http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (7): 1342-1349, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.1342.1349

Modified PSO Algorithm to the Logistical Network for Goods Transportation Based on Internet of Things

Huang Yongsheng and Du HuaMei Zhang Genglu
Tangshan Key Laboratory of Informationization Technologies and Engineering Control,
School of Management, Hebei United University, Tangshan, China

Abstract: By the technologies of the Internet of Things, the static and dynamic information of the logistical network can be integrated into an information system which can be used to the cost optimization of the logistical services. In this study a modified PSO algorithm is proposed with proper description for the relationship among the key elements in the logistical network. In the proposed algorithm, the similarity of the solution space vector is applied to the overlap generation. Simulative experimental results demonstrate the algorithm is efficiency and effective to the cost optimization of the goods transportation in logistical services.

Key words: Particle swarm optimization, internet of things, logistical network, goods transportation

INTRODUCTION

With the rapid development of the communication networks, the Internet of Things (IoI) which is taken as the joint technologies of the networks is now becoming a hotspot field of the network applications (Karnouskos, 2012; Miao and Wang, 2012). The internet of things can integrated utilize the functions of the networks such as the computer network, satellite communication and mobile communication network, etc. (Wang *et al*., 2011). Consequently, a system with motional and motionless thing can be managed in the internet of things (Yang, 2012; Oteafy and Hassanein, 2012). Accompanying with the distributed computation capacity of the computer network, the internet of things can be used to the optimization of the system topology, the service quality, etc. (Zhong, 2012; Zhang *et al*., 2012).

The logistical system with consists of goods providers, goods receivers, service spots and transport utilities is applied to implementing the receiving and dispatching of goods (Panda, 2010). In the logistical services, a logistical network can be constructed by the technologies such as web services, RFID and location technologies which are provided by the computer network, satellite communication and mobile communication network (Achillas *et al*., 2010). Consequently, utilizing the internet of things, the static and dynamic, the historical and real-time information of the elements in logistical network can be achieved, handled and utilized as integration (Pishvaee *et al*., 2010; Shimizu and Rusman, 2012). Furthermore, the distributed technologies make comprehensive utilization of the information possible. Correspondingly, as a research field of proper managing the resource of the logistical network, the distributed information is used to efficiency and effectiveness optimization in the integrated information system (Ramos and Oliveira, 2011; Thanh *et al*., 2010).

As a result, based on the internet of things, the research on the logistical optimization technologies is quickly booming and applied to the certain territories (Kutanoglu and Mahajan, 2009; Jeet *et al*., 2009). Based on analysis to the topology of the distribution network for usual parcel, Sebastian (2012) put forward modified model with optimization algorithm to achieve sub-network of the proposed network topology by Decision Support systems with better performance. Overmeyer *et al*. (2009) presented a concept which allows the automatic configuration and optimization of material flow systems by interconnecting logistics modules to form a cognitive logistic network. Utilizing the proposed strategy, the material flow systems will achieve better effectiveness in conforming to requirement variation and reacting to unexpected events than utilizing an overall scheduling strategy.

The space and time distribution of goods are the important attributes of the running logistical network (Pishvaee *et al*., 2010; Piplani and Saraswat, 2012). In view of this completely uncertain goods distribution Xu *et al*. (2012) proposed an expected model of robust restraint and carries uncertainty simulation on related parameter of network resource planning decision with Monte Carlo method. Creazza *et al*. (2012) puts forward a mixed integer linear programming model with a data mapping section. In

Corresponding Author: Huang Yongsheng, Tangshan Key Laboratory of Informationization Technologies and Engineering Control, School of Management, Hebei United University, Tangshan, China

order to conform to the configuration problem of the supply chains under the real-life global logistics networks with high level complexity, the proposed integrated model designed for the optimization to international logistical network has been developed with specific approaches involved.

Generally, mathematical transformation is a commonly used approach in logistical network modeling (Kumdee *et al*., 2012). In the study of Velazquez-Marti and Fernandez-Gonzalez (2010), a network model is proposed, in which the locations of the bio-energy plants with the selection of the actual points on the map are implemented by a proposed mathematical calculation method. In order to achieve a further performance increase to daily operations. Werbos *et al*. (2012) presented a integrated optimization model of approximate dynamic programming. In the proposed model, the multistage decision problems are solved by the building blocks consisting of the results from the shorter periods of the relative and theoretical experiments. Furthermore, the optimization system is involved by the neural network algorithms via., Critic-Model-Action cycles. Blum and Mathew (2011) puts forward an optimization system that synthesizes aspects of previous models into scalable, flexible, intelligent agent architecture. By the proposed system, a series of bus routes and schedules can be achieved with the maximization of the utilities in the urban bus system and the minimization of the operation cost meanwhile.

In the logistical network for good transportation based on the Internet of Things, the goods, the transport utilities, the service spots for goods loading and unloading and transport routes are all key element which can be expressed as an integrated service system by the relationship among them. In this study, by the description of the relations among the elements accompanying with their combination similarity, Particle Swarm Optimization algorithm (PSO) is cited to implement the cost optimization.

DESCRIPTIONS TO THE CONSTITUTIONS OF THE LOGISTICAL NETWORK

Key elements and the information processing in the logistical network: Based on the internet of things, four categories of key elements make up the logistical network. They are the goods, the transport utilities, the service spots for goods loading and unloading and transport routes. In order to express conveniently, the denotations, G, T, S, TR, are put forward to denote the sets of the goods, the transport utilities, the service spots and transport routes, respectively.

For a pack of goods which is denoted by g, there are four associated parameters: the service spot where g will be sent out, the service spot where g will be received, the time limit for the arrival to the destination of g and the cargo capacity demand of g. For a transport utility, its cargo capacity and the information of real-time location and goods loaded are key associated parameters. As to a service spot, the location information of it in the logistical network and the real-time information about the goods waiting to send out in it are important information. As for the transport route, the two key parameters are the information about the interconnections of it to the other transport routers in the logistical network and the time spend when the transport utility goes through the transport router.

Based on internet of things, accompanying with the submission of a pack of goods, the information about the service spots where the pack of goods will be send out and will be received can be achieved. At the same time, the time limit for the arrival to the destination and the cargo capacity demand of the pack of the goods are submitted to the logistical network. As to the service spots, the location information is static information in the logistical network and the information about the goods waiting to send out can be calculated by eliminating goods having sent out from the goods having been submitted to the service spot by providers. To all transport utilities in the logistical network, the cargo capacity of each of them is registered. Positioning system of the internet of things can provide the information of the real-time location of every transport utility. The real-time loaded goods of a transport utility can be achieved by synthesizing the information of the goods loaded and unloaded at the service spots it has gone through. Additionally, the interconnection among the transport routers and the information of a transport router about the time spend when the transport utility goes through the transport router are unchanged or almost not changed.

Proper doods transportation activities and procedures considering the logistical cost: If a pack of goods need to transfer from the provider to the receiver, the pack of goods is submitted to a service spot waiting to send out by the provider and the information about the pack of goods is input into the logistical network. At this time, there are usually a lot of packs of goods waiting to send out at a service spot. Considering the destinations of the goods waiting to send out, the usable transport utilities with scheduled itineraries and the time limit of the goods transportation, the packs of goods in a service spot are divided into a number of batches and transferred to another service spot. When a transport utility arrivals at a service spot, a batch of goods are unloaded and another batch of goods waiting to send out in this service spot are loaded. A portion of the unloaded goods exit from the logistical network as the service spot is their destination and the other are taken as goods waiting to send out if the service spot is not their destination. Consequently, the goods waiting to send out at a service spot can be divided into two portions, the goods in one portion are submitted by the providers directly and the goods in the other are the goods transferred from other services and will be transferred again.

In order to enhance the cargo capacity utilization ratio of the transport utilities, enough number packs of goods, in other words, lot size is a key parameter. On the other hand, accumulating large lot size of goods needs long period of time and it is usually impossible considering the time limit of the goods transportation. Additionally, for specially designated packs of goods with designated service spots of departure and destination, the total distance of all transport utilities going through for goods transport is shorter and the cost of the goods transport is smaller correspondingly. Consequently, proper scheme of the goods transport is important to reduce the cost of the goods transport.

General description of the scheme for goods transportation: To a designated period of time, the set G which consists of the goods waiting to send out is determinate and can be described as $G = [g_1, g_2,..., g_m]$. Accordingly, the set T which consists of the transport utilities usable in the logistical network can be denoted as $T = [t_1, t_2,..., t_n]$ and the set S which consists of the service spots in the logistical network can be denoted as $S = [s_1, s_2,..., s_k]$. Other parameters related to the scheme for goods transport are described as follows.

For a transport utility t_i, it cargo capacity is usually determinate and can be expressed by $CA(t_i)$.

More than one transport utilities is required to transfer from s_a to s_b when the following two conditions appear. The first one is the quantity of the goods waiting to transfer from s_a to s_b are large enough. The second one is a portion of the cargo capacity of the transport utilities from s_a to s_b have been taken up by the goods needing to transfer to s_b before arriving at s_a, FR (s_a, s_B) is put forward to denote the number of the transport utilities transfer from s_a to s_B.

For a transport utility t_i running from a service spot s_a to another service spot s_b, there are a certain number of packs of loaded goods and a portion of cargo capacity is taken up. The loaded goods on t_i when it is running from s_a to s_b are denoted by $G(t_i)_{s_b}^{s_a}$ which is a subset of G and the cargo capacity taken up can be expressed by $CA\,(G(t_i)_{s_b}^{s_a})$ correspondingly. In the designated time period, the service spots which t_i goes through can be denoted by a vector $\vec{V}(t_i) = (s_{i1}, s_{i2},..., s_{i(n(ti))})$, in which $n(t_i)$ is the number of service spots t_i goes through and the jth element of the vector $\vec{V}(t_i)_j$ is a service spot s_{ij}.

For a pack goods g_x, a time limit is denoted as TL (g_x) which means g_x should be send to the destination within a time period of $TL(g_x)$ after g_x is submitted to the service spot of departure. When the pack goods g_x is transferred by the transport utilities one by one and from a service spot to another, it will be an element of a sequence of sets such as $G(t_i)_{s_b}^{s_a}$. To a pack of goods g_x, the sequence of sets are denoted by a vector:

$$\vec{V}(g_x) = (G(t_{y1})_{s_{x2}}^{s_{x1}}, G(t_{y2})_{s_{x4}}^{s_{x3}},..., G(t_{y(n(gx)-1)})_{s_{x(n(gx))}}^{s_{x(n(gx)-1)}})$$

in which $n(g_x)$ is the number of service spots g_x is transferred by and s_{xj} a service spot g_x is transferred by.

When a transport utility t_i arrives at a service spot s_j, a certain number of packs of goods will be unloaded. In order to describe the variation of the goods on t_i, the packs of goods unloaded from t_i at s_j are denoted by a set $G(t_i)_{s_j}$.

For a service spot s_i, the packs of goods waiting to send out at it can be expressed by a set $G(s_i)$. Then $G(s_i)$ is divided into some subsets and each of the subsets is the goods waiting for a transport utility to be transferred to another service spot. For example, $G(s_i)_{t_j}$ is the subset of $G(s_i)$ and consists of goods waiting for t_i to be transferred to another service spot.

If a transport utility needs to transfer goods from a service spot s_a to another service spot s_b, there is usually an arrangement of routes with the shortest distance from s_a to s_b. The arrangement of routes with the shortest distance from s_a to s_b is expressed by $AR_{s_b}^{s_a}$. Let $TR = [tr_1, tr_2,..., tr_p]$ denote the set of routes in the logistical network and the $AR_{s_b}^{s_a}$ can be expressed as:

$$AR_{s_b}^{s_a} = \{tr_{a1}, r_{a2},...r_{aq}\}$$

Based on the denotation above, the cost and the restrictions about the goods transportation can be expressed. For the designated period which is denoted by time, the cost which is denoted by cost is described by the follow equation:

$$\text{Cost} = \sum_{i=1}^{n}\sum_{j=2}^{n(ti)} \text{dis}\left(AR_{\vec{V}(t_i)_{j-1}}^{\vec{V}(t_i)_j}\right) \tag{1}$$

To every transport utility t_i, it should go through all service spots of $\vec{V}(t_i)$ in order and then:

$$\frac{1}{PD(t_i)}\sum_{j=2}^{n(ti)} dis\left(AR_{\vec{V}(t_i)_{j-1}}^{\vec{V}(t_i)_j}\right) \le time, \exists t_i \in T \tag{2}$$

To every pack of goods g_x, it is should be transferred to the destination by the time limit and then:

$$\sum_{j=2}^{n(gx)} \frac{dis(AR_{s_{x1}}^{s_{x2}})}{PD(t_{y1})} \le TL(g_x),\ \exists g_x \in G \tag{3}$$

In the inequality (3) above, the denotation $G(t_{yj})_{s_{xj}}^{s_{x(j-1)}}$ is an element of the vector:

$$\vec{V}(g_x) = (G(t_{y1})_{s_{x2}}^{s_{x1}}, G(t_{y2})_{s_{x4}}^{s_{x3}}, \ldots, G(t_{y(n(gx)-1)})_{s_{x(n(gx))}}^{s_{x(n(gx)-1)}})$$

when a transport utility t_i arrives at a service spot, after unloading some packs of goods and loading another packs of goods, the cargo capacity requirement of loaded goods should less than $CA(t_i)$ and then:

$$\begin{aligned} &\exists t_i \in T \text{ and } \vec{V}(t_i) = (s_{i1}, s_{i2}, \ldots, s_{i(n(ti))}), \\ &CA(G(t_i)_{s_j}^{s_{x(j-1)}}) + CA(G(s_j)_{t_i} - CA(G(t_i)_{s_j} \le CA(t_i) \end{aligned} \tag{4}$$

MODIFIED PARTICLE SWARM OPTIMIZATION

Introduction to the basic particle swarm optimization algorithm: The Particle Swarm Optimization is a random search algorithm by activities simulation of the birds' food searching. In PSO, a group of particles (solutions) are selected at random for initialization and then the optimal solution is searched by overlapping generations one by one. In every overlapping generation, a particle updates itself by the solutions at two extremal values: one is the solution at the extremal value which the particle has found itself and the other solution at the extremal value which the group of particles has found.

In the process of the PSO, the variation of each particle is independent. An overlapping generation step of a particle is that a new solution is selected to examine whether it can achieve more optimized value. As a result, if more optimized value achieved after an overlapping generation step of a particle, the value and the solution are recorded as the extremal point and the extremal value, respectively. To a group of particles, after an overlapping generation step of all particle finish, the most optimized value of the particle achieved is selected as the extremal value of the particle group and the corresponding solution is taken as the extremal point.

The PSO is usually used to the problem with more parameters and the solution point is consequently a vector with multiply dimensions. Usually, a solution vector space is expressed as $\vec{x}$ which is the state of a particle at a moment. With time going on, a sequence of variants which is denoted as $\vec{v}$ are selected to implement the overlapping generation of the particle by the variation of $\vec{x}$. If $\vec{x}_{p[i]}(m)$ is the state of a particle p[i] at a moment m, then $\vec{x}_{p[i]}(m+1)$ can be presented as:

$$\begin{aligned} &\vec{v}_{p[i]}(m+1) = \vec{v}_{p[i]}(t) + c_1 r_1(t)(pbest_{p[i]}(t) \\ &-\vec{x}_{p[i]}(t)) + c_2 r_2(t)(gbest(t) - \vec{x}_{p[i]}(t)) \end{aligned} \tag{5}$$

$$\vec{x}_{p[i]}(t+1) = \vec{v}_{p[i]}(x+1) + \vec{x}_{p[i]}(t) \tag{6}$$

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). The learning coefficients weigh the deviations among the three points: the extremal solution point of the particle, the extremal solution point of the particle group and the new solution point of the particle in next overlapping generation step. The random values ensure that movement to the solution point of the particle in the next overlapping generation possesses certain randomness.

The $pbest_{p[i]}$ (m) is the solution at the extremal value to the particle p[i] itself the up to the moment m. Consequently, $pbest_{p[i]}$ (m) can be achieved accompanying with overlapping generation of the particle p[i] by the equation:

$$pbest_{p[i]}(m+1) = \begin{cases} \vec{x}_{p[i]}(m+1), EOF(pbest_{p[i]}(m)) < EOF(\vec{x}_{p[i]}(m+1)) \\ pbest_{p[i]}(m), EOF(pbest_{p[i]}(m)) \ge EOF(\vec{x}_{p[i]}(m+1)) \end{cases} \tag{7}$$

EOF (pbest(m)) is the Extremal value of the Objective Function (EOF) according to the solution pbest (m) up to the moment m for a particle. Correspondingly, EOF (pbest(m)) is the EOF according to the solution gbest(m) accompanying with overlapping generation of the group of the particles by the equation:

$$\begin{aligned} &gbest(m+1) = g_{bestp[i]}(m+1) \text{ when max} \\ &\{EOF(pbest_{p[i]}(m+1)), i = 1, 2..., t\} \end{aligned} \tag{8}$$

Overlapping generation in PSO for the logistical network: In the logistical network for goods transportation, both the key elements and the relationship among them are important factors to the variation of the logistical service overall cost. For the PSO algorithm, the larger the dimension of the solution space is, the more the complexity of the PSO algorithm will be. In order to reduce the complexity, the modified PSO algorithm for the logistical network needs to simplify the solution space.

According to the general description of the scheme for goods transportation in the logistical network, the parameters of the goods transfer with the transport utilities among the service spots are all much relative to the integration of all goods transfer between every two service spots. Correspondingly, the information about the goods transfer between every two the service spots can be presented by a matrix MaS = $[FR(s_a, s_b)]_{k\times k}$ which can be expanded as follows:

$$\begin{bmatrix} 0 & FR(s_1,s_2) & FR(s_1,s_3) & \dots & FR(s_1,s_k) \\ FR(s_2,s_1) & 0 & FR(s_2,s_3) & \dots & FR(s_2,s_k) \\ FR(s_{12},s_2) & FR(s_2,s_2) & 0 & \dots & FR(s_3,s_{2k}) \\ \dots & \dots & \dots & \dots & \dots \\ FR(s_k,s_1) & FR(s_k,s_2) & FR(s_k,s_3) & \dots & 0 \end{bmatrix}$$

The parameters in the equations or inequalities (1~4) are expansion of the matrix MaS and consequently, the matrix MaS is taken as the solution space of the modified PSO algorithm. When overlapping generation is going on, the matrix MaS is restored to the values of the parameters in the equations or inequalities (1~4).

In PSO algorithm, the solution space is usually a vector. In order to conveniently handle the process of the overlapping generation, the matrix MaS can be express by $[\vec{v}_1,\vec{v}_2,\dots,\vec{v}_k]^T$. The elements of the k number of vectors are jointed one by one consecutively and the solution vector space can be constructed as:

$$\vec{x} = [0, FR(s_1,s_2),\dots,FR(s_1,s_k), FR(s_2,s_1),\dots\dots, FR(s_k,s_{k-1}), 0]$$

As the solution vector space $\vec{x}$ and MaS are different methods of expression to the same thing, they are equivalence to be restored to he values of the parameters in the equations or inequalities (1~4). If $\vec{x}$ is taken as the parameter in Eq. 5 and 6, the solution vector space achieved by overlapping generation will not conform to the requirement for the restoration to the parameters in the equations or inequalities (1~4). Therefore, a modified PSO overlapping generation algorithm is presented as follows:

$$\begin{aligned} \vec{v}_{p[i]}(m+1) = \vec{v}_{p[i]}(t) + c_1 r_1(t)\,\mathrm{sim}(pbest_{p[i]}(t), \vec{x}_{p[i]}(t)) \\ + c_2 r_2(t)\,\mathrm{sim}(gbest(t), \vec{x}_{p[i]}(t)) \end{aligned} \quad (9)$$

$$\mathrm{sim}(\vec{x}_{p[i]}(t+1), \vec{x}_{p[i]}(t)) = \vec{v}_{p[i]}(x+1) \quad (10)$$

$\mathrm{sim}(\vec{v}_1,\vec{v}_2)$ is the similarity of the vectors $\vec{v}_1$ and $\vec{v}_2$ and consequently, it can be calculated by the Eq. 11:

$$\mathrm{sim}(\vec{v}_1,\vec{v}_2) = \frac{\vec{v}_1 \bullet \vec{v}_2}{|v_1| \times |\vec{v}_2|} \quad (11)$$

Modified algorithm of particle swarm optimization for the logistical network: According to the equation above, to the designated $\vec{x}_{p[i]}(t)$ and $\vec{v}_{p[i]}(x+1)$, there are usually more than one feasible $\vec{x}_{p[i]}(t+1)$. To the procedure of cost optimization by the modified PSO algorithm, the achieved $\vec{x}_{p[i]}(t+1)$ in every overlapping generation is a compressed characteristic vector.

In order to calculate the cost according to Eq. 1, the $\vec{x}_{p[i]}(t+1)$ should be extended to the variables about the key elements and the relations among them. In the procedure of the overlapping generation of the modified PSO algorithm, there are usually more than one good transport schemes which conform to the solution vector space $\vec{x}$ and the MaS.

In the overlapping generation of the PSO algorithm, the variation between the present step and the next step has certain randomness. In other words, it is not necessary that the computation by Eq. 9 and 10 when overlapping generations going on is completely accurate.

Consequently, the modified Particle Swarm Optimization algorithm can be divided into three parts with interrelation. The first part takes charge of the transformation from the solution vector space to the goods transportation scheme and the cost computation of the scheme. The second part is responsible for the overlapping generation of a particle. The third part takes charge of optimization by the particle swarm algorithm. These three parts correspond to the Procedure 3, 2, 1, respectively in Fig. 1. these three procedures implements the modified algorithm by the calling relationship.

SIMULATIVE EXPERIMENTS AND EXPERIMENTAL RESULTS

As the complexity of the logistical network, designing simulative experiments is a widely accepted method to demonstrate the effectiveness and the efficiency of the optimization model (Curcio and Longo, 2009; Gill 2009). For the sake of the cost optimization to the logistical network for goods transportation, the simulative software simulating the information handling of goods transportation activities by the modified PSO algorithm is designed and implemented. In the simulative experiments, the key elements of the logistical network that cover the service spots in the set S, the available transport utilities in the set S, the transport routes in the set TR and the goods waiting to transfer or transferring in the transport utilities in the set G are set up according to the certain rules beforehand.

A logistical network with 38 service spots and a daily throughput up to 50000 packs of goods is selected to provide data for the simulative experiments. In order to prove the optimization effectiveness of the proposed model the data related to 13, 18, 23, 28, 33, 38 service spots are extracted.

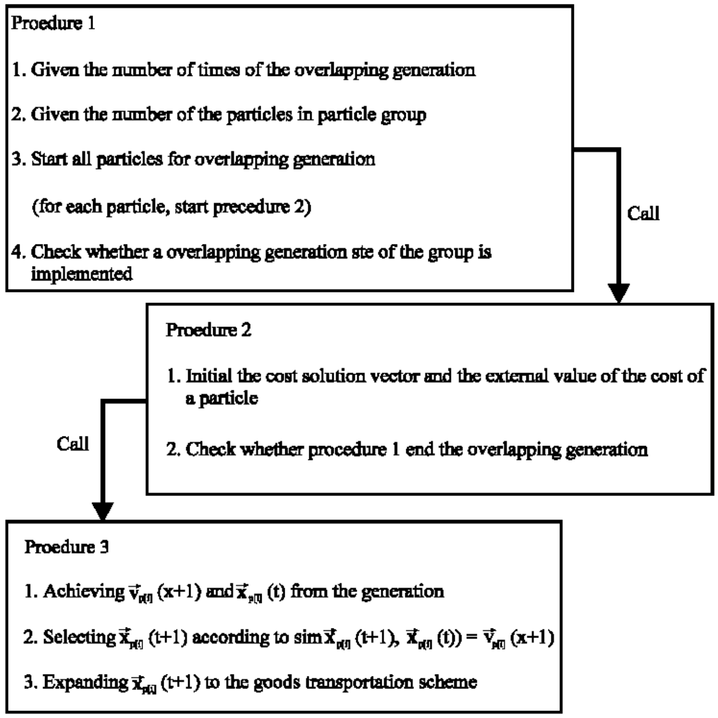

Fig. 1: Relative procedures which implement the modified algorithm

The effectiveness of the optimization model is usually evaluated by the comparison between the feasible schemes and the optimized scheme.

In the optimizing process of the PSO, large number of gbest() can be achieved which are all feasible solutions. Corresponding to the gbest(), the same number of interim costs can be acquired by calculation. The optimized cost gotten at the end of the optimizing process is smaller than each of the optimizing costs and the comparison the mean cost (the abbreviation for the average value of the interim costs) and the optimized cost is a solution to indicate the effectiveness of the algorithm.

Figure 2 demonstrates the comparison according to the dimension of the service spots with proper other parameters. The results in the Fig. 2 indicate that the optimized cost is much smaller than the mean cost accompanying with the dimension of the service spots increasing. Furthermore, there is less increase of optimized cost with the dimension of the service spots increasing which shows the modified PSO algorithm can achieve better effectiveness.

Generally, the efficiency, in other words, the time cost of PSO algorithm is relative to the dimensions of the problem solved. Reducing the added time cost accompanying with the increase of the dimensions of the logistical services becomes another objective of the optimization (Zeng and Li, 2009; Bochtis *et al*., 2010). Figure 3 demonstrates the time costs when better

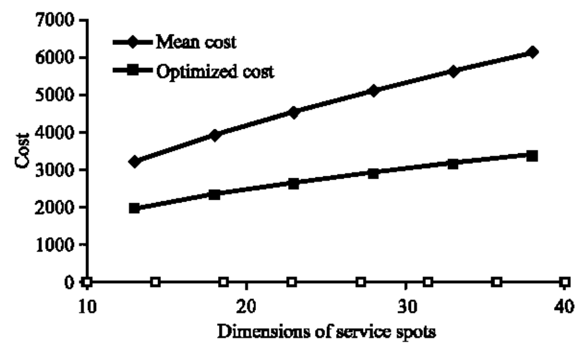

Fig. 2: Comparison of the mean cost and the optimized cost

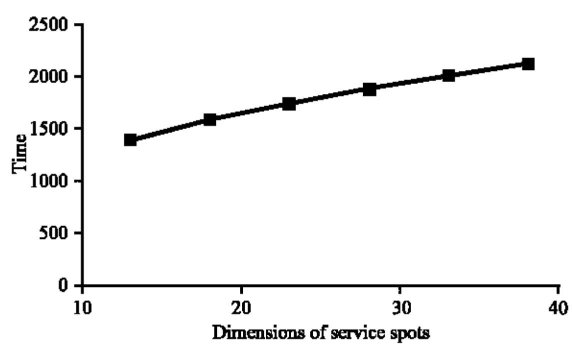

Fig. 3: Time cost variation with the variation of the dimension of the service spots

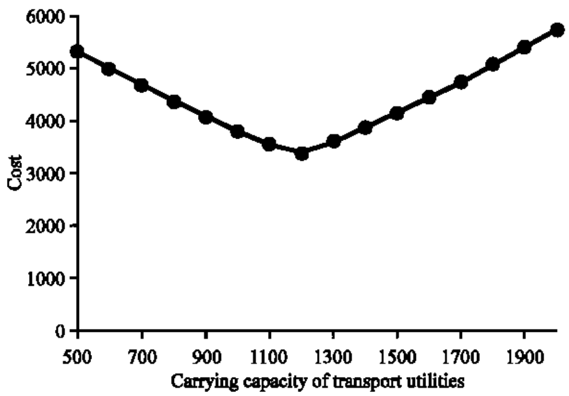

Fig. 4: Optimized cost variation accompany with the carrying capacity of the transport utilities

optimized costs are acquired. The results indicate the value increase of the time cost becomes smaller by smaller accompanying with the increasing of the dimension of the service spots. Consequently, the proposed algorithm can meet the optimization needs of the logistical network with large dimensions. In contradiction to the optimization models considering the effectiveness the key objective (Hu and Chang, 2010; Becker *et al*., 2012), the proposed model in this study can achieve stable efficiency with the dimensions increasing.

The efficiency of the optimization is relative to the available resources in the network (Inoue and Gen, 2012; Xidias *et al*., 2012). Too larger quantity of available resources results in idleness of them and too smaller quantity of available resources will influence the effectiveness of the optimization.

The proposed algorithm can be used to optimize the allocable carrying capacity of the transport utilities. By experiments, the proper configuration to the logistical network on available resources can be implemented. Figure 4 expresses variation of the optimized cost with the allocable carrying capacity increasing. The simulative results indicate better optimized cost requires proper allocable carrying capacity. Smaller carrying capacity will result in invalid moving back and forth of the transport utilities and on the contrary, larger carrying capacity will cause incomplete utilization.

CONCLUSION

Based on the Internet of Things, the static and dynamic information of the logistical network achieved can be used to the optimization of logistical services. In this study, by proper description to the relationship the key elements and the expression of the cost, a modified PSO algorithm along with vector similarity is put forward to optimize the cost of the logistical services. Simulative experimental results indicate the proposed algorithm not only can be used to achieve optimized cost of the logistical services effectively and efficiently but also can be applied to optimization for the allocable carrying capacity of the transport utilities.

ACKNOWLEDGMENT

This study was funded by the Science and Technology Department of Tangshan City (No.12140201A-7).

REFERENCES

Achillas, C., C. Vlachokostas, D. Aidonis, Í. Moussiopoulos, E. Iakovou and G. Banias, 2010. Optimising reverse logistics network to support policy-making in the case of electrical and electronic equipment. Waste Manage., 30: 2592-2600.

Becker, T., M.E. Beber, K. Windt and M.T. Hutt, 2012. The impact of network connectivity on performance in production logistic networks. CIRP J. Manuf. Sci. Technol., 5: 309-318.

Blum, J.J. and T.V. Mathew, 2011. Intelligent agent optimization of urban bus transit system design. J. Comput. Civil Eng., 25: 357-369.

Bochtis, D.D., C.G. Srensen and S.G. Vougioukas, 2010. Path planning for in-field navigation-aiding of service units. Comput. Electron. Agric., 74: 80-90.

Creazza, A., F. Dallari and T. Rossi, 2012. An integrated model for designing and optimising an international logistics network. Int. J. Prod. Res., 50: 2925-2939.

Curcio, D. and F. Longo, 2009. Inventory and internal logistics management as critical factors affecting the Supply Chain performances. Int. J. Simul. Process Modell., 5: 278-288.

Gill, A., 2009. Determining loading dock requirements in production-distribution facilities under uncertainty. Comput. Ind. Eng., 67: 161-168.

Hu, K.Y. and T.S. Chang, 2010. An innovative automated storage and retrieval system for B2C e-commerce logistics. Int. J. Adv. Manuf. Technol., 48: 297-305.

Inoue, H. and M. Gen, 2012. A multistage logistics system design problem with inventory considering demand change by hybrid genetic algorithm. Electron. Commun. Jpn., 95: 56-65.

Jeet, V., E. Kutanoglu and A. Partani, 2009. Logistics network design with inventory stocking for low-demand parts: Modeling and optimization. IIE Trans., 41: 389-407.

Karnouskos, S., 2012. Asset monitoring in the service-oriented internet of things empowered smartgrid. Service Oriented Comput. Appl., 6: 207-214.

Kumdee, O., T. Bhongmakapat and P. Ritthipravat, 2012. Prediction of nasopharyngeal carcinoma recurrence by neuro-fuzzy techniques. Fuzzy Sets Syst., 203: 95-111.

Kutanoglu, E. and M. Mahajan, 2009. An inventory sharing and allocation method for a multi-location service parts logistics network with time-based service levels. Eur. J. Oper. Res., 194: 728-742.

Miao, J. and L. Wang, 2012. Rapid identification authentication protocol for mobile nodes in internet of things with privacy protection. J. Networks, 7: 1099-1105.

Oteafy, S.M.A. and H.S. Hassanein, 2012. Resource re-use in wireless sensor networks: Realizing a synergetic internet of things. J. Commun., 7: 484-493.

Overmeyer, L., G. Heiserich, S. Falkenberg and A. Jungk, 2009. Automatische konfiguration und optimierung von materialflusssystemen durch kognitive logistikmodule [Automatic configuration and optimization of material flow systems through cognitive logistics module]. Proceedings of the 18th German Material Flow Congress, April 2-3, 2009, VDI Verlag, Dusseldorf, Germany, pp: 197-208 (In German).

Panda, D.K., 2010. Modelling and optimization of multiple process attributes of electrodischarge machining process by using a new hybrid approach of neuro-grey modeling. Mater. Manuf. Processes, 25: 450-461.

Piplani, R. and A. Saraswat, 2012. Robust optimisation approach to the design of service networks for reverse logistics. Int. J. Prod. Res., 50: 1424-1437.

Pishvaee, M.S., F. Jolai and J. Razmi, 2010. A stochastic optimization model for integrated forward/reverse logistics network design. J. Manuf. Syst., 28: 107-114.

Ramos, T.R.P. and R.C. Oliveira, 2011. Delimitation of service areas in reverse logistics networks with multiple depots. J. Oper. Res. Soc., 62: 1198-1210.

Sebastian, H.J., 2012. Optimization Approaches in the Strategic and Tactical Planning of Networks for Letter, Parcel and Freight Mail. In: Modeling for Decision Support in Network-based Services: The Application of Quantitative Modeling to Service Science, Dolk, D. and J. Granat (Eds.). Springer, New York, USA., ISBN-13: 9783642276118, pp: 36-61.

Shimizu, Y. and M. Rusman, 2012. Hybrid approach for huge multi-stage logistics network optimization under disruption risk. J. Chem. Eng. Jpn., 45: 597-603.

Thanh, P.N., O. Peton and N. Bostel, 2010. A linear relaxation-based heuristic approach for logistics network design. Comput. Ind. Eng., 59: 964-975.

Velazquez-Marti, B. and E. Fernandez-Gonzalez, 2010. Mathematical algorithms to locate factories to transform biomass in bioenergy focused on logistic network construction. Renewable Energy, 35: 2136-2142.

Wang, S.D., X.L. Wang and Y. Wang, 2011. Research on EPC logistics information system base on RFID. J. Harbin Inst. Technol, 18: 130-134.

Werbos, L., R. Kozma, R. Silva-Lugo, G.E. Pazienza and P.J. Werbos, 2012. Metamodeling and the critic-based approach to multi-level optimization. Neural Networks, 32: 179-185.

Xidias, E.K., A. C. Nearchou, N.A. Aspragathosa, 2012. Integrating path planning, routing, and scheduling for logistics operations in manufacturing facilities. Cybern. Syst. Int. J., 43: 143-162.

Xu, X.F., J.L. Zhao and J.K. Song, 2012. Uncertain control optimization of resource planning for collaborative logistics network about complex manufacturing. Syst. Eng. Theory Pract., 32: 799-806.

Yang, L.Q., 2012. Analysis and design of campus safety management system based on internet of things. J. Convergence Inform. Technol., 7: 400-408.

Zeng, S. and F. Li, 2009. Response surface-based performance reliability optimization design method. Hangkong Xuebao/Acta Aeronautica et Astronautica Sinica , 9: 1655-1660.

Zhang, Z., Z. Lu, Q. Chen, X. Yan and L.R. Zheng, 2012. Code division multiple access/pulse position modulation ultra-wideband radio frequency identification for internet of things: Concept and analysis. Int. J. Commun. Syst., 25: 1103-1121.

Zhong, X.Q., 2012. Blind channel estimation of relaying cooperative communication in IoT systems. Proceedings of the International Conference on Environment Science, January 15-16, 2012, Melbourne, Australia, pp: 85-95.