Acta Technica 62 (2017), No. 6B, 259–270

Construction of the training standard system and integration of teacher education resources for chinese language education

Li Mo[1]

Abstract. One optimization algorithm for course scheduling of Chinese language and literature based on multi-subgroup objective segmentation differential evolution algorithm has been proposed to solve the NP hard issue in course scheduling of Chinese language and literature. First, research on course scheduling model for Chinese language and literature has been made, optimization objective function and constraint conditions for course scheduling issue have been proposed and its optimization mathematical model has been established. Second, differential evolution algorithm has been introduced and one differential evolution algorithm of multi-population objective segmentation optimization has been designed to solve the difficulty in confirming weighting coefficient. For one sub-objective in each subgroup optimization objective function, subgroup evolves independently, which not only solves the weighting coefficient issue, but also improve the convergence speed and accuracy of algorithm. Last, comparative experiment with standard differential evolution algorithm has been made to verify the effectiveness of the proposed algorithm; at the same time, systematic design for algorithm in course scheduling optimization of Chinese language and literature has been realized.

Key words. Differential evolution, Multi-subgroup, Course scheduling of Chinese language and literature, Algorithm evolution, Multi-objective optimization.

1. Introduction

Course scheduling of Chinese language and literature in university is a very heavy work as it is with numerous uncertain factors of many courses, many students and many classrooms etc [1, 2]. Especially with the enrollment expansion in colleges and universities in recent years as well as the emphasis of school on teaching quality, how to schedule courses more reasonably and effectively is an important focus of school.

[1]Department of Teacher education, Qujing Normal University, QuJing Yun Nan, 655000

In particular, with the proposing of sharing curriculum resources among schools, the course scheduling of Chinese language and literature is becoming increasingly important [3].

The essence of course scheduling of Chinese language and literature in university is a NP hard combinatorial optimization problem with multiple objectives and constraints [4]. There are a lot of mature algorithms to solve this problem, such as branch and bound [5], grouping optimization decision [6] and association rule algorithm [7] etc. There are some effects for these algorithms in solving NP hard combinatorial optimization problem, but they have following problems: (1) In the solution process, the algorithm only solves one problem and it can't form a universal course scheduling method for Chinese language and literature; (2) There are few judgment standards for the effect of course arrangement. Algorithm solution puts emphasis on optimization of one direction and can't realize global optimization; (3) Association rule method, there are problems which are difficult to attain by association rule in solution process, which causes it does not have generality and the solution result is not ideal. Evolutionary computation is an emerging intelligent bionic calculation method in recent years [8]. It only needs to consider about objective function and constraint conditions in the optimization process and there is no need for gradient or other auxiliary information. In addition, it is with generality for each field and is a relatively effective solution for NP hard combinatorial optimization problem. Differential evolution algorithm (differential evolution) is one of the intelligent evolution algorithms [9] and its design inspiration is from the observation and summarization for water flow composed of differential evolution. How to cross over the barriers in the river and reach the lake and ocean in the shortest path is the research direction of differential evolution algorithm. The same as standard particle swarm [10], ant colony [11] and other biological evolutionary algorithms, differential evolution algorithm has premature and other algorithm convergence failure problems in solving high dimension multimodal NP hard combinatorial optimization problem. At present, there are few research results for differential evolution algorithm and most of them are focusing on parameter adaptive [12] and evolution formula improvement [13] and other aspects. This algorithm can't improve the performance of algorithm effectively and can only improve to some extent.

One steady multi-subgroup objective segmentation optimization algorithm has been adopted in this paper, which helps to realize adaptive updating of differential evolution in searching region and then decrease the computing complexity of algorithm, improve convergence speed and improve the course scheduling effect of Chinese language and literature while ensuring the best quality point in the searching region.

2. Course scheduling model of Chinese language and literature

2.1. Description of model

Assume there are Gsubstitute teachers, Cclasses to be scheduled, Lcourses, T scheduling periods for Chinese language and literature and R classrooms in the school executing course scheduling for Chinese language and literature. Its mathematical model can be described as:

Set form of class to be scheduled is$C = \{c_1, \cdots, c_C\}$, student number set in each class is$K = \{k_1, \cdots, k_C\}$. Set composed of substitute teachers is$G = \{g_1, \cdots g_G\}$, course number of each teacher is$Y = \{y_1, \cdots y_G\}$. Set description of course is$L = \{l_1, \cdots l_L\}$, class number for each course is$Z = \{z_1, \cdots z_L\}$. Set description of classroom is$R = \{r_1, \cdots, r_R\}$, student number for each teacher is$X = \{x_1, \cdots, x_R\}$. Set in each time period is$T = \{t_1, \cdots, t_T\}$.

Through calculating time and Cartesian product of classroom, course scheduling of Chinese language and literature is converted into model set between course and suitable time classroom. The form is:

$$M = T \cdot R = \{(t_1, r_1), \cdots, (t_T, r_R)\} . \tag{1}$$

2.2. Model constraints

Constraint 1: there can't be more than one lesson in the same time and in the same class. The constraint form is:

$$\sum_{g=1}^{G} \sum_{l=1}^{L} \sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1 . \tag{2}$$

In the formula$c = 1, 2, \cdots, C$, $t = 1, 2, \cdots, T$, if class $c_c$is in classroomr_r, during time periodt_t, substitute teach $g_g$will teach the lessonl_l, and then its expression form is $c_c g_g l_l r_r t_t = 1$, or else, it is 0.

Constraint 2: one teacher can't teach more than one lesson during the same time. Its constraint form is:

$$\sum_{c=1}^{C} \sum_{l=1}^{L} \sum_{r=1}^{R} c_c g_g l_l r_r t_t \leq 1 . \tag{3}$$

In the formula, $g = 1, 2, \cdots, G$, $t = 1, 2, \cdots, T$, If teacher $g_g$is in classroomr_r, during time periodt_t, the teacher only teach lessonl_l to classc_c, and then its expression form is$c_c g_g l_l r_r t_t = 1$, or else it is 0.

Constraint 3: there can't be more than one lesson in the same classroom during the same time period. Its constraint form is:

$$\sum_{c=1}^{C} \sum_{g=1}^{G} \sum_{l=1}^{L} c_c g_g l_l r_r t_t \leq 1 . \tag{4}$$

In the formula$r = 1, 2, \cdots, R$, $t = 1, 2, \cdots, T$, if classroomr_r is used by teacher $g_g$to teach lesson l_l to class $c_c$during time period t_t, and then its expression form is$c_c g_g l_l r_r t_t = 1$, or else it is 0.

3. MSSODE algorithm

Based on the analysis in chapter one, this chapter has designed one differential evolution algorithm of multi-subgroup objective segmentation with adoption of differential evolution algorithm. It equals to make dimension reduction to optimization problem through designing multi-subgroup. But the method designed in this chapter is only suitable for segmentation objective functions without coupling phenomenon and it is suitable to handle objective function in formula (2) form. To improve the convergence speed of algorithm and maintain variety of group, it improves variation mode and introduces gradient acceleration algorithm.

3.1. Improvement of mutation mode

Premature convergence or low efficiency happen to mutation modes listed in former literature easily. One mutation mode considering about both population variety and searching efficiency has been designed in this paper:

$$x_i^{t+1} = x_i^t + F\left(x_{r1}^t - x_i^t + x_{r2}^t - x_{r3}^t\right) . \tag{5}$$

In above mutation mode, based vector still adopts $x_i^t$for No. i individual $x_i^t$of No. t generation population, which indicates to make mutation based on x_i^t. It is good for keeping the diversity of initial population and also considers about the evolution direction of population. Following item $x_{r2}^t - x_{r3}^t$is introduced as disturbance. The mutated individual keeps big difference after this processing and then it keeps the diversity of population.

For the selection of$r1, r2, r3$, we consider about population evolution direction during random selection. Three unequal numbers$c1 \neq c2 \neq c3 \in Z\left[0, 1\right]$ are produced randomly with this selection method. Select based on individual objective function value. For the minimization issue, $r1$ selects the smallest objective function value and $r3$ selects the biggest objective function value, which is:

(1) $r1 = \text{find}\left\{c1, c2, c3\right\}$,

$$\text{s.t.} \quad \min\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$$

(2) $r2 = \text{find}\left\{c1, c2, c3\right\}$,

$$\text{s.t.} \quad mid\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$$

(3) $r3 = \text{find}\left\{c1, c2, c3\right\}$,

$$\text{s.t.} \quad \max\left\{\text{val}\left(x_{c1}^t\right), \text{val}\left(x_{c2}^t\right), \text{val}\left(x_{c3}^t\right)\right\}$$

After this process, the all mutated individuals take themselves as base variables, which keep the biggest difference and keep the diversity of population. At the same time, sorting method selects$r1, r2, r3$, which considers about the evolution direction of population, so it is an effective mutation method.

3.2. Local search based on gradient

For function$f(\boldsymbol{x})$, $\boldsymbol{x} = (x_1, x_2, ..., x_n)$, its gradient can be expressed as [5]:

$$\Delta f(\boldsymbol{x}) = \left[\frac{\partial f(\boldsymbol{x})}{\partial x_1}, \frac{\partial f(\boldsymbol{x})}{\partial x_2}, ..., \frac{\partial f(\boldsymbol{x})}{\partial x_n}\right]^{\mathrm{T}}. \tag{6}$$

Negative gradient direction is the steepest descent direction of function.

When population particle makes local search, it makes one linear searching for superior individual in the population in negative gradient function and then confirm the shift step size. Linear searching adopts golden section method and algorithm pseudo-code is as shown in figure 1:

$[\boldsymbol{a}, \boldsymbol{b}]$ is the gradient searching range of tentative determination. ε is threshold value and the relative optimal value is $\varepsilon = 0.1$. The introduction of gradient information makes the particle move in a target way and the movement is with greater efficiency. Linear search algorithm of gradient has been introduced in local search, which can increase the convergence speed of algorithm and has little influence on the complexity of algorithm.

$\vec{t}_2 = \vec{a} + \beta(\vec{b} - \vec{a})$; $f_2 = f(\vec{t}_2)$;
$\vec{t}_1 = \vec{a} + \vec{b} - \vec{t}_2$; $f_1 = f(\vec{t}_1)$;
while $|\vec{t}_1 - \vec{t}_2| \geq \varepsilon$
    if $f_1 \leq f_2$
        $\vec{b} = \vec{t}_2; \vec{t}_2 = \vec{t}_1; f_2 = f_1$;
    else
        $\vec{a} = \vec{t}_1; \vec{t}_1 = \vec{t}_2; f_1 = f_2$;
        $\vec{t}_2 = \vec{a} + \beta(\vec{b} - \vec{a}); f_2 = f(\vec{t}_2)$;
    end
end
$x_i^{t+1} = \frac{\vec{t}_1 + \vec{t}_2}{2}$;
end

Fig. 1. Algorithm pseudo-code

3.3. MSSODE algorithm steps

Step 1: set population size at *NP*, dimension as D, zoom factor as F, crossover probability factor as *HR*, maximum iterative algebra as G, search space as$\left[l^0, u^0\right]$, $s = 1$;

Step 2: in$\left[l^0, u^0\right]$, population P^1 with initial size of *NP* divides group into

Nsubgroups for objective problem N. Adaption $J_1, J_2, ..., J_n$ of each subgroup has been calculated respectively. The total objective adaptation is$J = J_1 + J_2 + ... + J_n$;

Step 3: if Jmeets termination conditions, and then terminate and output results;

Step 4: judge if J_1meets termination condition. If meet, jump the operation for population 1; if not meet, make mutation operation with probability $p$based on formula (5). Make gradient acceleration operation at probability 1-$p$based on pseudo-do code in figure 3 and then make crossing and selection operation; operate subgroup 2$\sim$ n based on above method;

Step 5: calculate total objective adaptability$J = J_1 + J_2 + ... + J_n$, turn to Step 3;

Making one linear search based on gradient information can speed up the convergence speed of population, but it can also increase the possibility of algorithm trapped in local extreme. The mutation method of formula (8) designed for this increases the diversity of population. The algorithm can balance the relationship between convergence speed and population diversity effectively. If ε selection is appropriate, it has small influence on time complexity of algorithm. For original mutation operations, the complexity of algorithm is mainly presented in the crossing operation part. If theε is appropriate, the operation times in gradient cycling part are smaller than the dimension of population, and then the time complexity of this part is superior to original operation.

3.4. Algorithm performance test

For the form of objective function (1), select two testing functions to test, which are unimodal independence and unimodal non-independence.

(1)$f1 = \sum\limits_{i=1}^{30} x_i^2,\ \ |x_i| \le 100,\ \ \min(f1)\ = 0$

(2)$f2 = \frac{1}{4000} \sum\limits_{i=1}^{30} x_i^2 - \prod\limits_{i=1}^{30} \cos\left(x_i/\sqrt{i}\right) + 1,\ \ |x_i| \le 100,\ \ \min(f2) = 0$

Set simulation parameter: set simulation dimension$D = 30$ based on international standards; population size is 5-10 times of dimension [6], big population size is good to keep the diversity of population and good for jumping out of local extreme value, but the operation time of algorithm is long, here select$NP = 200$; iterative maximum is 8000; the value range of zoom factor listed in literature [6] is $F \in [0.4,\ 0.8]$, select $F = 0.6$; changing range of crossover probability factor is $HR \in [0.3, 0.9]$ [7–9].

Setting of SACPMDE and ASMDE parameters is as shown in literature [10]. Setting of DERL parameter is as shown in literature [4]. Zoom factor of standard DE algorithm is$F = 0.6$, crossover probability factor is$HR = 0.8$, simulation accuracy is VTR=10-6. Set MSSODE algorithm into to populations and set zoom factor as$F = 0.6$, crossover probability factor as$HR = 0.8$, simulation accuracy of subgroup as $VTRi$=10-7. Simulation results are as shown in table 1 and figure 2-3. Draw by selecting adaptive value of logarithm from figure 2-3 for easy comparison.

Table 1. The algorithm runs 20 times for the average

		Optimal performance	Average performance	Iteration times	Variance	Time/s
	MSSODE	7.32×10^{-7}	8.87×10^{-7}	198	3.15×10^{-19}	1.4
	SACPMDE	6.13×10^{-6}	8.85×10^{-6}	297	9.77×10^{-18}	8.6
$f1$	ASMDE	6.47×10^{-6}	9.01×10^{-6}	1087	8.21×10^{-18}	9.3
	DERL	7.54×10^{-6}	9.13×10^{-6}	314	4.89×10^{-13}	3.6
	DE/rand/1/bin	7.12×10^{-6}	9.18×10^{-6}	2178	5.14×10^{-13}	23.0
	DE/best/2/bin	7.42×10^{-6}	9.02×10^{-6}	2363	4.80×10^{-13}	25.5
	MSSODE	$8..32\times10^{-7}$	9.53×10^{-7}	221	6.71×10^{-17}	2.7
	SACPMDE	6.98×10^{-6}	9.00×10^{-6}	301	6.16×10^{-13}	9.3
$f2$	ASMDE	6.85×10^{-6}	9.04×10^{-6}	1159	7.19×10^{-13}	18.8
	DERL	7.50×10^{-6}	1.29×10^{-2}	5813	2.07×10^{-4}	85.3
	DE/rand/1/bin	5.93×10^{-6}	3.78×10^{-4}	2170	2.73×10^{-6}	30.1
	DE/best/2/bin	7.86×10^{-6}	6.28×10^{-3}	5110	7.05×10^{-5}	73.3

Data in table one indicates that MSSODE algorithm performance has been improved greatly. Multi-subgroup objective segmentation differential evolution algorithm designed in this paper can search the optimal solution in its adopted testing functions and the search speed is fast. For testing function, this algorithm is obviously superior to other algorithms. This algorithm is with strong exploration and development capacity, which can jump out of local extreme value effectively, prevent premature of algorithm and converge to global optimal value quickly.

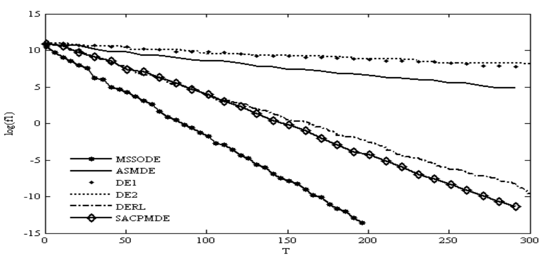

Fig. 2. Convergence curves of f_1

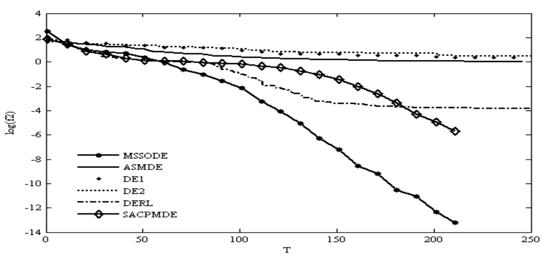

Fig. 3. Convergence curves of $f2$

4. Experimental analysis

Class table of graduate school in China Academy of Social Sciences has been selected as experimental object. Its course scheduling elements of Chinese language and literature are as shown in table 2. Its developed course scheduling system of Chinese language and literature is realized based on visual c++.

Table 2. Course scheduling elements of Chinese language and literature

Element	Student	Teacher	Class	Course	Classroom	Task book
Qty	6200	387	125	669	168	669

Standard differential evolution algorithm has been selected in this experiment as comparison algorithm. Select objective function value and evolution time as evolution indexes. Experiments have been made for 20 times and evolutionary algebra has been made per 100 times. Check and attain its current optimal individual adaptive value. Figure 4 lists average convergence curve of the recorded optimal individual adaptive value; comparison of algorithm operation time has been made with adoption of above method, simulation results are as shown in figure 5. Some course scheduling results for Chinese language and literature are as shown in figure 6.

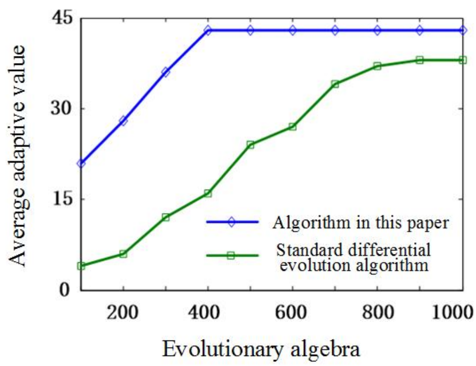

Fig. 4. convergence curves of average adaptive value

Figure 4 offers convergence curves of average adaptive value between algorithm in this paper and differential evolutionary algorithm. It can be seen that the convergence speed of algorithm in this paper is faster than that of differential evolution algorithm; in addition, the convergence accuracy proposed in this paper is higher. Figure 5 offers comparison of operation time between algorithm listed in this paper and differential evolution algorithm in course scheduling of Chinese language and literature. It can be seen that the time used by algorithm in this paper is less than that of differential evolution algorithm obviously. Figure 6 is diagram of course scheduling system of Chinese language and literature based on visual c++ and algorithm in this paper.

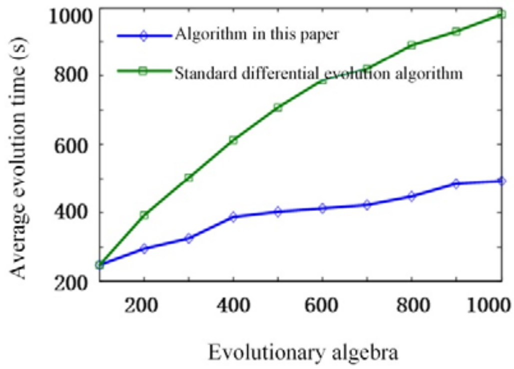

Fig. 5. Convergence curves of average evolutionary time

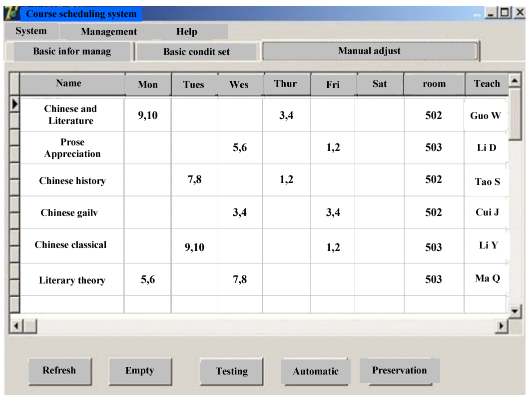

Fig. 6. Diagram of course scheduling system of Chinese language and literature

Table 3. Comparison of course scheduling effects of Chinese language and literature

Method	Class days per week	Class interval of the same course	Average classes per day
Differential evolution	2.3	1.3	6.3
This paper	2.7	1, 5	4.8
Classroom utilization ratio (%)	Number of missed courses	Teacher satisfaction degree	Conflict ratio of course scheduling of Chinese language and literature
89.5	18	86.4	16.3
99.3	0	99.5	1.2

Table 3 offers the comparison of course scheduling effects of Chinese language and literature between algorithm in this paper and differential evolution algorithm. It can be seen from the table that the algorithm in this paper is superior to differential evolution algorithm in classroom resource utilization ratio, number of missed courses, classroom satisfaction degree and conflict ratio of course scheduling of Chinese language and literature etc. It presents the effectiveness of algorithm in this paper for application of course scheduling system of Chinese language and literature.

5. Conclusions

One course scheduling optimization algorithm for Chinese language and literature based on multi-subgroup objective segmentation differential evolution algorithm has been proposed from the perspective of improving differential evaluation algorithm and course scheduling optimization of Chinese language and literature. Optimization objective function and constraint conditions for course scheduling of Chinese language and literature have been listed based on visual c++. In addition, the performance of differential evolution algorithm has been improved based on multi-subgroup objective segmentation optimization. Simulation results have shown that the proposed algorithm has realized algorithm performance improvement and effective optimization for course scheduling of Chinese language and literature. In the following, how to integrate with cloud computation, realize course alignment among schools and realize further optimization of education resource are the following research directions.

References

[1] Jian S: (2013) *The Integration of Quality-Oriented Education and Instrument-Driven Training in Chinese College English Teaching.*[J]. English Language Teaching, 6(5):304-10.

[2] Yuen C Y M: (2013) *Assimilation, Integration and the Construction of Identity: The experience of Chinese cross-boundary and newly arrived students in Hong Kong schools*[J]. Multicultural Education Review, 2(2):1-30.

[3] Wang Y: (2014) *The Study of Distance Education System Based on Cloud Computing and Resource Integration*[J]. Applied Mechanics & Materials, 687-691:2841-2844.

[4] Bali N, Zayed W, Hassen Z, et al.: (2014) *The Conceptions of Integration of Tunisian Physical Education Cooperative Teachers and Student Teachers*[J]. Creative Education, 05(4):279-289.

[5] Dai H, Ling K E, Luo Z: (2016) *Integrating Urban and Rural Areas to Develop Jointly——The Second Stage Construction Practice Mode of Chengdu City's Exploration into Pilot Region for Comprehensive Reforms of Overall Planning for Urban and Rural Education*[J]. Education & Teaching Research.

[6] Hsu L: (2015) *Modelling Determinants for the Integration of Web 2.0 Technologies into Hospitality Education: A Taiwanese Case*[J]. The Asia-Pacific Education Researcher, 2015(4):1-9.

[7] Sun C L, Chen R, Tong T Y, et al.: (2014) *On the Construction of Chemical Analysis Technology Curriculum Standard Based on Integration of Working and Learning*[J]. Journal of Liaoning Higher Vocational.

[8] Liu R X: (2014) *Reflection and Practice on the Construction of Campus Training Base in Higher Vocational Colleges with Integration of Enterprise Culture*[J]. Journal of Southern Vocational Education.

[9] Yang B X, Huang J, Liu K, et al.: (2014) *Ontology Construction and Semantic Modeling Method Research of Education Resources within the Architecture of Cloud Service*[J]. Applied Mechanics & Materials, 631-632(2):1016-1022.

[10] Tunsch C, Enoch C: (2015) *The Meaning Of The Domicile For the Education And Vocational Integration Of Young People*[J]. Journal of Orthopaedic Research, 24(8):1670-8.

[11] Yue S M: (2014) *On the Integration of the Continuing Education with the Teachers' Educational Informationization*[J]. Journal of Interventional Cardiology, 27(6):555-62.

[12] Zhang Y: (2014). *Study on the Construction of Curriculum System in Mechanical and Electrical Integration for Connection of Secondary and Higher Vocational Education*[J]. Value Engineering.

Received May 7, 2017