Acta Technica *62* (2017), No. 7A, 673–684

An analysis on effect of physical education strategy based on factor auto-scaling particle swarm optimization algorithm

Yuyang Qin[1]

Abstract. In order to improve the effectiveness of effect analysis algorithm of physical education strategy, an effect analysis method for physical education strategy based on improved particle swarm optimization algorithm of factor auto-scaling is proposed. Firstly, the physical education problem model is studied to propose the optimal objective function and constraint condition of physical education problem, establish its optimized mathematical model and give its multi-objective weight self-adaption form; secondly, particle swarm optimization algorithm is introduced to solve by means of its effect model of physical education strategy; in addition, in order to further improve the performance of PSO algorithm in the model solution, factor auto-scaling is utilized to carry out self-adaption learning of related parameters of PSO algorithm, in order to improve the algorithm convergence; finally, example analysis is carried out to verify the effectiveness of proposed effect analysis algorithm of physical education strategy.

Key words. Physical education, Effect analysis, Particle swarm optimization algorithm, Auto-scaling

.

1. Introduction

Physical education becomes a very heavy workload [1-2] due to many uncertainties, including many involved courses, many students and many grounds. In particular, with enrollment expansion of colleges and their focus on the teaching quality in recent years, how to more reasonably and effectively achieve the physical education course distribution has become an important content attracting the attention of schools. Especially as course resource sharing concept in many schools

[1]Bengbu Medical College, Anhui, Bengbu, 233000

has been proposed, the physical education has become increasingly important [3]. Physical education problem, in essence, is a multi-objective and multi-constraint NP hard combinational optimization problem [4]. For such problem solution, there have been many matured algorithms, such as branch and bound [5], grouping optimization decision-making algorithm [6] and association rule algorithm [7]. Such algorithms have achieved certain effect in solving NP hard combinational optimization problem, but have the following problems: (1) during the algorithm solving, it only solve certain problem and it is difficult to form general physical course scheduling method; (2) there is fewer judgment standard for the quality of course scheduling, and the algorithm solving overstresses the optimization of certain point, but fails to achieve global optimization; (3) for association rule form, it is very difficult to obtain the association rule during solving, resulting in the generality failure and undesirable solving result.

Evolutionary computation [8] is an intelligent bionic computation method emerging in recent years, only considering the objective function and constraints during optimization, without gradient or other auxiliary information, and it is common to other areas; therefore, it is a relatively effective solution to hard combinational optimization problem. In order to compute the efficient frontier in the combinational problem model of physical education, how to obtain more accurate weight becomes essential for problem solving during asset computation. In this respect, in addition to some classical algorithms, the evolutionary computation algorithm may also be used. American scholar James, based on bird flock's behavior in food searching, designed the evolutionary computation algorithm and obtained the particle swarm optimization (PSO) algorithm [3]. In PSO algorithm, food-searching birds are modeled as a "particle" and optimized in set search space in order to achieve algorithm solving. The particle in the algorithm contains two major attributes: adaptive value and flight direction; the former may be determined by set optimization function and the latter by the direction parameter. In the algorithm optimization, the trend of particle running in the algorithm heads to the particle in the optimal position in current population. The computation speed of the particle swarm optimization algorithm is related to the scientific and technological development level of computer hardware, and with hardware development, the algorithm performance has also been continuously improved. In recent years, with the progress in combined research on physical education, the application of evolutionary computation has also been increasingly widened. For instance, in Literature [4], ant colony optimization algorithm is utilized for principle analysis and modeling, and for model weight computation. In Literature [5], the teaching yield is taken as major research objective and its expected yield as major constraints to minimize the most important solving objectives for the expected yield weight, so as to obtain the optimal teaching yield. In Literature [6], genetic algorithm is utilized to study the teaching problem and improve the algorithm coding during model soling, and the experimental results show that proposed methods have better teaching optimization performance. In Literature [7], the teaching yield problem is studied and compared with the quadratic programming problem, so as to analyze the teaching problem performance advantage of proposed algorithm. In Literature [8], study is mainly carried out for the teaching quantity problem under equal yield level for major purpose of achieving teaching minimization. In Literature [9], binary system is utilized to code the combined weight of teaching, so as to obtain an optimized function and take risk and yield as two objectives that can be balanced to form a multi-objective teaching optimization problem and finally utilize the differential evolution algorithm to achieve model solving. In Literature [10], the integer coding substitutes binary coding in order to improve the genetic algorithm and to apply the improved algorithm into the teaching model solving. In Literature [11], in terms of transaction cost limit, the teaching preference parameter is utilized, and optimization algorithm is mainly the genetic algorithm of which the set constraint is the maximum value of upper limit of teaching. In the searches of said algorithms, there are two problems: the first one is the optimized performance problem about algorithm and the guarantee problem of algorithm convergence; the second one is scientific evaluation problem about effect-feasible evaluation index is absent for the algorithm performance.

In this thesis, particle swarm optimization algorithm is mainly used to study the physical education problem, mainly concerning two points, that is, algorithm performance improvement and evaluation of algorithm efficiency. The physical education problem model is studied to propose the optimal objective function and constraint condition of physical education problem, establish its optimized mathematical model and give its multi-objective weight self-adaption form; in the meantime, particle swarm optimization algorithm is introduced to solve by means of its effect model of physical education strategy; in addition, in order to further improve the performance of PSO algorithm in the model solution, factor auto-scaling is utilized to carry out self-adaption learning of related parameters of PSO algorithm, in order to improve the algorithm convergence.

2. Physical education problem model

2.1. Description on physical course scheduling model

It is assumed that the school executing the physical course scheduling has G physical education teachers, C classes with physical course to be scheduled, L courses, T physical course scheduling periods of time and R grounds. Its mathematical model is described as:

The set form of classes with physical course to be scheduled is: $C = \{c_1, \cdots, c_C\}$ and the set of each class size is $K = \{k_1, \cdots, k_C\}$. The set consisting of teachers is $G = \{g_1, \cdots g_G\}$ and the number of courses in the charge of teachers is $Y = \{y_1, \cdots y_G\}$. The set of physical course is described as $L = \{l_1, \cdots l_L\}$, and the class size for each course is $Z = \{z_1, \cdots z_L\}$. The set of classroom is described as $R = \{r_1, \cdots, r_R\}$, and the number of students accommodated by each teacher is $X = \{x_1, \cdots, x_R\}$. Each period of time is $T = \{t_1, \cdots, t_T\}$.

By means of computation of Cartesian product of time and ground, the physical education problem is transformed into the model pair of course and proper time &

ground in the form of:

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

2.2. Model constraints

Constraint 1: at the same time, the same class should not have more than one course, and the constraint form is:

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

Where, $c = 1, 2, \cdots, C$ and $t = 1, 2, \cdots, T$. If class c_c is on ground r_r, and teacher $g_g$is responsible for teaching course l_l in the period of time t_t, and then its expression form is $c_c g_g l_l r_r t_t = 1$, or it will be zero.

Constraint 2: at the same time, the same teacher should not teacher more than one course and the constraint form is:

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

Where, $g = 1, 2, \cdots, G$ and $t = 1, 2, \cdots, T$. If teacher g_g only teaches the course l_l in class c_c on ground r_r, and in the period of time t_t, and then its expression form is $c_c g_g l_l r_r t_t = 1$, or it will be zero.

Constraint 3: at the same time, the same ground should not be available for more than one course and the constraint form is:

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

Where, $r = 1, 2, \cdots, R$ and $t = 1, 2, \cdots, T$. If the ground $r_r$is only available for teacher g_g to teach the course l_l in class c_c in the period of time t_t, and then its expression form is $c_c g_g l_l r_r t_t = 1$, or it will be zero.

2.3. Optimization objectives

The physical course scheduling system, in nature, is a multi-objective optimization problem and its optimization objectives are as follows:

Objective 1: important course is scheduled in the period of time with good teaching effect. If $a_i\,(i = 1, 2, 3, 4, 5)$ shows five teaching classes are available every day, and based on actual teaching experience, the teaching effect of the first, third and fifth classes is the best and recorded as $a_i = 1\,(i = 1, 3, 5)$, and the teaching effect of the second and fourth classes is poor and recorded as $a_i = 0\,(i = 2, 4)$. Use parameter $\beta_j = 1\,(j = 1, 2, 3, 4)$ represents the course importance degree, such as different weight assignments for the elective, basic, specialized and degree courses, and then the optimization objective is:

$$\max(f_1) = \sum (a_i \beta_j) . \tag{5}$$

Objective 2: The time and place for class proposed by the teacher is considered and the professional title coefficient χ_i $(i = 1, 2, 3, 4)$ is set, respectively for teaching assistants, instructors, associate professors and professors. Teachers' willingness of set class hours may be expressed in $\delta_i = 0, 1, 2$, including no, yes and willingness. Its optimization objective is in the form of:

$$\max(f_2) = \sum (\chi_i \delta_j) . \tag{6}$$

Objective 3: course with more weekly periods (such as $n \geq 4$) should be scheduled every other day as much as possible to ensure the teaching effect. The definition of $\beta_j = 1$ $(j = 1, 2, 3, 4)$ is the same as that of Objective 1 and definition ε_i $(i = 1, 2, 3, 4)$ represents the teaching effect of course scheduled at the interval of i days, and its optimization objective is in the form of:

$$\max(f_3) = \sum (\beta_i \varepsilon_j) . \tag{7}$$

Objective 4: the resource utilization objective; the more proportion of maximum capacity of ground occupied by k_c students having class, the higher the utilization rate is, and the optimization objective is:

$$\max(f_4) = \sum (k_c / r_r) . \tag{8}$$

Among said objective function, there are problems, including more optimization objectives, unclear final optimization scheme non-optimal scheme when the multi-objective functions are utilized for optimization. Problems about different magnitudes of objective values, and weight is combined for traditional scheme, but the weight selection requires prior knowledge; during actual optimization process, the magnitudes of objectives change real-timely and thus it is obvious that the fixed weight is improper; for this reason, the following self-adaption weight form is proposed:

$$f = \max\left(\sum_{m=1}^{4} \frac{f_m - f_m^{\min}}{f_m^{\max} - f_m^{\min}} \right) . \tag{9}$$

Where, f_m is current individual adaption value of m generation of population, $f_m^{\max}$ the maximum adaption value of such population and $f_m^{\min}$ the minimum adaption value of such population; such means is used to achieve the weight self-adaption and improve the search accuracy.

3. Improved particle swarm optimization algorithm based on factor auto-scaling

3.1. Basic particle swarm optimization algorithm

In computation of by PSO algorithm, the particle swarm is initialized at random as a set of random candidate solution to get the optimal solution through the evolution process. During the solving by PSO algorithm, each particle tracks two particles with extreme values to update its foraging position. These two particles with extreme value are respectively current optimal solutions *pbest* in PSO algorithm population and the historical optimal value *gbest* of current particle itself; specific model of PSO algorithm is as follows [14∼15]:

It is assumed that real-time position of evolution of particle i in PSO algorithm is X_i=(X_{i1}, X_{i2}, ..., X_{in}); the real-time value of velocity of particle i in PSO algorithm is V_i=(V_{i1}, V_{i2}, ..., V_{in}); the optimal position of particle i in PSO algorithm during historical evolution process is $P_i(t)$=(P_{i1}, P_{i2}, ..., P_{in}), that is the optimal position of particle i in PSO algorithm and also the optimal position of particle individual. For the minimization solving model, it shows, the smaller the objective, the better the position represented by the particle is. Then the optimal particle position in current PSO algorithm is $P_g(t)$=(P_{g1}, P_{g2}, ..., P_{gn}), which is also called the global optimal adaptive value (position) of PSO algorithm population. Then, the attainable standard particle swarm evolution model is:

$$\begin{aligned} &V_{ij}\left(t+1\right) = V_{ij}\left(t\right) + c_1 r_{1j}\left(t\right) \\ &\left(P_{ij}\left(t\right) - X_{ij}\left(t\right) + c_2 r_{2j}\left(t\right)\left(P_{gj}\left(t\right) - X_{ij}\left(t\right)\right).\end{aligned} \tag{10}$$

$$Xij(t+1) = Xij(t) + Vij(t+1)\,. \tag{11}$$

Where, suffix "j" of the parameter represents particle with dimension of j in the particle swarm, and similarly, suffix t is the algebra of particle swarm evolution, "i'' is particle i in the particle swarm, and c_1 and c_2 are the acceleration constants of swarm optimization algorithm, with value interval of 0-2. Random functions $r_1 \sim \bigcup(0,1)$ and $r_2 \sim \bigcup(0,1)$ satisfy the mutual independence.

Based on the particle evolution model shown in Equation (5) and Equation (6), there are two parameters of c_1 and c_2 in the model, of which the first one is used to adjust the evolutionary direction of particle in the algorithm to enable it to always evolve towards the direction of its optimal position; the latter is also used to adjust the evolutionary direction of particle in the algorithm to enable it to always evolve towards the global optimal direction. In order to avoid particle in PSO algorithm away from the value interval during evolution, in general, the value interval of V_{ij} is set, that is, set interval $V_{ij} \in [-V_{\max}, V_{\max}]$. If the value interval of physical education combination problem is $[-V_{\max}, V_{\max}]$, $V_{max} = k \cdot X_{max}$ can be got, where $0.1 \le k \le 1.0$. Therefore, PSO algorithm may be initialized as per the following steps:

Step 1: group size parameter for setting particle swarm optimization process is N;

Step 2: for particles with suffix of i and j in the population, utilize uniform distribution function within the interval of $[-X_{\max}, X_{\max}]$ to select the population individual x_{ij};

Step 3: for particles with suffix of i and j in the population, utilize uniform distribution function within the interval of $[-X_{\max}, X_{\max}]$ to select the population individual y_{ij};

Step 4: for particles with suffix of i in the population, establish the relationship $y_i = x_i$.

Computation process of standard particle swarm optimization algorithm is:

Step 1: according to initialization process of said particle swarm optimization algorithm, initialize the velocity and position information about the particle swarm optimization algorithm.

Step 2: carry out adaptive value computation for all particles in the particle swarm optimization algorithm;

Step 3: for all particles in the particle swarm optimization algorithm, compare all historical optimal position P_i and current adaptive value; if adaptive value of current position is better, it will be taken as the optimal position of current particle;

Step 4: for all particles in the particle swarm optimization algorithm, compare all global optimal position P_g and current adaptive value; if adaptive value of current position is better, it will be taken as the optimal position of current particle;

Step 5: according to the evolution model of standard particle swarm optimization algorithm, update the position of particle swarm optimization algorithm and the velocity model;

Step 6: if the evolutionary process of particle swarm optimization algorithm fails to meet the preset termination conditions, jump to Step 2 to proceed with the algorithm evolution.

3.2. Factor auto-scaling improvement

Main problem of particle swarm optimization algorithm during convergence is premature convergence, and in order to effectively avoid such premature problem, factor auto-scaling process of particle swarm optimization algorithm is introduced here; factor diffusion and attraction are to present more diversified characteristics of the particle swarm individual and achieve better convergence rate. The improvement velocity evolution model of proposed factor auto-scaling particle swarm optimization algorithm is as follows:

$$\begin{aligned} V_i\left(t+1\right) = &\chi(V_i\left(t\right) + dir(c_1 r_1 (P_i - X_i\left(t\right) \\ &+ c_2 r_2 (P_g - X_i\left(t\right)))) \,. \end{aligned} \tag{12}$$

Where:

$$dir = \begin{cases} -1, if(dir > 0)\&(diversity < d_{low}) \\ \ \ 1, if(dir < 0)\&(diversity > d_{high}) \end{cases} \tag{13}$$

In the meantime, given model form to keep the population diversification is:

$$diversity(S) = \frac{1}{|S| \cdot |L|} \cdot \sum_{i=1}^{|S|} \sqrt{\sum_{j=1}^{N} (Pij - \overline{Pj})^2} \,. \tag{14}$$

Where, S is a population in the particle swarm optimization algorithm for evolution, $|S|$ the individual quantity of such evolutionary population, $|L|$ the maximum interval radius of search interval in the particle swarm, N the dimension of particle swarm evolution process, and P_{ij} the component of particle i. During the evolution of particle swarm optimization algorithm, if the diversification of population individual meets the condition $diversity(S) < d_{low}$, it is allowed to set dir=-1 and then the evolution of particle swarm population terminates and it will gradually run towards the direction away from this position, which is called the "diffusion" process; in the meantime, if the diversification of population individual in the particle swarm increases and exceeds it upper limit, then it is allowed to set dir=1, and then the particle swarm population runs towards the direction of optimal position, which is called the "attraction" process. Simultaneously, the d_{low} value is set 5.0×10^{-6} and d_{high} parameter value is 0.25, then:

$$\chi = \frac{2}{|2 - \ell - \sqrt{\ell^2 - 4\ell}|} \,. \tag{15}$$

Where, parameter $\ell = c_1 + c_2$ and $\ell > 4$, and parameter is set $c_1 = c_2 = 2.05$; $\ell = c_1 + c_2 = 4.1$ is substituted into Equation (15) to obtain the model result $\chi = 0.7298$ which is substituted into Equation (16) to obtain:

$$\begin{aligned} &V_i\,(t+1) = 0.7298(V_i\,(t) + \\ &dir(2.05r_1(P_i - X_i\,(t) + 2.05r_2(P_g - X_i\,(t)))) \,. \end{aligned} \tag{16}$$

Due to $2.05 \times 0.7298 = 1.4962$, it is attainable that parameter $c_1 = c_2 = 1.4962$ used in the velocity update model during the process of such model and standard PSO algorithm evolution and the model obtained from $W = 0.7298$ are equivalent.

4. Experimental analysis

Physical course schedule in certain domestic university is taken as the experimental subject for experimental verification of subject, and its physical course scheduling elements are shown in Table 1.

Table 1. Physical course scheduling elements

Element	Student	Teacher	Class	Course	Ground	Assignment
Quantity	6200	387	125	669	168	669

Standard PSO algorithm is selected as the comparing algorithm in experiment, and objective function value and evolution time are selected as the valuation indices. The experiment is carried out for 20 times, with evolution algebra at the interval of 100 times to check and obtain optimal individual adaption value of current population. Fig. 1 shows the mean value convergence curve of optimal individual adaption value recorded; similarly, the algorithm operation time is also compared in the same manner as said one, and the simulation result is shown in Fig. 2. Some physical course scheduling results are shown in Fig. 3.

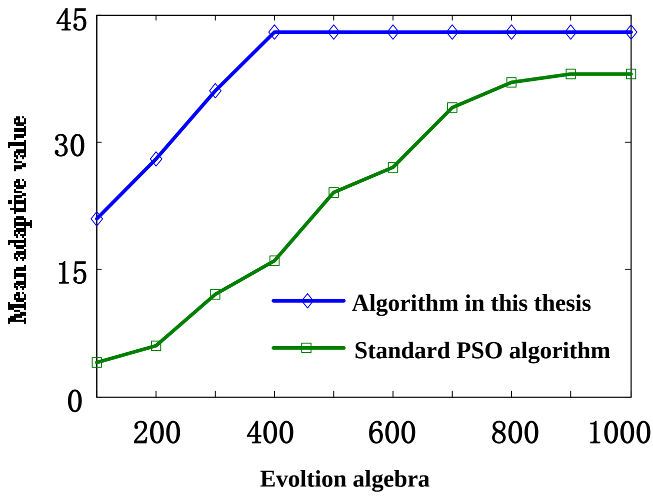

Fig. 1. Convergence curve for mean value of adaptive value

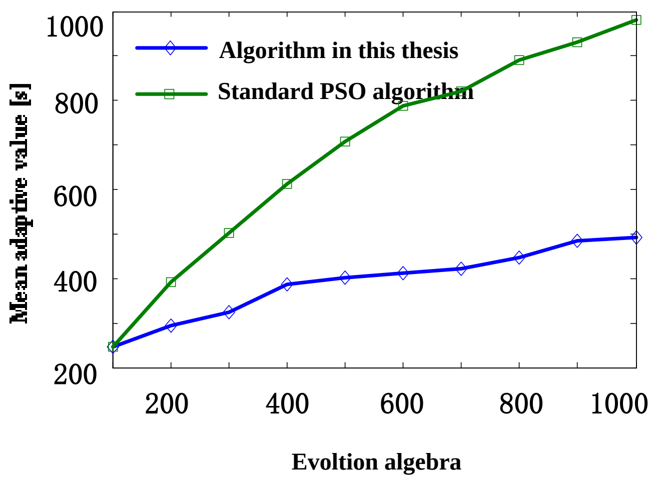

Fig. 2. Convergence curve for mean evolution time

Fig. 1 shows the convergence curve for mean value of algorithm in this thesis and PSO algorithm, indicating that convergence velocity of algorithm in this thesis is faster than that of PSO algorithm and its convergence accuracy is also higher than the latter. Fig. 2 shows the comparison of operation times of algorithm in this thesis and PSO algorithm in the physical course scheduling system, indicating the use consumed by the algorithm in this thesis is obviously less than that of PSO algorithm. Table 2 shows the comparison of physical course scheduling effects.

Table 2. Comparison of physical course scheduling effect

Method	Weekly school days of major course	Class interval of the same course	Mean Daily number of classes
PSO	2.3	1.3	6.3
This thesis	2.7	1, 5	4.8
(%) Ground utilization (%)	Number of omitted course	Teacher's satisfaction degree	Conflict rate of physical course scheduling (%)
89.5	18	86.4	16.3
99.3	0	99.5	1.2

Table 2 shows the comparison of physical course scheduling effects of the algorithm in this thesis and PSO algorithm and indicates the ground resource utilization, class omission quantity, ground satisfaction degree, conflict rate of physical course scheduling and such obvious indices of the algorithm in this thesis are superior to those of PSO algorithm, reflecting the effectiveness of algorithm in this thesis in the application of physical course scheduling system.

The optimal computation results of selected three comparison methods are shown in Table 2.

Table 3. Optimal solutions of the algorithms

Algorithm	GA	PSO	IAFS
1	0.165	0.155	0.161
2	0.123	0.144	0.140
3	0.052	0.142	0.131
4	0.065	0.039	0.049
5	0.121	0.143	0.098
6	0.194	0.027	0.062
7	0.007	0.117	0.122
8	0.065	0.031	0.046
9	0.140	0.011	0.017
10	0.060	0.184	0.169
Optimal solution	-0.241	-0.273	-0.293

Results shown in Table 3 indicate that, for the same setting constraint, the algorithm in this thesis has relatively better physical education yield, the physical education scheme is more reasonable and the satisfaction degree of physical educator increases. Said experimental results show the algorithm in this thesis is efficient for the solving process of combined analysis model of physical education, and is of more excellent performance.

In order to further verify the combined analysis performance of physical education in the algorithm, the yield indicator is elected to compare with the algorithm performance. The comparison of yield indicators in selected three comparing algorithms is shown in Table 3.

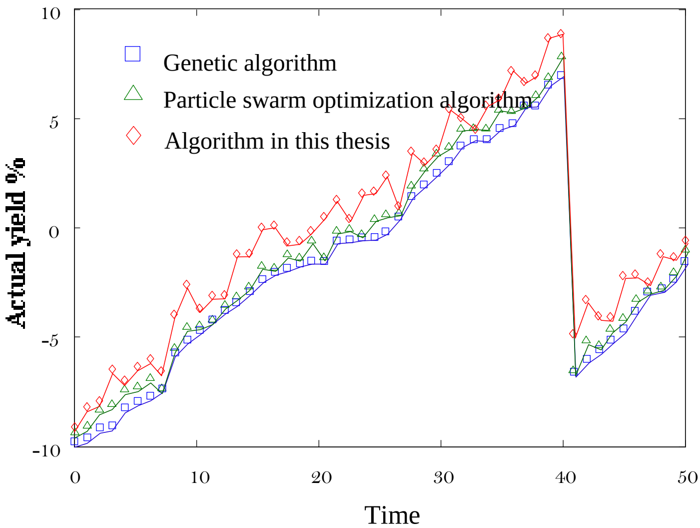

Fig. 3. Comparison of yield indicators on physical education

The results shown in Fig. 3 indicate that the yield indicator computed from the combined scheme of physical education through the algorithm in this thesis, compared with GA and PSO comparing algorithms, is of more excellent performance. 25 days later, the computation result of yield indicator of algorithm in this thesis is positive. The experimental results show, for physical education, if the yield maximization is taken as an objective, the time of physical education should be selected more than 25 days.

5. Conclusion

An effect analysis method for physical education strategy based on improved particle swarm optimization algorithm of factor auto-scaling is proposed in this thesis. The optimized mathematical model of physical education yield is established and its multi-objective weight self-adaption form is also given; particle swarm optimization algorithm is introduced to solve by means of its effect model of physical education strategy; factor auto-scaling is utilized to carry out self-adaption learning of related parameters of PSO algorithm, in order to improve the algorithm convergence; finally, example analysis is carried out to verify the effectiveness of proposed effect analysis algorithm of physical education strategy.

References

[1] L. R. Stephygraph, N. Arunkumar: *Brain-actuated wireless mobile robot control through an adaptive human-machine interface* Advances in Intelligent Systems and Computing, *397* (2016), 537–549.

[2] L. R. Stephygraph, N. Arunkumar, V. Venkatraman: *Wireless mobile robot control through human machine interface using brain signals* 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials, ICSTM 2015 - Proceedings, art. (2015), No. 7225484, 596–603.

[3] N. Arunkumar, V. Venkataraman, Thivyashree, Lavanya: *A moving window approximate entropy based neural network for detecting the onset of epileptic seizures*, International Journal of Applied Engineering Research, *8* (2013), No. 15, 1841–1847.

[4] N. Arunkumar, K. Ramkumar, S. Hema, A. Nithya, P. Prakash, V. Kirthika: *Fuzzy Lyapunov exponent based onset detection of the epileptic seizures* 2013 IEEE Conference on Information and Communication Technologies, ICT 2013, art. (2013), No. 6558185, 701–706.

[5] M. P. Malarkodi, N. Arunkumar, V. Venkataraman: *Gabor wavelet based approach for face recognition* International Journal of Applied Engineering Research, *8* (2013), No. 15, 1831–1840.

[6] N. Arunkumar, S. Jayalalitha, S. Dinesh, A. Venugopal, D. Sekar: *Sample entropy based ayurvedic pulse diagnosis for diabetics* IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012, art. (2012), No. 6215973, 61–62.

[7] N. Arunkumar, V. S. Balaji, S. Ramesh, S. Natarajan, V. R. Likhita, S. Sundari: *Automatic detection of epileptic seizures using independent component analysis algorithm* IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012, art. (2012), No. 6215903, 542–544.

[8] N. Arunkumar: Mohamed Sirajudeen, K.M. *Approximate Entropy based ayurvedic pulse diagnosis for diabetics - A case study*, TISC 2011 - Proceedings of the 3rd International Conference on Trendz in Information Sciences and Computing, art. (2011), No. 6169099, 133–135.

[9] W. S. Pan, S. Z. Chen, Z. Y. Feng.: *Investigating the Collaborative Intention and Semantic Structure among Co-occurring Tags using Graph Theory.* International Enterprise Distributed Object Computing Conference, IEEE, Beijing, (2012), 190–195.

[10] J. W. Chan, Y. Y. Zhang, and K. E. Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, *26* (2015), No. 7, 1359–1369.

[11] Y. Y. Zhang, E. Mintzer, and K. E. Uhrich: *Synthesis and Characterization of PEGylated Bolaamphiphiles with Enhanced Retention in Liposomes*, Journal of Colloid and Interface Science, *482* (2016), 19–26.

[12] J. J. Faig, A. Moretti, L. B. Joseph, Y. Y. Zhang, M. J. Nova, K. Smith, and K. E. Uhrich: *Biodegradable Kojic Acid-Based Polymers: Controlled Delivery of Bioactives for Melanogenesis Inhibition*, Biomacromolecules, *18* (2017), No. 2, 363–373.

[13] Z. Lv, A. Halawani, S. Feng, H. Li, & S.U. Réhman: *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), *11* (2014), No. 1s, 10.

[14] Y. Z. Chen, F. J. Tang, Y. Bao, Y. Tang, G. D. Chen: *A Fe-C coated long period fiber grating sensor for corrosion induced mass loss measurement.* Optics letters, *41* (2016), 2306–2309.

Received May 7, 2017