of the element, tabu model stores the characteristics about taboo individuals.

The functions of the four key concepts are listed as follows.

Table I. The functions of key operators or models

Operator /model	Function
EHM	For sampling to generate new individuals
NHM	For sampling to generate new individuals
Tabu list	For avoiding search specific individuals
Tabu model	For avoiding search specific solution space

Tabu models have same statistical connotation as EHM or NHM, and can be defined as following formulas and updating methods according to associated sampling models.

$$\begin{cases} G_{TN} = [g_{tn}(i,x_i)]_{n\times n} \\ G_{TN} = (1-\mu_{tn})\cdot G_{TN} + \mu_{tn}\cdot G'_{TN} \end{cases}$$
$$\begin{cases} G_{TE} = [g_{te}(i,x_i)]_{n\times n} \\ G_{TE} = (1-\mu_{te})\cdot G_{TE} + \mu_{te}\cdot G'_{TE} \end{cases} \tag{10}$$

where G_{TN}, G_{TE} are different tabu models associated with NHM and EHM. $\mu_{tn}, \mu_{te} \in (0,1)$ are the learning rates, and G'_{TN}, G'_{TE} is the new probability matrix extracted from the taboo solutions.

What should be pointed out is that if a solution has been stored into tabu model, it will not be taken out. The learning rate provides such a way to weaken effect of the solution which is no longer taboo in tabu model.

Sampling model and tabu model also act on the macroscopic solution space and have the same format. They can achieve more complex operators.

3.2. Similarity between solution and tabu model

In this section, the similarity $Sim \in [0,1]$ between solution and tabu model is introduced to judge whether a solution is taboo. The formula is as follows:

$$Sim(A, G_T) = \sum_{i=1}^{n}\sum_{j=1}^{n} a(i,j)\cdot g_t(i,j) \tag{11}$$

where $A = [a(i,j)]_{n\times n} (i, j \in \{1,2,...,n\})$ is a solution that is transformed according to the coded method of tabu model, and $G_T = [g_t(i,j)]_{n\times n}(i,j \in \{1,2,...,n\})$ means the general formula of tabu model.

For example, a permutation $x=(1,2,4,3)$ can be recoded as A according to NHM. A, G_{TN} are as follows.

$$A=\begin{bmatrix} 0.25 & 0 & 0 & 0 \\ 0 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0.25 \\ 0 & 0 & 0.25 & 0 \end{bmatrix}, G_{TN}=\begin{bmatrix} 0.5 & 0.1 & 0.4 & 0 \\ 0.3 & 0 & 0.6 & 0.1 \\ 0 & 0.4 & 0 & 0.6 \\ 0.2 & 0.5 & 0 & 0.3 \end{bmatrix} \quad (12)$$

Therefore, according to the formula (10), the similar between A and G_{TN} is $Sim(A, G_{TN}) = 0.275$.

The concept of similarity reflects the tabu degree of solution by tabu model. If a solution is taboo completely, the similarity is 1. On the contrary, if the similarity value is 0, the solution is free completely.

3.3. Flowchart of the proposed algorithm

Based on the above tabu model, this paper presents a new EDA frame. The EDA framework is shown as follows:

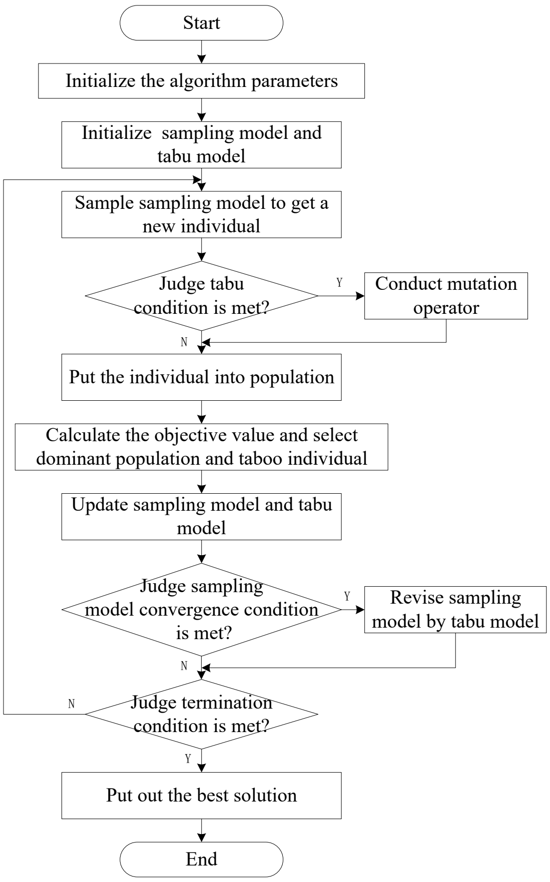

Fig 2. The flowchart of proposed EDA

Although the motivation of design is to improve the ability of EDAs to jump out of the local optimum, the operators in tabu-model-based EDA framework have amusing correspondences with the general Tabu Search. They verify the rationality of the proposed framework from the side, and they are shown in the following table.

From the above flow, beside the general steps of EDA, there are some new operators which is based on the tabu model, including the criterion of tabu condition, mutation operator and modification strategy of sampling model.

Table II. The correspondence between proposed EDA with TS

Operators or concept in proposed framework	The corresponding things in TS
Sampling model	Searching operator
Tabu model	Tabu list
Similarity	Whether being in tabu list
Learning rate	Remove taboo individual

3.3.1. The criterion of tabu condition

The previous section has discussed about the similarity between the solution and tabu model. In this paper, the criterion of tabu condition for a solution as follows:

$$J_t(x, G_t) = \begin{cases} true & , sim(x, G_t) \geq \varepsilon \\ false & , sim(x, G_t) < \varepsilon \end{cases} \quad (13)$$

where $J_t(x, G_t) = true$ means the solution is taboo and cannot be satisfied directly. $J_t(x, G_t) = false$ means the solution is free and can be put into population. ε is a threshold and needs to be set empirically.

3.3.2. The mutation operator

In order to the waste of taboo solutions, a mutation operator is adopted to reduce the similarity. The steps of the mutation operator are shown as follows:

Step 1: Randomly extract randomly a series of continuous components in the permutation;

Step 2: Randomly shuffle and reorganize this set of components;

Step 3: Put the set of components to the original location in the permutation.

The mutation operator is only to reduce the similarity. Many operators which are not the focus in this paper can achieve this motivation.

3.3.3. The modification method for sampling model

The mutation operator provides a chance for EDAs to jump out of the local optimum. However, when the diversity of the population is completely lost, this operator which is based on the existing individuals can hardly work.

In the existing research, many scholars used restart mechanisms to make population regain a various diversity. Considering the proposed tabu model, this paper opens a new path to get the diversity.

It is obvious that the loss of the diversity causes that the components sampled by sampling model are often taboo by tabu model. That means the search area and taboo area overlap most. Meanwhile, the other space still needs to be searched besides the taboo area.

So, in order to keep the information of the previous search results and avoid the taboo search area, the modification strategy of sampling model based tabu model is proposed. The formula is shown as follows:

$$G_S = Norm(G_S - G_T) \quad (14)$$

where G_S, G_T are sampling model and tabu model respectively, and $Norm(G_S - G_T)$ is used to map the difference of the two matrices to $[0,1]$.

4. Computational experiments

In this section, a simple illustrative instance is used to show the influence of tabu model and the associated operators.

In the comparative experiments, two general EDAs (namely *NHM* and *EHM*) employing NHM and EHM respectively are designed, and two tabu-model-based EDAs (namely *T-NHM* and *T-EHM*) based on NHM and EHM respectively are designed according to the proposed framework to solve QAP and TSP. A larger number of benchmarks from QAPLIB and TSPLIB are used to test the framework and operators.

In this paper, all the algorithms run 20 times on a computer configured as Inter(R) Xeon(R) CPU E5-2620 v4, 32GB RAM, windows 7 operation system in MATLAB 2017b.

4.1. Parameters setting

The key parameters about the four algorithms are shown in the following table. In order to keep the fairness of comparative experiments, the mainly parameters are set to the same values as much as possible.

Table III. The setting of parameters

Parameters	*NHM*	*EHM*	*T-NHM*	*T-EHM*
p	$10\cdot n$	$10\cdot n$	$10\cdot n$	$10\cdot n$
$Iter_{max}$	1000	1000	1000	1000
η	0.1	0.1	0.1	0.1
μ_n, μ_e	0.2	0.2	0.2	0.2
μ_{tn}, μ_{te}	-	-	0.2	0.2
ε	-	-	0.5	0.5

*-: the data is not available in this algorithm.

4.2. An illustrative example

In this section, the example of a QAP whose scale is 20 is used to show the actual effect of the mainly operators.

In Fig 3, in order to clear the effect about the mutation operator and motivation method based tabu model, the normalized curve of the current optimum and proportion of the mutations to total are placed in the below figure.

In Fig 3, the curve of the proportion shows few jumps from 1 to 0, because the motivation method for sampling model is conducted when the diversity is lost. After the taboo part is removed from the sampling model, the algorithm often jumps out of a local optimum. And then, the similarities between the tabu model and individuals in population become smaller, and the frequency of using the mutation operators decreases correspondingly.

The jumps can divide the evolutionary process into several stages. According to the motivation method, in different stages, the mainly search areas of algorithm are different. The effect of the two proposed operators is verified when better solutions are found out at different stages.

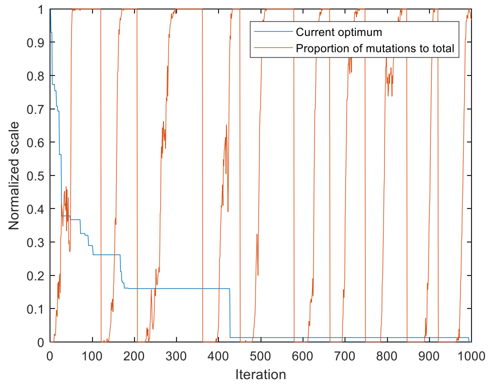

Fig 3. Effect of mainly operators

Fig 4 shows the convergences of the four EDAs with the iteration. It can be seen that the convergence speed of *EHM* and *T-EHM* are slower than *NHM* and *T-NHM*. In the same evaluation times of solutions in this paper, EDAs based on NHM can find a better solution and are more suitable for QAP. Besides, from the curves of *EHM* and *T-EHM*, algorithms based tabu model have a slower convergence speed.

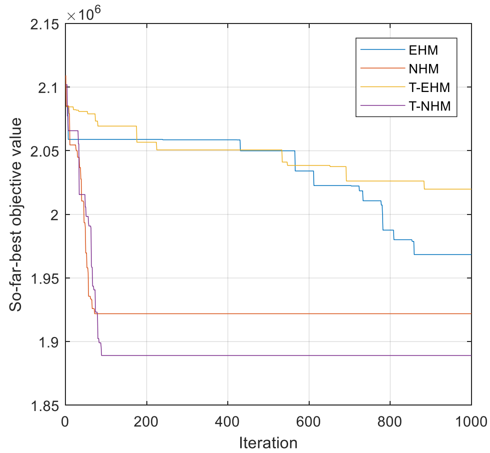

Fig 4. So-far-best objective value (QAP, *n*=30)

4.3. Comparative experiments

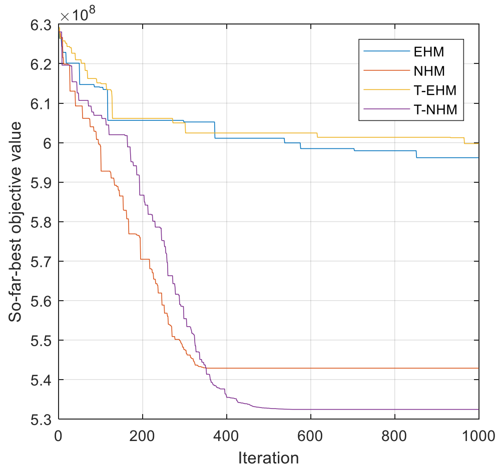

Fig 5. So-far-best objective value (QAP, *n*=150)

1 Table IV. Test results for benchmarks

Problem	Index	Optimal value	*EHM*		*NHM*		*T-EHM*		*T-NHM*	
			value	time(s)	value	time(s)	value	time(s)	value	time(s)
QAP	Tai20	1818146	1953480	95.34	1917857	54.37	1973093	96.05	**1890497**	56.24
	Tai50	4938796	5614162	290.61	5243052	170.01	5610312	247.02	**5195172**	144.08
	Tai100	21052466	23508296	1129.06	22201626	705.36	23501952	1145.11	**22075406**	712.12
	Tai150	498896643	597205986	2948.99	538641648	1931.24	599287102	2942.48	**537152050**	1911.64
TSP	Eil51	426	449	190.31	702.23	108.08	**440**	192.88	624	108.38
	St70	675	746	369.01	1385	211.22	**738.97**	373.68	1239	214.85
	Pr76	108159	119241	404.04	217386	222.83	**116837**	338.47	193515	227.13
	Eil101	629	703.06	760.68	1328	467.98	**701**	754.01	1183	452.83

2

In this experiments, eight benchmarks from QAPLIB and TSPLIB are tested. The test results about average objective values and running time of the four EDAs are shown in Table IV.

It is obvious that *T-NHM* can always find out the best solutions to QAP benchmarks among the four EDAs, and *T-EHM* can always find out the best solutions to TSP benchmarks. The effectiveness is shown clearly. Because it is not suitable for EDAs based on EHM to solve QAP and the proposed mutation operator based the tabu model may decrease slightly the convergence speed in part of benchmarks. The proposed framework does not well on *T-EHM* compared with *EHM* for QAP. Similar situation also occurs in solving TSP. The illustrative graph is shown in Fig 5.

From the perspective of the algorithm running time, the new EDAs do not bring too much or even unacceptable increment to the running time of the algorithms because of the proposed operators based on the tabu model.

5. Conclusion

In this paper, tabu model, a novel meaningful concept, is proposed which has many meaningful characteristics. Then, the calculation method about the similarity and the learning rate of the tabu model are introduced. Based on the above contents, a tabu-model-based EDA framework is presented which involves various applications of the tabu model. Two new algorithms, *T-EHM* and *T-NHM*, are designed to solve the benchmarks of QAP and TSP. Through the comparative experiments, the effectiveness of the proposed algorithm framework for finding better solutions is verified.

As a new concept and model, the tabu model has initially shown the stronger practicability in this paper. It still has great potential to be researched, and more precise operators for tabu model need to be designed.

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