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A Logistical Model Based on the Hamming Competitive Neural Network Algorithm

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Abstract: Based on the Internet of Things, the achieving of the dynamical information about the logistical network becomes a practical matter. With enough information utilizable, the deeply optimization of the logistical service is more possible. In this study, the static and dynamic information of the logistical network for goods dispatching is reformatted. Integrated with the particle swarm optimization algorithm, an optimization model utilizing the algorithm of the Hamming competitive neural network is proposed. In the logistical model, the particle swarm algorithm is used to implement the optimization to the logistical services based on the complex logistical network. In order to reduce the time cost of the particle swarm algorithm, the hamming neural network algorithm is put forward to involve the iteration procedure. Simulative experiments demonstrate that the proposed model can not only reduce the time cost of the optimization procedure but also is effective to achieve optimized service scheme.

Key words: Logistical model, hamming algorithm, neural network, particle swarm optimization

INTRODUCTION

With the development of the technologies of the Internet of Things and the logistical network, the information about more categories can be achieved and comprehensively utilized in an integrated information system (Ning and Wang, 2011; Mulligan, 2010). Supported by the superior available of the logistical network, the applications to the logistical services based on the technologies become one of the hot research spots (Grandinetti *et al*., 2012; Creazza *et al*., 2012). Based on the integrated logistical information (Amaya *et al*., 2010) describe a solution procedure for a capacitated arc routing problem with refill points and multiple loads. By presenting an integer formulation and a route first-cluster second heuristic procedure, the proposed model can simultaneously determine the vehicle routes that minimize the total cost of the two vehicles.

Utilizing the static and dynamic information of the logistical network, Perugia *et al*. (2011) put forward a solution to the home-to-work bus service in urban zone. In the solution, a model with a cluster routing algorithm is designed to scheme the routing and the bus stop location based on the real-time information achieved from the metropolitan transportation networks. By the search algorithm, the restrictions about efficiency, equity and effectiveness come to an equilibrium state.

In contrast to search feasible scheme utilizing the integrated logistical information, the exploring of the optimization solution is another key application in the research of the logistical service (Leiva *et al*., 2010; Iyoob and Kutanoglu, 2013). To the logistical service with multiple categories of elements involved, the design of the optimization algorithm is usually very complicated work due to the complexity of the logistical information (Miranda and Garrido, 2009; Pishvaee *et al*., 2010). In consideration of constrains relative to riding in the urban routing networks, a framework is put forward to achieve a set of Pareto-optimal feasible solution by Chang and Yen (2012). Utilizing the information about the urban routing network, the city-courier routing and scheduling problem is transferred into a multiple routing salesman problem with multiple objectives. In order to decrease the expenditures relative to school operations and student transportation, Mandujano *et al*. (2012) proposed an optimization scheme, in which a methodology with two mixed-integer programming models is used to reduce transportation costs by optimize the transportation of students and the location of the schools for the designated area. In order to meet the coordination requirements of a supply chain, Yildiz *et al*. (2010) proposed a modified mixed-integer programming methodology, by which the probability to reduce the cost of distribution is enhanced.

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By comprehensively analyzing the algorithm mentioned above, it is the common insufficiency that the time cost of the optimization procedure increases rapidly and unevenly with the dimension increasing of the logistical network. To solve the problem, an optimization model based on Hamming competitive neural network is put forward. In the proposed model, the goods dispatching requirement of the logistical service is formulated by the combination of preconditions. Then a input vector is reformulated by the combination of preconditions and taken as the input data to the modified particle swarm optimization algorithm with the Hamming competitive neural network algorithm involved. Simulative experiments indicate the proposed model is efficient and effective to the optimization of the logistical service.

DESCRIPTION TO THE STATIC AND DYNAMIC INFORMATION ABOUT THE LOGISTICAL NETWORK

To implement the logistical services, the goods ready to be delivered distributed in the service spots should be loaded and dispatched by proper transport utility and route selection. The service spots and the routes connected with the service spots consist of the backbone of the logistical network (Song and Dong, 2012). The set $S = (s_1, s_2, ..., s_n)$ represents the set of the service spots. Figure 1 represents a logistical network with eight service spots and ten routes. In the figure, S_1 denotes a service spots in the backbone of the logistical network and $\leftrightarrow$ expresses the route between two service spots. When a pack of goods is required to be dispatched from a service spot to another, a proper routes combination through which the pack of goods can be transported to the destination can be selected by certain approaches. For example, the routes combination for the pack of goods which should be dispatched from the service spot S_3 to the service spot S_6 can be $S_3 \rightarrow S_1 \rightarrow S_6$, $S_3 \rightarrow S_9 \rightarrow S_6$, or $S_3 \rightarrow S_5 \rightarrow S_4 \rightarrow S_8 \rightarrow S_6$ according to the selection strategies.

Correspondingly, the dynamic information of the logistical network consists of not only the back bone but also the goods distribution at the service spots and the real-time information of the transport utilities with goods at the designated time. In Fig. 2, the dynamic information of a certain time point is shown as an example of the running logistical network. In the figure, the denotations, S_4 connecting to S_1 describe a pack of goods waiting at a service spot S_1 and to be dispatched to the destination S_4. Accordingly, the denotation T_1, which is at the route between the service spot S_1 and S_2, represents a transport utility with or without goods moving from the service spot S_1 and S_2 by the route between them.

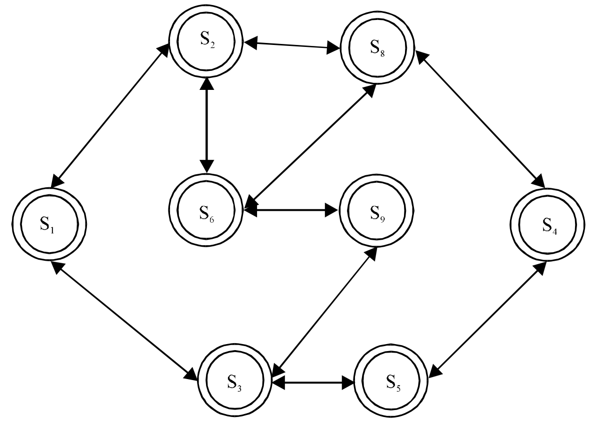

Fig. 1: Logistical network with eight service spots and ten routes

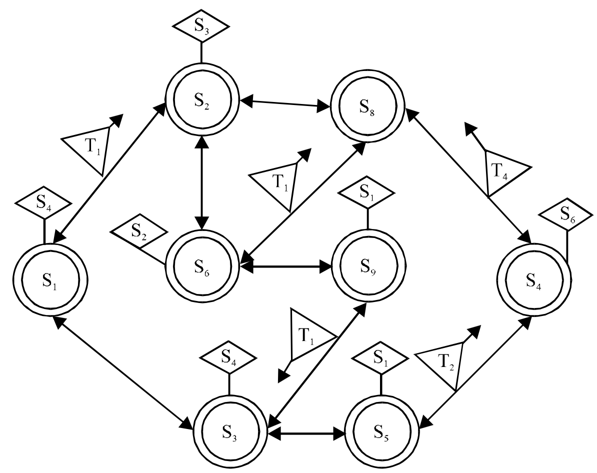

Fig. 2: Dynamic state of the logistical network at certain time point

CRUCIAL FACTORS ABOUT THE LOGISTICAL SERVICE OPTIMIZATION

The service spots take charge of the receiving and dispatching of the goods in the logistical network. In the two figures above, the basic information about the logistical service scheme designing is represented in detail.

In order to comfort to the requirement of the algorithm and service scheme designing, the packs of goods are expressed specially. In the proposed model, a pack of goods being dispatched from one service spot to another is expressed by three parameters. The first and second parameters are the service spot of departure and the service spot of destination, respectively. The Carrying Capacity Requirement (CCR) of the packs of goods is taken as the third parameter.

The CCR can be the unit of weight or bulk. For sake of expressing comprehensively, The CCR is put forward to describe the carrying capacity requirement of goods uniformly. As an integrated logistical network, the relationship among the service spots and the packs of goods being dispatched can be represented by a matrix as follows:

$$\begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1n} \\ l_{21} & l_{22} & \cdots & l_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & \cdots & l_{nn} \end{bmatrix}$$

In the matrix, l_{ij} denotes the CCR of goods which will be transfer from the service spot s_i to the service spot s_j. The matrix which is named as $[M_{ij}]_{n\times n}$ can integrated express the requirement of the goods being dispatched. For a designated period of time, the goods in the logistical network is determined and can be described by a set $G = (g_1, g_2, ..., g_s)$. Let G_j^i denote the subset of G which consists of packs of goods with the service spot of departure S_i and the service spot of destination S_j and ccr (g_i) is the CCR of the g_i, then l_{ij} can be represented as:

$$l_{ij} = \sum_{g_i \in G_j^i} ccr(g_i) \quad (1)$$

In order to implement the task of the goods dispatching, the states about the transport utilities are also key parameters. As the carrying capacity of all the transport utilities usable is constant, the location distribution and the goods on loading of the transport utilities will influence the designing of the proper scheme for the goods dispatching. Let the set $T = (t_1, t_2, ..., t_m)$ represent the available transport utility set of the logistical network. For the sake of meeting the information requirement of the transport utilities for the logistical service scheme designing, the vectors V_t and V_c are put forward to represent the location distribution and the goods on loading of the transport utilities:

$$V_t = [s^1, s^2, s^3, \ldots\ldots, s^m]$$

$$V_c = [l^1, l^2, l^3, \ldots\ldots, l^m]$$

In the vector V_t, the element s^i means the transport utility with the order number i is going to or at the service spot with the order number s^i. To meet the need of convenient denotation, s^i represents a order number of a service spot and i is the order number of the transport utility. If s^i is the order number the service spot s_j, then the value of the s^i is j. In the vector V_c, the element l^i means the CCR of the goods on loading of the transport utility with the order number i. To comprehensively represent the carrying capacity distribution of the logistical network, the information of the vectors V_t and V_c can be fused into the following vector:

$$V_f = [f_1, f_2, f_3, \ldots\ldots, f_n]$$

In the vector V_f, the element f_i represents the carrying capacity available at the service spot s_i during the designated time period, which is the comprehensive information of the transport utilities going to or at s_i and the CCR of goods on loading of the transport utilities.

Summarily, the matrix $[M_{ij}]_{n\times n}$ and the vector V_f are preconditions to the drawing up of the logistical service scheme. Consequently, the matrix and the vector can be taken as the crucial information to the logistical service optimization.

OPTIMIZATION MODEL TO THE LOGISTICAL SERVICE

Algorithm for the optimization of the logistical services: At a designated time point, given the real-time information of the logistical network, there are usually a great many feasible service schemes to accomplish the task of all goods dispatching. The optimization of the logistical service is the procedure of searching for the proper service scheme with cost expenditure as small as possible. The cost expenditure mainly depends on the moving distance and the per unit distance cost expenditure of every transport utility. To the service scheme designing, accomplishing all tasks of goods dispatching is a basic constraint. For the sake of representing the basic constraint, the following sequences are put forward to denote the CCR of the goods loading on and unloading from the transport utility t_i with time going on:

$$o(t_i^1), o(t_i^2), o(t_i^3), \ldots\ldots, o(t_i^{k-1}), o(t_i^k), \ldots\ldots$$

$$d(t_i^1), d(t_i^2), d(t_i^3), \ldots\ldots, d(t_i^{k-1}), d(t_i^k), \ldots\ldots$$

With the logistical network running on ceaselessly, the transport utility t_i loads and unloads the packs of goods and the sequences above are achieved in order. To conveniently describe the service scheme, every two elements of the two sequences with identical order number make up a pair. For example, $p(t_i^x) = (o(t_i^x), d(t_i^x))$ is pair to represent the CCR of goods loading on and unloading from the transport utility t_i at a certain service spot. For meaningfulness, the two elements of a pair should not be zero simultaneously. That one element of a pair is zero means either loading or unloading is taken place.

Based on the denotation above, the goods dispatching constraint can be represented as follows:

$$\sum_{p(t_i^j)\in s_x(p)} o(t_i^j) = relay_x + \sum_{y=1}^{n} l_{xy},\ x = 1, 2, ..., n \quad (2)$$

$$\sum_{p(t_i^j)\in s_x(p)} d(t_i^j) = relay_x + \sum_{k=1}^{n} l_{kx},\ x = 1, 2, ..., n \quad (3)$$

Let P denote the set of pairs which the transport utilities will generate in the designing service scheme. In the above equation, S_x (p) is the subset of P which consists of the pairs generated at the service spot S_x. The denotation $relay_x$ expresses the CCR of goods will be relayed by the service spot S_x. In other words, $relay_x$, the CCR of goods relayed from S_x is unloaded by some transport utilities and loaded by others to relay on. The relay of the goods plays a role in better utilization of the carrying capacity of the transport utilities. In order to simplify the description of the constraint, let Eq. 2 be subtracted by Eq. 3 and then:

$$\sum_{p(t_i^j)\in s_x(p)} o(t_i^j) - \sum_{p(t_i^j)\in s_x(p)} d(t_i^j) = \sum_{y=1}^{n} l_{xy} - \sum_{k=1}^{n} l_{kx},\ x = 1, 2, ..., n \quad (4)$$

The carrying capacity of every transport utility is another constraint when the packs of goods are unloaded and loaded at every service spot. The constraint can be represented as follows:

$$\sum_{j=1}^{u} (o(t_i^u) - d(t_i^u)) \le Cap(t_i),\ \forall u,\ p(t_i^u) \quad (5)$$

is a pair in the service scheme designing.

In the designed service scheme, every packet of goods is transferred by the relay of the transport utilities and moves from one service spot to another by in order. Consequently, the transport utility a pack of goods being loaded on and the packs of goods a transport utility loading on is probable to change. G (t_i, s_j) represents the set of the packs of goods being loaded on t_i when t_i leaves from s_j to another service spots and then the variation of the set of the packs of goods being loaded on t_i in a designed service scheme can be expressed by a sequence as follows:

$$Seq\ (t_i) = G\ (t_i, s_{j1}), G\ (t_i, s_{j2}), ..., G\ (t_i, s_{jd}),\ 1 \le i \le m,\ 1 \le j_y \le n$$

Accordingly, in the designed service scheme, a pack of goods g_a with the service spot of departure s_p and the service spot of s_q destination should be appeared in such a sequence as:

$$G\ (t_{i1}, s_{j1}), G\ (t_{i2}, s_{j2}), ..., G\ (t_{ic}, s_{jd}),\ 1 \le i_x \le m,\ 1 \le j_y \le n$$

Meanwhile:

$$p = j_1,\ q = j_d \quad (6)$$

Let Dis (s_i, s_j) represent the distance between the service spots s_i and s_j and then the cost expenditure only considering the sum distance of all transport utilities can be expressed as:

$$Scost = \sum_{i=1}^{m} \sum_{G(t_i, s_{jx})\in Seq(t_i)} Dis(s_{j_x}, s_{j_{x+1}}) \quad (7)$$

In the equation above, G (t_i, s_{jx})∈Seq (t_i) is the sequence of the sets of the packs of goods t_i being loaded on during the designed service scheme without the last element of the sequence.

From the representation of the constraints and the equation of the cost expenditure, the designing of the service scheme is related to complicated arithmetic and set operations. To accomplish the optimization by the proper service scheme selection, the Particle Swarm Optimization (PSO) algorithm is chosen. In the PSO algorithm, the selected service scheme is represented as the solution vector space (Selleri *et al*., 2006). By the overlapping generations from one feasible service scheme to other, the optimized scheme will be achieved. The following are equations for overlapping generations of a particle in the PSO algorithm:

$$\vec{v}_{p[i]}(t+1) = \vec{v}_{p[i]}(t) + c_1 r_1(t)(pbest_{p[i]}(t) - \vec{x}_{p[i]}(t)) + c_2 r_2(t)(gbest(t) - \vec{x}_{p[i]}(t)) \quad (8)$$

$$\vec{x}_{p[i]}(t+1) = \vec{v}_{p[i]}(t+1) + \vec{x}_{p[i]}(t) \quad (9)$$

In the equations, p [i] represents a particle. $\vec{x}_{p[i]}$ (t) is the feasible service scheme of current iteration. The denotation $\vec{x}_{p[i]}$ (t+1) is the feasible service scheme of the next iteration. $\vec{v}_{p[i]}$ (t) and $\vec{v}_{p[i]}$ (t+1) are the variation of the feasible service scheme of the last and the current overlapping generation. c_1 and c_2 are constant quantity and taken as the learning coefficients. r_1 and r_2 are random values in value zone (0, 1). In PSO algorithm, a group of particles are selected to walk in the feasible solutions. $pbest_{p[i]}$ (t) is the extremum point of the particle p[i] until the current iteration. Correspondingly, gbest(t) is the extemum point of the particle group until the current iteration.

From the description above, the iterations of the particles is random walking in feasible zone of the solution under the control of the pbest of the particle and the gbest of the particle group (Prado *et al*., 2010). As the calculation of cost expenditure and the constraints is related to the set operation in the service scheme of this study, the iteration formulas above are modified and the following iteration equations are created (Thakker *et al*., 2009):

$$\vec{v}_{p[i]}(t+1) = \varphi(\vec{v}_{p[i]}(t),\ pbest_{p[i]}(t),\ gbest(t)) \tag{10}$$

$$\vec{x}_{p[i]}(t+1) = \xi(\vec{v}_{p[i]}(t+1),\ \vec{x}_{p[i]}(t)) \tag{11}$$

In the above equations, $\vec{v}_{p[i]}$ (t) is a feasible service scheme vector space. φ ($\vec{v}_1$, $\vec{v}_2$, $\vec{v}_3$) is a function to achieve a service scheme (maybe infeasible) which is approximate to both $\vec{v}_2$ and $\vec{v}_3$ by the random modification of $\vec{v}_1$. The function ξ ($\vec{v}_1$, $\vec{v}_2$) is used to achieve a feasible service scheme in midway of transforming $\vec{v}_1$ to $\vec{v}_2$ by adjustment.

Optimization strategy based on the hamming neural network: The much more computation complexity of the cost expenditure, the constraints and the PSO algorithm with respect to the large scale of the logistical network makes the optimization of logistical service being a time consuming procedure. To enhance the real-time performance, another optimization strategy should be utilized.

With respect to the optimization procedure, the beginning of it is achieving feasible service scheme based on a matrix $[M_{ij}]_{n\times n}$ and a vector V_f and considering the constraints. In other words, an optimization feasible service scheme is corresponding to a combination of a matrix $[M_{ij}]_{n\times n}$ and a vector V_f as the preconditions. Usually, that the preconditions are similar means the optimization feasible service schemes are also approximate. Consequently, a designated logistical network will achieve a certain number of combinations of the preconditions at first. And meanwhile, the corresponding optimization feasible service schemes are also acquired. Then the later optimization procedure can be simplified to finding a combination of the precondition having been appeared formerly. Finally, the modified PSO can be started with the optimization feasible service scheme corresponding to the found combination. Owing to the similarity of the two combinations of preconditions, their optimization feasible service schemes are also approximate. As a result, the later optimization procedure is started directly at the point near to the optimization point with the modified PSO algorithm and the computation efficiency will be much enhanced.

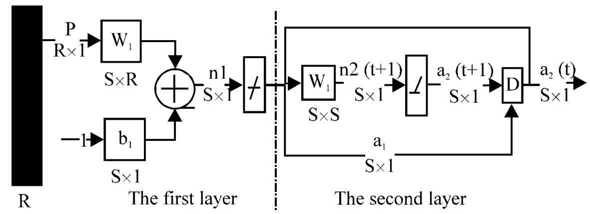

Fig. 3: Two layers competitive hamming neural network

In order to conform to the requirement of the similar combination selection, the Hamming neural network with competitive learning feature is employed. The Fig. 3 represents the construction of the Hamming competitive neural network. In order to improve the computation efficiency of the optimization procedure of logistical service described above, the two layers competitive neural network is put to use (Ghanavti and Shomalnasab, 2009). In the competitive network, the input is a vector. Consequently, the combination of the preconditions is reformulated to the following vector:

$$p = [l_{11}, l_{12}, ..., l_{1n}, l_{21}, l_{22}, ..., l_{2n}, l_{n1}, l_{n2}, ..., l_{nn}, f_1, f_2, f_3, ..., f]$$

The vector above consists of the elements of the horizontal vectors of matrix $[M_{ij}]_{n\times n}$ connected by order and the vector V_f being appended.

In the first layer of the competitive Hamming neural network, a combination of preconditions reformulated to a R dimensions vector (R = n×(n+1)) is taken as the input waiting for finding the most similar vector to achieve the optimization service scheme by further computation. The denotation W_1 is the weight matrix consisting of selected S number of R dimensions vectors which are corresponding to the combinations of preconditions having achieved the optimization service schemes. A selected R dimensions vector transposed becomes a horizontal vector of W_1 which becomes the prototype patterns (Guimaraes *et al*., 2006). The denotation b_1 is the bias vector which is set equal to the number of the elements of the input vector. Consequently, W_1 and b_1 can be represented as:

$$W_1 = \begin{bmatrix} w_1^T \\ w_2^T \\ \vdots \\ w_s^T \end{bmatrix} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_s \end{bmatrix} b_1 = \begin{bmatrix} R \\ R \\ \vdots \\ R \end{bmatrix}$$

Summarily, the output of the first layer a_1 can be expressed as the follows equation:

$$a_1 = \text{purelin}(W_1p+b_1) \tag{12}$$

The outputs of the first layer indicate the correlation between the prototype patterns and the input vector. In contrast, the second layer is the competitive layer in which the neurons are initialized with the outputs of the first layer. Then the neurons compete with each other to determine a winner. After the competition, only one neuron will have a nonzero output. The winning neuron indicates which prototype is the most correlative to the input vector and the winner is selected to be used to further optimize the logistical service.

The first layer output a_1 is used to initialize the second layer, that is to say:

$$a_2(0) = a_1 \tag{13}$$

Then the output of the second layer is updated according to the following recurrence relation:

$$a_2(t+1) = \text{poslin}(W_2\, a_2(t)) \tag{14}$$

The weight matrix W_2 of the second layer is set so that the diagonal elements are 1 and the off diagonal elements have a small negative value. Then the elements of W_2 can be represented:

$$w_{ij} = \begin{cases} 1, & \text{if } i = j \\ \varepsilon, & \text{otherwise} \end{cases}$$

Where:

$$0 \le \varepsilon \le \frac{1}{S-1} \tag{15}$$

As a result, at each iteration, the output of each neuron will decrease in proportion to the sum of the output of the other neurons. The output of the neuron with largest initial condition will decrease more slowly than that of the other and eventually the neuron will be the only one with positive output and becomes the winner.

Utilizing the competitive Hamming network, the procedure of the optimization will be reorganized. When initializing, a table named Prototype Selection Table (PST) is created to record the input vector and the corresponding optimization service scheme. Meanwhile, a positive integer number S should be given as the row vector number of W_1, namely, the number of the prototypes. At the beginning, the row vector number of W_1 named as ϖ is set to 0. When the first logistical service is submitted and the combination of preconditions is reformatted to the format of the input vector and executes the optimization procedure without the Hamming neural network involved because of no prototype available. After the optimization service scheme having been achieved, the input vector accompanying with the optimization service scheme and a positive integer number μ will be acquired. The triple be inserted into the PST as a record for further use. At this time, there are only one vector can be selected as a prototype in which the value of ϖ is set to 1. When $0<\varpi<S$, the optimization of the logistical service is executed with the Hamming neural network involved. After the optimization finished, the input vector is selected as a prototype and $\varpi = \varpi+1$ and correspondingly, the information will be inserted into the PST. When the Hamming neural network is involved in the optimization, a prototype becomes the winner a time. Then the value μ recorded in PST according to the winner is added by 1. On the contrary, the failure is subtracted by 1. Until $\varpi = S$, the number the selected prototype will not increase. If the value μ recorded in PST according to a prototype is decreased to negative number, the prototype is a new prototype which is last input vector.

Simulative experiments and experimental analysis: As the complexity of the components and their interaction in the logistical network, the effectiveness and the efficiency of a logistical service model are usually testified by the simulative experiments (Yaghini *et al.*, 2012; Thompson and Hagstrom, 2008). In the simulative experiments, the logistical networks with different dimensions are simulated. The Table 1 lists the dimensions of the logistical networks in the simulative experiments. To represents the dimensions of the logistical networks, two factors are selected. The first one is the Number of the Service Spots (NSS), which the dimension of the key elements in the logistical network. The second one is the average number of the packs of goods (ANPD) dispatched during a certain period of time, which the service dimension of the logistical network (Castillo-Villar *et al.*, 2012; Abu-Ali and Hassanein, 2008).

Five simulative experiments are implemented with the dimension listed in Table 1. In each experiment, the optimization procedures with and without Hamming competitive network (denoted by With HCN and Without HCN, respectively) are implemented, respectively. For every procedure, about 200 input vectors reformatted by

Table 1: Configurations of the logistical network in the simulative experiments

Order No.	No. of the Service Spots (NSS)	Average No. of the packs of goods (ANPD)
1	26	1500
2	51	4000
3	103	10000
4	211	20000
5	356	50000

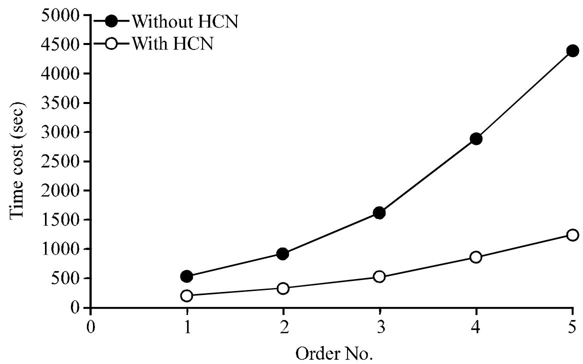

Fig. 4: Average time cost according to the optimization procedures with and without HCN

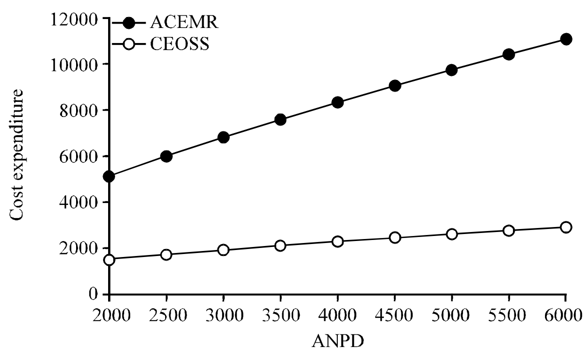

Fig. 5: Comparison of ACEMR and CEOSS

the combinations of preconditions are input to achieve the optimization service schemes. The average time cost for achieving an optimization service scheme is represented in Fig. 4. Figure 4 indicates that the time cost of HCN is much smaller with the dimension increasing of the logistical network. Consequently, utilizing the Hamming competitive network, the optimization efficiency will be enhanced especially when the dimension of the logistical network is large enough.

In the procedure of the optimization for a combination of the preconditions without the Hamming competitive network involved, a series of feasible service schemes are presented and the cost expenditure is achieved as midway results. The comparison between the Average Cost Expenditure of the Midway Results (ACEMR) and the cost Expenditure of the Optimized Service Scheme (CEOSS) indicates the optimization efficiency of the proposed algorithm (Becker *et al*., 2012; Biehl *et al*., 2007).

Figure 5 represents the comparison of ACEMR and CEOSS with the variation of ANPD and the fixed number of service spots (NSS = 51). The variations of ACEMR and CEOSS demonstrate that the CEOSS is much less and increases more slowly than ACEMR, which indicates the proposed algorithm is effective in the optimization and the optimization effectiveness is more remarkable accompanying with the dimension increasing of the logistical network.

Summarily, the optimization model of the logistical service can not only enhance the efficiency in reducing the time cost of the optimization procedure but also is more effective to achieve the optimized service scheme.

CONCLUSION

To solve the problem that the time cost of the optimization procedure rapidly and unevenly increases with the dimension increasing of the logistical network, an optimization model of logistical service is put forward. In the proposed model, the goods dispatching requirement and the other static and dynamic information of the logistical network are taken as the combination of preconditions and the constitution of the feasible service scheme. By formulate the combination of preconditions into the input vector with designated format, the input vectors are corresponding with the optimized service scheme. Taken the historical input vectors as prototypes, the Hamming competitive neural network algorithm can enhance the efficiency and effectiveness of the optimization procedure.

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