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Model and Algorithm for Closed-loop Logistics System Considering Time-satisfaction Degree and Returns under E-commerce Environment

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Model and Algorithm for Closed-loop Logistics System Considering Time-satisfaction Degree and Returns under E-commerce Environment

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Abstract: Facility location, inventory control and vehicle routes scheduling are critical and highly related problems in the design of logistics system for e-business. Meanwhile, the return ratio in Internet sales was significantly higher than in the traditional business. At the same time, the customer's time-satisfaction degree had become one of the important factors for competition .A multi-objective integrated optimization model of location-inventory-routing problem (LIRP) taking the cost of the returned merchandises and time-satisfaction degree into account is proposed for closed-loop logistics system. An improved adaptive genetic algorithm (IAGA) is designed to solve the model. Finally, the real instance is presented to show the effectiveness of the model and algorithm.

Keywords: closed-loops, location-inventory-routing problem, time-satisfaction degree, improved adaptive genetic algorithm

1. INTRODUCTION

The increasing progress of information and prevalence of internet in the 21st century has forced the ecommerce to develop in world-wide rage. In 2012, ecommerce sales topped $1 trillion for the first time in history on the whole world [1]. Contrasts to traditional commerce, customers are liable to return goods under e-commerce environment. Note that many customer returns on line accounts for 35% of original orders [2, 3]. At the same time, the importance of time has been recognized since Stalk introduced the paradigm of time-based competition [4]. The customer's time-satisfaction degree had become one of the important factors for competition. Here, we consider logistics systems as an important support system in e-commerce need to make some adjustments and improvements. To adapt to the reality of e-commerce market environment, closed-loop logistics system and highly integrated logistics process should be the necessities.

Facility location, inventory control, and vehicle routing decisions are critical problems in the design of logistics system. There is much previous work on these three areas. In fact, there is a mutually dependent relationship among these problems in logistics system. Comprehensive optimizing and logistics activities management should be based on this relationship [5]. According to this idea, besides location allocation problem and vehicle routing problem, two-two integration such as location-routing problem (LRP), inventory-routing problem (IRP), and location-inventory problem (LIP) and three integration problem (location-inventory-routing problem, LIRP) start to be researched.

Many papers about the LIP, LRP, and IRP are studied deeply and have made some abundant achievements. However, research on the integration of location-inventory-routing problem is limited. Some researchers strongly appeal to carry out research on LIRP [6, 7]. Liu & Lee [8] was the earliest literature in the LIRP research, they built a model for single merchandise, multi-DPs LRP taking inventory control decisions into consideration, and proposed a two-stage heuristic algorithm. In order to avoid being trapped in local optima, Liu & Lin [9] proposed a global optimum heuristic based on the algorithm in the above papers to solve the LIRP. Shen & Qi [10] established a nonlinear integer programming model to minimize the total cost that includes location costs, inventory costs and transportation costs, and proposed a Lagrangian relaxation based algorithm to solve the

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model. Ahmadi-Javid & Azad [11] presented an LIRP model in a stochastic supply chain system, and established a heuristic method based on a hybridization of tabu search and simulated annealing to solve the LIRP model. Ahmadi-Javid & Seddighi [12] considered the LIRP of a multi-source distribution logistics network. A mixed-integer programming formulation was presented and a three-phase heuristic was developed to solve the problem.

The papers on the integrated optimization of reverse logistics system taking return into account are rarely, Kris & Vandaele [13] presented a mixed integer nonlinear program model in order to deal with the higher degree of uncertainty and congestion, typical characteristics of a reverse logistics network, and proposed a genetic algorithm to solve this problem. Sahyouni, Savaskan & Daskin [14] developed three generic facility location models that account for both forward and reverse logistics networks for the integrated distribution and collection of products. A Lagrangian relaxation-based solution algorithm that was both quick and effective was developed. Srivastava[15] provided an integrated holistic conceptual framework that combine descriptive modeling with optimization techniques at the methodological level for analyzing the reverse logistics network model. Easwaran & Uster [16] presented a mixed-integer linear program model to minimize the total cost associated with forward and reverse flows in the network. Two tabu search heuristics that is proposed to solve this problem.

The papers on the integrated optimization of logistics system in the time competitive environment are rarely, Kutanoglu & Cassady [17] studied the LIP which had random demand in the time competitive environment, they regarded the respond time as a set of constraints of the model; Candas & Kutanoglu [18] set up a LIP optimization model to reveal the relationship between site selection and inventory control in the time-competitive strategy.

The aim of this study is to develop a practical LIRP model with considering returns and time-satisfaction degree for closed-loop logistics system under e-commerce environment and provide a new heuristic algorithm. To our best knowledge, this work is the first step to introduce returns and time-satisfaction degree into the LIRP under e- commerce environment, which makes it become more practical. We also provide an effective algorithm named improved adaptive genetic algorithm (IAGA) to solve this model. Results of numerical examples show that IAGA outperforms genetic algorithm (GA) on optimal solution.

2. MULTI-OBJECTIVE PROGRAMMING MODEL

2.1 Problem description

The system in this study consists of one plant, multiple distribution centers (DCs), and multiple demand points (DPs), which is a third-phrases (production base - distribution centers - demand points) e-commerce logistics system. Considering the return police in e-commerce and customer's time-satisfaction degree, we optimize system construction, operation of the facility location, inventory control and co-ordinate arrangements of vehicle routing.

The objective of this problem is to determine the locations, order times and order size of DCs and arrange the routes that vehicles visiting the DPs in the closed-loop logistics network. The involved decisions are as follows: (1) location decisions, where to locate the DCs and the optimal number of DCs; (2) inventory decisions, the optimal order times and order size of customers on one route; (3) routing arrangement, the vehicle routes for serving the customers starting from a DC; (4) the time-satisfaction degree, the sum of the customers' time-satisfaction degree.

2.2 Assumptions

The assumptions of this paper are as follows: (1) There is a single merchandise; (2) The vehicle type is homogeneous; (3) Each route begins and ends at the same DC; (4) The vehicles in forward delivery service at the same time assume the task of collecting returns reversely; (5) The daily demand of each customer is deterministic and each customer is served by exactly DC; (6) The returned merchandises are quality defects; (7) Merchandises are repaired at the plant.(8) A linear relationship between customer' satisfaction degree and time.

2.3 Notations

The notations of this paper are as follows:

R: candidate DC location notes set; I: customer notes set; I^+: candidate DCs and customers note set; K: set of routes; H_r: ordering and handling cost at DC$_r$, $r\in R$; T_r: transportation cost perunit merchandise from plant to DC$_r$, $r\in R$; d_i : mean (daily) demand at customer i, $i\in I$; f_r : fixed (annual) cost of locating at DC$_r$, $r\in R$; F_r: fixed cost of vehicle per unit time at DC$_r$, $r\in R$; h: inventory holding cost per unit merchandise per unit year; Q: vehicle capacity; g_i: quantity of merchandises returned per day for customer i, $i\in I$; r: repairing cost per unit returned merchandise; ρ: delivering cost per unit distance; d_{ij}:the distance between customer i and customer j; λ: a constant used to convert daily demand into annual demand; t_i: time of arriving depot i in a route, $i\in I^+$; $F(t_i)$: time-satisfaction degree of customer i, $i\in I$; t_{max}: upper limits of time that the customer is willing to wait; t_{min}: lower limits of time that the customer is willing to wait; t_{ij}: the delivering time from depot i to depot j, $i, j \in I^+$; n_r: the order time per year at DC$_r$, $r\in R$; z_r= 1, if candidate DC i is selected as a DC location, and 0 otherwise; $x_{ijr}^v = 1$, if depot j is from depot i served by a DC r on routing v, and 0 otherwise.

2.4 Model formulation

The first objective function of model is to minimize the location, inventory, transportation, distribution costs, administrative cost, the second objective function of model is to maximize the customer' time-satisfaction degree. We can formulate the following models:

$$\min Z_1=\sum_{r\in R}\left(\begin{array}{c} f_r z_r+\lambda\sum_{v\in V}\sum_{i\in I^+}\sum_{j\in I^+}T_r(d_i+g_i)x_{ijr}^v+\dfrac{\sum_{v\in V}\sum_{i\in I^+}\sum_{j\in I^+}\lambda h(d_i+g_i)x_{ijr}^v}{2n_r} \\ +H_r n_r+\sum_{i\in I^+}\sum_{j\in I^+}\sum_{v\in V}\rho n_r d_{ij}x_{ijr}^v+\lambda\sum_{v\in V}\sum_{i\in I^+}\sum_{j\in I^+}rg_i x_{ijr}^v+F_r n_r \end{array}\right) \tag{1}$$

$$\max Z_2=\sum_{i\in S}\frac{d_i F(t_i)}{\sum_{i\in S}d_i} \tag{2}$$

s.t. $$z_r \geq 1, r\in R; \tag{3}$$

$$\sum_{v\in V}\sum_{r\in R}\sum_{i\in I^+}x_{ijr}^v=1, j\in I; \tag{4}$$

$$\sum_{r\in R}\sum_{j\in I}x_{rjr}^v\leq 1, v\in V; \tag{5}$$

$$\sum_{j\in I^+}x_{pjr}^v-\sum_{i\in I^+}x_{ipr}^v=0, p\in I^+, v\in V, r\in R; \tag{6}$$

$$\sum_{i\in I^+}\sum_{j\in I^+}\lambda d_i x_{ijr}^v\leq Q, v\in V, r\in R; \tag{7}$$

$$x_{rjr}^v-z_r\leq 0, r\in R, j\in I, v\in V; \tag{8}$$

$$z_r = \{0,1\}, r \in R; \tag{9}$$

$$x_{ijr}^{v} = \{0,1\}, i \in I^+, j \in I^+, r \in R, v \in V; \tag{10}$$

Where $$F(t_i) = \begin{cases} 1 & t_i \le t_{\min} \\ \dfrac{t_{\max} - t_i}{t_{\max} - t_{\min}} & t_{\min} < t_i < t_{\max} \\ 0 & t_{\max} \le t_i \end{cases}. \tag{11}$$

Eq. (3) ensures at least one DC is established; Eq. (4) ensures each customer is served by the only vehicle; Eq. (5) ensures that each customer is served by the exactly DC; Eq. (6) ensures every customer will be continuity; Eq. (7) ensures the total demand for each vehicle is less than or equal to vehicle capacity; Eq. (8) ensures that the distributions can only be made to DCs. Eq. (9) and Eq. (10) ensure the integrality of decision variables.

3. SOLUTION APPROACH

In this section, we first give the formula for solving optimal order times n_r. Since calculating n_r still rely on the decision variables x_{ijr}^{v}, and z_r, so we present a heuristic algorithm to get the optimized x_{ijr}^{v}, and z_r.

3.1 Finding the optimal order times

In the model (1)-(10), the decision variable n_r only has appeared in the objective function Eq. (1). Also, the objective function is convex for n_r >0. Consequently, we can obtain the optimal value of n_r by taking the derivative of the objective function Eq. (1) with respect to n_r as:

$$n_r = \sqrt{\frac{\sum_{v \in V} \sum_{i \in I^+} \sum_{j \in I^+} \lambda h(d_i + g_i) x_{ijr}^{v}}{2(F_r + H_r)}} \tag{12}$$

3.2 Heuristic algorithm

As we know, the VRP is an NP-hard problem. The LIRP mentioned above contains the VRP is more complicated. It is generally believed that there is no complete, accurate, and not too slow analytic algorithm to solve NP-hand problems. Noting bioinspired computation for solving optimization problems such advantages and widely applied, we designed an improved adaptive genetic algorithm (IAGA) to solve the proposed model.

3.2.1 Initial population

This study adopts the natural number coding method; using do not repeated R+S natural numbers constitute a sequence, which represents an individual. While 1, 2, ..., R indicate candidate DCs, and R+1, ... R+S indicate DPs, the encoding can described an candidate solution of the above optimization problem.

We assume that the size of the population is M, then select M arrangement which conforms to the constraint conditions as the initial individual, which forms an initial population.

3.2.2 Fitness function and selection operator

By calculating the fitness value of individuals, we determine whether to keep the individual. We choose the following fitness function:

$$f_k = \frac{1}{Z_1 * (1 - Z_2)} \tag{13}$$

3.2.3 Crossover operator

The role of crossover operator is to produce a new individual mode, optimizing the search process to achieve through it. Ameliorated OX operator is selected. From Lei's view [19], the expression of p_c which means adaptive crossover probability is:

$$p_c = p_{c0} + \alpha_c \frac{(f_{av})^{n_c}}{(f_{\max} - f_{\min})^{n_c} + (f_{av})^{n_c}} \tag{14}$$

Where p_{c0} is the initial crossover probability, p_c is crossover probability; f_{max}, f_{min} and f_{av} respectively represent the maximum fitness value, the minimum fitness value and the average fitness value of each generation; α_c and n_c are the coefficient.

3.2.4 Mutation operator

In order to maintain population diversity and prevent premature convergence of algorithm, reverse mutation operator is introduced to retain a good gene fragments, which can be transmitted to next generation, at the same time, new individual which is more complex is produced, and the scope of the search expands effectively. In order to speed up the convergence and increase the diversity of individuals, an adaptive variation factor is designed, that is:

$$p_m = p_{m0} + \alpha_m \frac{(f_{\max} - f_{\min})^{n_m}}{(f_{\max} - f_{\min})^{n_m} + (f_{av})^{n_m}} \tag{14}$$

Where p_{m0} is the initial mutation probability, pm is mutation probability, α_m and n_m are the coefficient, then new individuals produced by the process of crossover and mutation can form a next-generation populations.

3.2.5 Stopping conditions

IAGA is a kind of iteration searching algorithm, it approaches the optimal solution after multiple evolution. Assuming that the number of iterations is N, each generation's best individual which is recorded in the iterative process, if the individual can remain the best to N generations, the algorithm terminates.

3.2.6 Algorithm process

Specific steps are as follows:

Step1: Initialize the control parameters: population size N, crossover probability p_{c0}, mutation probability p_{m0}, the maximum evolution algebra M;

Step2: Generate the initial population: calculate the fitness value of each individual in the population, if the current evolution generation is less than the maximum evolution generation, then transfer to the next step, otherwise, the algorithm terminates and returns to the current optimal solution;

Step3: Calculate the crossover and mutation probability and execute operations such as individual selection, crossover and mutation operation to generate new population, calculate the fitness value;

Step4: If $f_i<f_j$ $(j>i)$, use new individual instead of old individual, otherwise, accept the new individual;

Step5: Determine whether the predetermined number of iterations has been performed, if it is met, we regard the individual which has the best fitness value in the evolutionary process as the optimal solution, output it, and terminate calculation; otherwise, return to Step2.

4. COMPUTATIONAL RESULTS

A commodity enterprise where the plant was located in Zhengzhou of Henan province intends to reconstruct its logistics sales system and transforms from self-dominated distribution model to the third agency model. For instance, as the plant of bided third-party logistics enterprise in Henan, In order to reduce cycle of turnover and logistics costing, It reconstructed its distribution network of Henan province. Preliminary it confirmed five candidate distribution centers and took eighteen cities of Henan province where the sale store located as demand points. By inquiring latitude/longitude coordinates and central meridian of these cities, transform the coordinates to three degree strap plane coordinate system of Xian80 geographic coordinate system. The unit distance of coordinate system indicate one kilometer in reality. The data are as follows: the inventory holding cost per unit of product h=2; the vehicle capacity Q=5000; fixed cost of vehicle per time F_r=40; population size N=40; the coefficient n_c=n_m=2; the initial crossover probability p_{c0}=0.8; the initial mutation probability p_{m0}=0.005; the coefficient α_c=1; the coefficient α_m=0.001; lower limits of time that the customer is willing to wait t_{min}=30; upper limits of time that the customer is willing to wait t_{max}=90; evolution number M=500; the conversion constant λ=300; delivering cost of the unit distance ρ=60; repairing cost of the unit returned merchandise r=3; T_r, F_r ,g_i, H_r generates from the uniform distribution U[6,10], U[35,40], U[10,15], U[20,25].

Table 1. Parameters of customers

Customer	Coordinates	Demand	Customer	Coordinates	Demand
Zhengzhou (i_1)	(3848.1,38468)	425	Kaifeng(i_{10})	(3851.4,38532)	330
Luoyang (i_2)	(3842.3,37631.9)	415	Luohe (i_{11})	(3714.9,38501.9)	370
Pingdingshan(i_3)	(3736.2,38434.2)	400	Sanmenxia (i_{12})	(3848.1,37517.4)	320
Xinxiang(i_4)	(3909.1,38486.4)	365	Nanyang(i_{13})	(3654.9,38362.6)	378
Xuchang(i_5)	(3766,38482.5)	335	Shangqiu(i_{14})	(3813.4,39375.9)	354
Jiaozuo(i_6)	(3901.6,38428.1)	410	Xinyang (i_{15})	(3556.3,38507.5)	324
Hebi(i_7)	(3974.5,38515.3)	384	Zhumadian(i_{16})	(3650.6,38501.9)	312
Anyang(i_8)	(3996.8,38531.5)	412	Jiyuan(i_{17})	(3884.5,38369.6)	365
Puyang (i_9)	(3953.9, 38588.7)	345	Zhoukou (i_{18})	(3722.9,38558.5)	300

Table 2. Parameters of candidate DC

Candidate DC	Coordinates	f_r	Demand
Zhengzhou (i_1)	(3848.1,38468)	50	425
Luoyang (i_2)	(3842.3,37631.9)	50	415
Pingdingshan(i_3)	(3736.2,38434.2)	50	400
Xinxiang(i_4)	(3909.1,38486.4)	50	365
Xuchang(i_5)	(3766,38482.5)	50	335

Based on Matlab®6.5 platform, we programmed the IAGA and then run it 30 times on a computer. One of the solutions is showed in table3 and figure 1.

Table 3. Solutions obtained by IAGA

DC	Vehicle	Routing	Order Time	Order Size
i_1	1	i_1-i_2-i_6-i_2-i_{12}-i_1	111	4243
i_1	2	i_1-i_{17}-i_{10}-i_{14}-i_1	111	2836
i_4	3	i_4-i_9-i_8-i_7-i_4	92	4911
i_5	4	i_5-i_3-i_{13}-i_{15}-i_{16}-i_5	114	4603
i_5	5	i_5-i_{18}-i_{11}-i_5	114	1764

For comparison, GA is programmed by Matlab ® 6.5 as well, and the instance was run 30 times on the same computer. The table 4 shows the total costs and the customers' time-satisfaction degrees by GA and our IAGA.

Table 4. Values of objective functions by two algorithms

Algorithm	Total cost	Time-satisfaction degree
GA	8213300	0.9002
IAGA	7524500	0.9449

The following figure 2 shows the fitness value's different change with the evolution generations increase by using GA and IAGA.

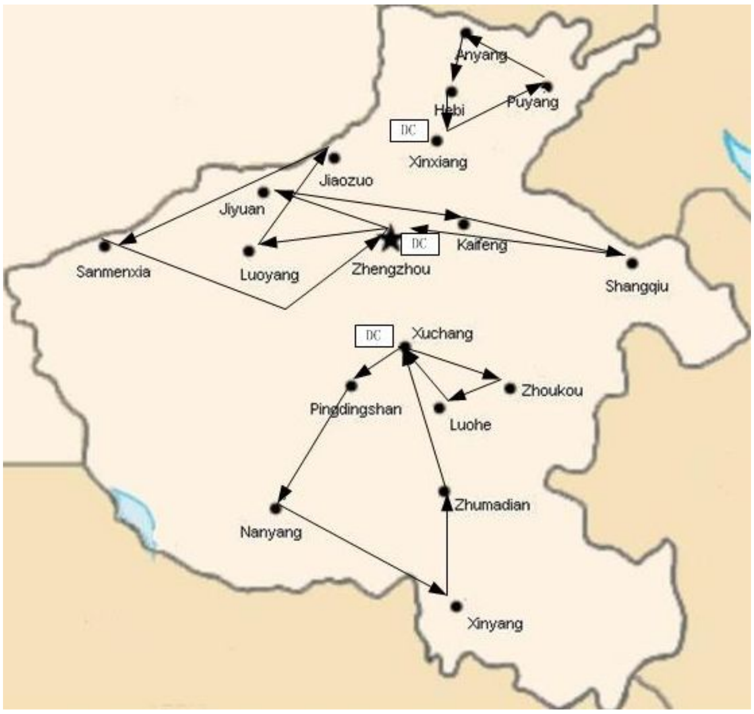

Figure 1. The distribution programs topology

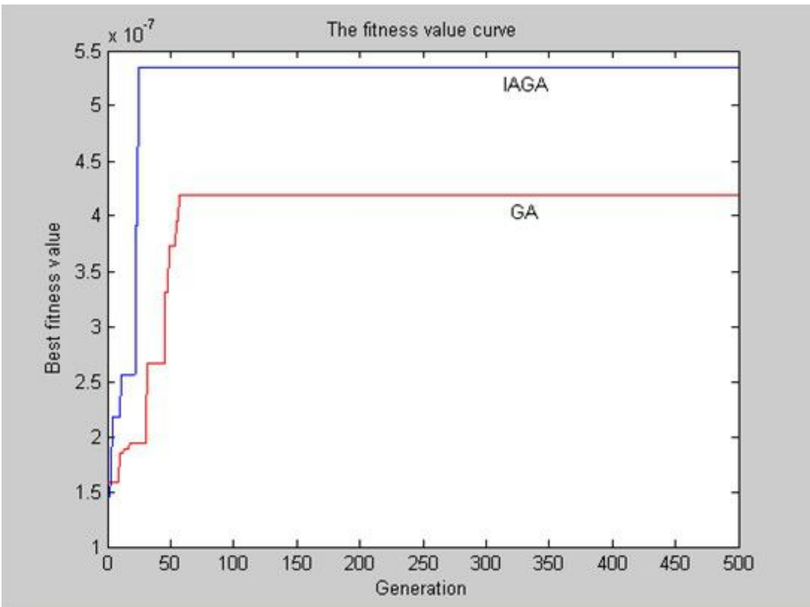

Figure 2. Trends of best fitness value by GA and IAGA

5. CONCLUSIONS

Under the e-commerce environment, customers have a higher return rate, and the customers are sensitive to time-satisfaction degree. This study handles the above interesting problem and provides an effective heuristic. The main contributions are as follows:

(1) We firstly establishes a multi-objective integration LIRP model which considers reverse logistics network and the customers' time-satisfaction degree. It is very useful to help managers make the right decision under e-commerce environment.

(2) An integration LIRP model with returns and time-satisfaction degree is an NP-hard problem and very hard to be solved by analytical method. So, a heuristic algorithm named IAGA is designed.

(3) Results of experimental data show that IAGA outperforms GA. IAGA is a good candidate to solve the proposed LIRP model effectively.

However, this paper just show a real instance with small scale, medium and large scale instances need to be tested. On the other hand, the stability of the IAGA not yet be discussed. These work should be done in the further.

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