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Research Article

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Storage planning of automated pharmacy based on an improved adaptive chaotic particle swarm optimization algorithm

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ABSTRACT

With the target of achieving dense storage of packed medicine of rapid dispensing system in automated pharmacy, an improved adaptive chaotic particle swarm optimization (IACPSO) algorithm was proposed to solve the storage planning problem. According to the proposed IACPSO algorithm, the diversity of the particle swarm was enhanced by using the ergodicity of the chaos motion to initialize the swarm; a part of particles were chosen on the basis of their fitness value and optimized by chaos optimization algorithm to help the inert ones jump out the local extremum region at each iteration; the capability of global and local search was improved by introducing an adaptive inertia weight factor for each particle to adjust its inertia weight factor adaptively in response to its fitness. The IACPSO algorithm was used to solve mathematical model. Simulation results showed that this algorithm got rid of the shortcomings that the Particle Swarm Optimization (PSO) was easy to fall into of the local extreme point, while kept the rapidity in early search. The algorithm improved the efficiency of intelligent storage system, and implemented intensive storage.

Key words: improved adaptive chaotic particle swarm optimization algorithm; automation pharmacy; storage planning ; rapid dispensing system

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INTRODUCTION

The efficiency of Rapid dispensing system of automatic pharmacy mainly depended on the allocation strategy of the reservoir area and storage spaces. Currently, scholars in many countries have made a lot of achievements of the storage planning. J.P van den Berg and W.H.M Zijm classified the methods of allocation of storage spaces in the reservoir area into three main ways: class-based storage, randomized storage and dedicated storage [1]. Byung Chun Park et al. divided the storage spaces into two storage zones: high turnover and the low turnover, and the high turnover items are stored in the region closer to the I/O (input/output) point while the low turnover items are stored in the more distant region [2]. S Hsieh and K.C Tsai proposed a BOM oriented class-based storage assignment method [3]. A method applying turnover rate and classification in a random environment to allocate storage was presented in 1998 [4] . In 1997, a cycle-time computation and dedicated storage assignment method was proposed [5]. A genetic algorithm with a new crossover operator is developed to solve the allocation problem of the automated warehouse replenishment in 2001 [6]. V.R Muppani and G.K Adil constructed a nonlinear integer programming model by considering the minimization of AS / RS storage space and the least expensive of picking and solved the model by using the branch and bound method ,and also studied the re-allocating storage [7]; J.J Bartholdi and L.K Platzman proposed two heuristic algorithms for chosen path of rotating shelves [8], and both the heuristic algorithm could optimize chosen path of rotating shelves, however, they did no solve space allocation problem of fixed shelves by heuristic algorithm. Liu Sainan et al. adopted genetic algorithm based on Pareto optimal solution to solve the scheduling policy of storage [9]. To solve the problem of storage/retrieval frequently and dynamic change storage locations, a multi-objective mathematical model was formulated for storage spaces assignment of the fixed rack system, and an improved GA (Genetic Algorithms) with Pareto optimization and Niche Technology was developed

[10]. X Zhao et al. studied the irregular storage problem of automated pharmacy, and put forward to a multi-objective reservoir allocation model to improve the storage efficiency and space utilization, and presented a two-level genetic algorithm to solve the above problem [11]. All the above researches laid theoretical foundations of our projects, however, the above methods with the traditional models could not describe the rationalized allocation of medicine storage in warehousing system better, and moreover, though the genetic algorithm achieved fruitful results of solving combinatorial optimization problems, due to the slow convergence speed and being easy to fall into local optimum of the genetic algorithm, it was urgent to explore new ways to solve optimization problems of storage spaces in automated warehouse system.

In the existing logistics environment, storage planning needed to consider many principles, such as shelves carrying, turnaround speed, reliability, efficiency, and relativity of products etc. In this paper, the multi-objective optimization model of dense storage was established to improve the access efficiency of cargo and the utilization of storage space according to optimization target, ways and principles of storage together with actual operating conditions in automated pharmacy system. Therefore, the optimization of storage spaces in logistics and warehousing system was a multi-objective optimization problem (MOP), and currently, the intelligent optimization algorithms were the most widely used to solve this problem, in which the Particle Swarm Optimization (PSO) algorithm was a simple and effective one. The PSO algorithm came from the study on the feeding behavior of birds, which was first proposed by Kenney and Eberhart in 1995 [12]. Particle swarm optimization has been widely used for it had following features that its concept was simple, its algorithm was easy to implement and its optimization function was not strictly. However, due to the lack of population diversity, PSO was prone to emerge premature convergence. Chaos is a common phenomenon in nonlinear systems, and it has some specific properties. The chaotic motion can traverse all the states by their own non-repetitively within a certain range, and the extremely weak changes of the initial values will cause great change of system behavior. Based on the above two points, by using the combination of the chaos and particle swarm optimization [13], an improved adaptive chaotic particle swarm algorithm was proposed to solve the multi-objective optimization model of dense storage, and the effectiveness and feasibility of the proposed algorithm were verified through the actual data of the rapid dispensing system.

THE MATHEMATICS MODEL OF STORAGE SPACES

Before establishing the optimization model of storage spaces, some constants and variables essential to build models needed to be defined in advance. For convenience, the following assumptions were made: □ Storage storeroom had m layers and n columns, and the column nearest medicine-output exit was recorded as the first column, the lowest level as the first layer, the storage spaces in Layer a and Column b as (b,a), $(a=1,2,\ldots,m;b=1,2,\ldots,n)$, and the location of the storage port was noted as (0,0). When encoding each storage space, the space which was located in Layer a and Column b was encoded as $(a-1)n+b$. The coding of storage spaces were arranged from small to large, and formed a one-dimensional array. If there was cargo in the storage space, then the corresponding element in the array was denoted by 1; if not, then as 0;□ The length of each storage space was same, but width and height were different. The height of the same storage layer was same. □ The total weight of the storage goods on the shelf did not exceed bearing capacity of the shelf. □The storage area can store s kinds of medicines, and each storage space can only store one kind medicine. □Medicine storage time was ignored.

In order to make the medicines easier to find, the similar medicines in appearance were put together or in adjacent spaces. Certain types of medicines were placed in corresponding position according to their loading/unloading frequencies, and thus we could define a central coordinate of the storage spaces of such medicines and could put the medicines on the closer position away from the center coordinate. The storage method could set different specifications of storage spaces according to the dimensions of the medicines to maximize the use of spaces and to contribute to the picking operations and adjustment operations of inventory, which facilitated searching of medicines, saving time and improving the working efficiency.

According to the above strategy, model of storage location was established as follows:

$$\min F=\sum_{i=1}^{l}\sum_{j=1,i\neq j}^{s} f_j(h_i-h_j)x_{ij} \qquad (1)$$

s.t.

$$h_j\in\{\min h_i,\max h_i\} \qquad (2)$$

$$x_{ij}\in\{0,1\};\sum_{i=1}^{l}x_{ij}=1,\ j=1,2,\ldots,s\,;\sum_{j=1}^{s}x_{ij}=1, i=1,2,\ldots,l \qquad (3)$$

Where, f_j was the frequency of the medicines of the kind j ; h_i was the height of the layer i in the storage area; h_j was the height of the medicines of the kind j ; l was the number of layers whose height were h_i . x_{ij} was the decision variable. When $x_{ij} = 1$, it expressed that the medicines of kind i were put in layer j ; $x_{ij} = 0$ expressed that the medicines of kind i were not in layer j .

Equation (1) indicated that the smaller the difference in height of the reservoir area and the kit was, the more intensive medicines were placed. Constraint formula (2) expressed that the total height of the reservoir layers was not allowed to exceed the height of the effective storage. Constraint formula (3) showed that when determining the height of the reservoir layers, all medicines meeting the requirements of the layer height should be placed in this area; a storage area stored one height range of medicines, a height range of medicines into one district can not be placed in other districts, and after being placed medicines within a certain height, a district should not be put into other height range of medicine.

THE STORAGE PLANNING BASED ON THE PROPOSED IACPSO ALGORITHM

Intelligent optimization algorithm was a calculate method that was developed by using the various principles and mechanisms of natural phenomena or organism and had the adaptive capacity of the environment. Currently intelligent optimization algorithms were mainly used to solve the multi-objective optimization problem, and the PSO algorithm was a simple and effective one among them.The PSO algorithm simulates social group behavior, searches for the optimal solutions through collaboration between individuals, and updates the velocities and positions of particles by counting the optimal values found by each particle itself and the groups in iterative process. In particle swarm optimization algorithm for storage spaces allocation, consider two different store ways as a group of replacement, i.e. the difference between the two particles. Take X as a way to store items, i.e. the position of particle; and take V as two different ways of storing replacement, namely the speed of the particle. Use the total number of storage spaces as the search space dimension of PSO. Set V_1 and V_2 as the replacement set of items in two different storage methods, and then the sum of V_1 and V_2 was $V_1 \oplus V_2$. In accordance with the above method of calculating velocity change for the position difference, and taking $m \times n$, the total of the storage locations, as search space dimension of particle swarm , the speed of iterative equation was obtained :

$$v_{id}^{k+1} = w \times v_{id}^{k} \oplus c_1 \times r_1 \times \left(p_{id}^{k} - x_{id}^{k} \right) \oplus c_2 \times r_2 \times \left(g_{gd}^{k} - x_{id}^{k} \right) \qquad (4)$$

The sum of the position X and the velocity V was referred to as $X \oplus V$, which indicated that the replacement of V was applied to the position X , i.e. the storage space required replacing was applied to such a storage way of X , and the result remains a storage method. The iterative equation of optimization problem of storage location based on particle swarm algorithm was:

$$x_{id}^{k+1} = x_{id}^{k} \oplus \lambda \times v_{id}^{k+1} \qquad (5)$$

Where, v^k was the velocity vector of the particles; x^k was the current location of the particles; p^k was the position of the optimal solution found by the particle itself; g^k was the location of the optimal solution found by the entire population; r_1 and r_2 were pseudo-random numbers from 0 to 1; w was inertia weight; c_1 and c_2 were acceleration constants; k was iterative number; λ was constraint factor of the particles.

Speed iteration of conventional particle swarm algorithm had four factors: ω, $c1$, $c2$ and $rand()$. In the optimization problem of storage allocation, the speed was used to exchange store states of a corresponding storage spaces in the two storage methods, and $\left(p_{id}^{k} - x_{id}^{k} \right)$ expressed the replacement of the best storage itself and the current storage, $\left(g_{gd}^{k} - x_{id}^{k} \right)$ expressed the replacement of the best storage way of the whole group and the current storage. In conventional particle swarm algorithm, the four factors were real numbers, however, it was difficult to determine the meaning of the product of a real number and a replacement, therefore, in conventional algorithm the factors were taken as 1. In the calculation of the above formula, $w \times v_{id}^{k}$, $c_1 \times r_1 \times \left(p_{id}^{k} - x_{id}^{k} \right)$ and

$c_2 \times r_2 \times \left(g_{gd}^k - x_{id}^k\right)$ all represented a set of some replacements.

The particle swarm optimization based on the scheduling problem was to solve full array problem, but the actual goods storage did not guarantee each storage needing access operation, therefore, the following treatments were needed in the storage replacement: comparison and record the storage difference between the current population respectively and g_{gd}^k, the globally optimal individuals and p_{id}^k, the current local optimal individuals, and if the storage state of some individual changed from in storage into idle, X was recorded as 0, conversely, as 1.

In the optimization strategy of medicine storage in this paper, the shelves storing medicines were divided into a number of areas, and the types and the frequencies of medicines were different in different partitions. To ensure that the medicines would not be stored in other area after replacement, the replacement in each library performed separately, and two storage states of different storage spaces could not be replaced.

Due to the characteristic of PSO algorithm that it was easy to fall into local minimum and its convergence speed was slow in late evolutionary, the original algorithm needed improving in the practical application. From equation (6), the values of w, the inertia weight, have important influence on the convergence of the algorithm [14]. If a larger value was conducive to escape from local optima, while a smaller value of w would help speed up the algorithm convergence. In order to overcome the deficiencies of fixed parameters of the standard PSO, the inertia weight method based on adaptive adjustment of population was used, which was shown in (6).

$$w = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min})(f - f_{\min})}{f_{avg} - f_{\min}}, f \le f_{avg} \\ w_{\max}, f \ge f_{avg} \end{cases} \qquad (6)$$

Where, $w_{\max}$ and $w_{\min}$ respectively were the maximum and minimum of w; f was the objective function of the particle; f_{avg} and $f_{\min}$ respectively were the current average of all the particles target value and the minimum target value.

To solve the problem that PSO method was easy to precocious, chaos algorithm and particle swarm optimization algorithm were combined. Firstly, the diversity of the particle swarm was enhanced by using the ergodicity of the chaos motion to initialize the swarm. Secondly, when the particles fell into premature convergence, chaotic disturbance was used to escape from local optima and to quickly find the optimal solution, which could improve the accuracy and the convergence speed of the solutions. In the chaotic particle swarm algorithm in this article, the Logistic map was selected to generate chaotic variable as shown in the formula (7).

$$z_{j,k+1} = \mu z_{j,k}(1 - z_{j,k}), k = 0,1,2,...,0 \le z_{j,0} \le 1 \qquad (7)$$

Where, k was the current iteration; $z_{j,k}$ and $z_{j,k+1}$ were the chaotic variables among [-1,1]; μ was the control variable， when $\mu = 4,\ z_0 \notin \{0,0.25,0.5,0.75\}$, Logistic was in a chaotic state.

$$x_j = x_j^* + \eta_j z_{j,k} \qquad (8)$$

Where, x_j^* was the current optimal solution; η_j was the adjustment coefficient .

In the early search stage, we hoped the variables change greatly to jump out of local optimum, therefore, the value of η_j should take greater; and as the search for variables was close to the optimal value, the value of η_j should be gradually reduced. In the paper, the value of η_j changed adaptively according to equation (9).

$$\eta_j = \gamma\left[(k_{\max} - k + 1)/k_{\max}\right]^2 x_j^* \qquad (9)$$

Where, γ was the neighborhood radius，$\gamma = 0.1$；$k_{\max}$ was the maximum number of iterations of the algorithm.

As previously mentioned, the steps of chaos particle swarm optimization algorithm based on the strategy of adaptive parameter were as follows:

1) Initialize the position and velocity of each particle in the chaos motion ;
2) Evaluate the fitness of each particle, and save the values of g^k, the global best position, and p^k, the personal best position;
3) Update the speed and position of each particle by formula (4) and (5), and update the inertia weight by the formula (6) ;
4) Calculate the objective function value of each particle, and then retain the particles whose performance were the best in the group ;
5) Execute chaotic local search on the optimal particles according to formula (7) to (9), and update p^k and g^k ;
6) If the stopping condition was met, the search stopped, then output the results, otherwise go to step 2);

RESULTS AND DISCUSSION

The above optimization algorithm of storage allocation delivery system was used for a large hospital in china. In order to ensure the loading/unloading of medicines smoothly, the clearances between the medicine storage tank and kits must be kept within certain limits. The rational allocation of medicine storage grooves could not only improve the medicine storage efficiency, but also convenient processing and installation to improve system reliability.

The shelves of rapid dispensing system were fixed shelves with 15 layers, 43 columns, and the total number of storage was 645. Because the medicines were relatively light, and the design of shelf completely satisfied the bearing requirement, the storage load problem was not to consider. The storage numbers and average demand frequencies of the four categories of goods in A, B, C, D were shown in Tab. 1.

Tab. 1 Classification information table of medicines

classification of medicines	Frequencies out of the library	number of storage spaces
A	38.29%	247
B	29.15%	188
C	17.67%	114
D	14.89%	96

The particle swarm optimization (PSO) algorithm, genetic algorithm（GA） and an improved adaptive chaotic particle swarm optimization(IACPSO) algorithm proposed in this paper were chosen by the contrast test. The particle number was all set to 50 and the iteration number was 200. The PSO parameters were set to: w=0.73, $c_1 = c_2$=2. The parameters of GA were set to: crossover probability was 0.9; mutation probability was 0.2; and the adaptive elimination of acceleration index was 2. In the IACPSO algorithm, encoding method used real value encoding. And the change of the optimal value using the PSO algorithm, GA algorithm and the IACPSO algorithm and the optimal path of medicine storage were respectively shown in Fig. 1 and Fig. 2 (taking the storage size as 30 for example). And the optimum, the iteration number achieving the optimum and the optimal time were listed in Tab. 2.

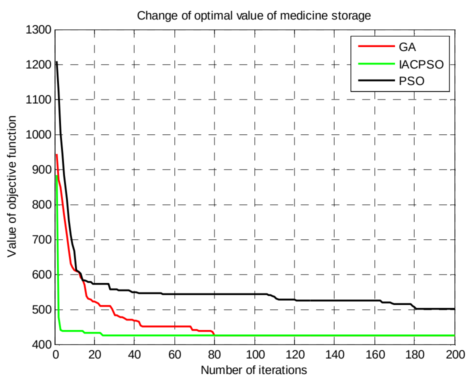
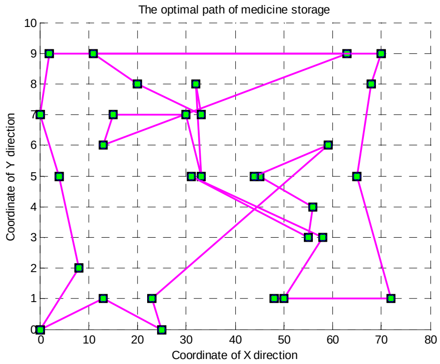
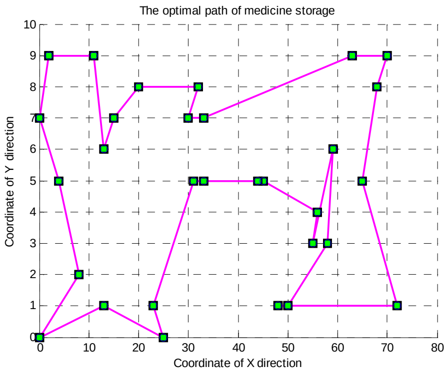


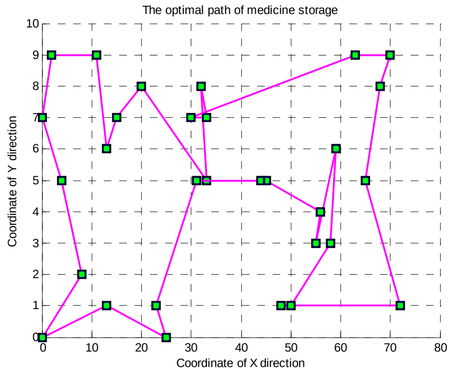
Fig. 1: Change of the optimal value of medicine storage of different algorithms



(a) Using the PSO algorithm



(b) Using the GA



(c) Using the IACPSO algorithm

Fig. 2: The optimal path of medicine storage

Tab. 2 Contrast of medicine storage optimization of different algorithms

algorithm	the optimum	iteration number	the optimal time(s)	optimal rate
GA	1.0e+003*5.4189	81	176	0
PSO	1.0e+003*5.2683	182	171	2.84%
IACPSO	1.0e+003*5.1162	25	166	5.68%

In the multi-objective storage optimization model, the objective function was to achieve the smallest running time. From the results of Fig. 1 and Fig. 2 and Tab. 2 of the three algorithms, we could find that the iteration number of the IACPSO algorithm adopted in this paper was the least, and that the permutation of storage position by this algorithm got rid of the shortcomings that the PSO algorithm was easy to fall into of the local extreme point. And the results also showed that the optimal time of the IACPSO algorithm was the smallest, and the optimal rate was higher than PSO. Therefore, the optimum result and searching performance of the IACPSO algorithm was better than that of GA and PSO. Experiments verified that the algorithm proposed in this paper significantly improved storage efficiency and had strong practical significance.

CONCLUSION

The improved adaptive chaotic particle swarm optimization algorithm proposed in the paper got rid of the shortcomings that the PSO was easy to fall into of the local extreme point, while it kept the rapidity in early search. The algorithm improved the efficiency of intelligent storage system, and implemented intensive storage. However, for the arrangement of medicine storage, if you want to satisfy multiple constraints, getting the real optimal solution is impossible. In this paper, the storage arrangement was sub-optimal solutions by adopting the proposed algorithm. And the parameters such as size, search space and speed of particle swarm population were set according to the reference literature, therefore, the rationality of the parameters setting needs further study.

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