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INVENTORY MANAGEMENT IN NETWORKED SERVICE SYSTEMS

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Abstract. The globalization of economy and market leaded to increased networking in the field of manufacturing and services. The processes of these manufacturing and services including logistics became more and more complex. The design and operation of these complex processes can be described as NP-hard optimization problems. These problems can be solved using sophisticated models and methods using metaheuristics based algorithms. Much of the researches in this area are focusing on manufacturing. This paper aims to report a firefly metaheuristics based optimization method, by the aid of which it is possible to support the solution of design and control problems of networked service processes. The authors describe a general model and present a new metrics to measure permutation distances used in the algorithm.

Keywords: optimization, firefly algorithm, route planning, heuristic

1. Introduction

Beside production processes, logistics plays an increasing role in the field of service activities. There are plenty of literatures in planning of production processes, but there are significant gaps in the area of design and operation of service activities. In this research topic, there are perspectives that deliver significant benefits for the development and operation of service processes [1, 2].

This work presents a general model based on a metaheuristic algorithm, which is suitable for optimizing production processes and service support systems.

In the literature several research work discuss the planning and management of logistics processes related service activities. Some of this literatures examine the optimal development of a properly functioning network for logistics processes [3], but only on a concept level, while others have specific models and algorithms used to solve the optimization problems [4, 5, 6].

One of the richest topics of logistics activities in the service area is the city logistics, where distribution problems involve social, cultural and economic effects. Optimizing this particular segment is very important in many aspects [7, 8].

The optimal design of logistics services affects not only the traditional areas of logistics (purchasing, production, distribution, recycling). Significant research is being conducted with the aim to develop methods and algorithms that could improve the logistics service system and greatly reduce the total environmental load [9].

The quality assurance and risk assessment is an interesting aspect in an operating logistic service network, because most of the literature just examine the risk of each participant of a properly functioning network system, There is little research work found in the literature, that manages the risk of a network-based logistics service system [10]. The environmental impact inevitable when planning logistic activities, and this is especially true in the case of logistics processes where service activities supported with high transport costs and performance arise due to the nature of the activities [11].

2. The Model

The present research work aims to create a model to describe logistics processes related to network-based service systems. During the development the aim was to create a common model, from which specialized branch models can be created taking into account various restrictions. The model includes three groups of elements, which is absolutely necessary in logistic processes:

- central warehouses,
- logistic resources,
- objects to be served.

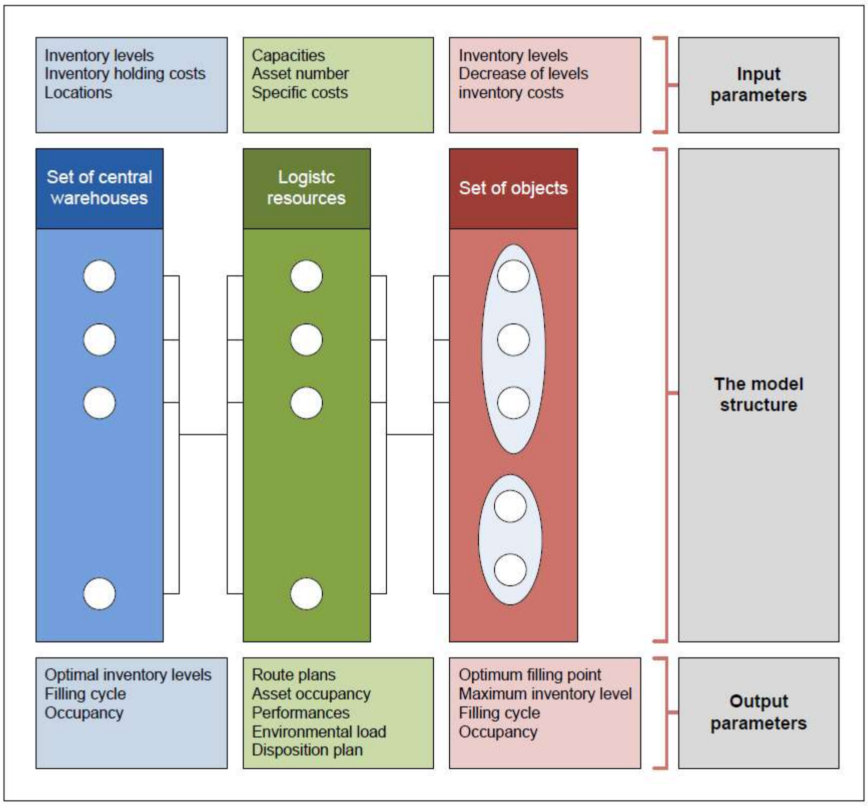

Figure 1. The general model of network-based service systems

The model in Figure 1 explains the relationships among each elemental groups, that can be a subject of optimization.

First, the objective functions need to be described based on Figure 1. The main objective function is to minimize the distance in every route in a time-frame. A route length can be described as a length between the central warehouse and the first object, plus the distances among each objects, and add the length between the last object and the central warehouse:

$$L = \sum_{t=1}^{\tau} \sum_{\alpha=1}^{\delta(t)} \left(l^{KR}_{f(t,\alpha),p_{t,\alpha(t),1}} + \sum_{s=1}^{m(t,\alpha)-1} l_{p_{t,\alpha(t),s},p_{t,\alpha(t),s+1}} + l^{KR}_{p_{t,\alpha(t),m},f(t,a)} \right) \rightarrow min. \tag{2.1}$$

Notations	**Explanation of notations**
τ	the number of cycles of the investigation period
α	the route ID
$\delta(t)$	the number of routes in the t^{th} investigation period
$f(t,\alpha)$	the central storage ID in the t^{th} investigation period visited by the α^{th} route
β	the objects number in a given route
$p_{t,\alpha,\beta}$	the objects ID number in the t^{th} investigation period visited by the α^{th} route in the β^{th} place
$m(t,\alpha)$	the number of objects in the t^{th} investigation period visited by the α^{th} route
c^L	the specific cost depending on the routes length
$K^{max}_{p_{t,\alpha,\beta}}$	the maximum storage capacity of the β^{th} object
$K^{act}_{p_{t,\alpha,\beta}}$	actual filled capacity of the β^{th} object
K^J_α	the α^{th} route assigned vehicle capacity
T^C	the central storage replenishment cycle time
c^{SZ}	the order-processing cost related to the central storages refill process
β_0	maximum attraction value of the Firefly algorithm
Y	absorption coefficient: usually the value is between 0.1 and 10
r_{ij}	the i^{th} and j^{th} firefly distance
α_t	size of the steps in the algorithm
ϵ_t	randomization parameter

Table 1. Explanation of notations

From the route length an objective function for minimum handling costs can be clearly defined:

$$C = L \cdot c^L \rightarrow min. \tag{2.2}$$

The occupancy rate for each route will define the next objective function. In this case we summarize each vehicle occupancy in the given time period for each objects, depending on the quantities of the delivery.

$$\eta^J = \sum_{t=1}^{\tau} \sum_{\alpha=1}^{\delta(t)} \frac{\sum_{\beta=1}^{m(t,\alpha)} K_{p_{t,\alpha,\beta}}^{max} - K_{p_{t,\alpha,\beta}}^{act}}{K_\alpha^J} \rightarrow max. \tag{2.3}$$

It is also important to minimize the investment costs in terms of the number of routes.

$$\alpha_{max} \rightarrow min. \tag{2.4}$$

The central warehouse plays an important role in the system. During the optimization process we have to take into account the transportation and storage costs because these affect the optimization process of the supply chain's qualities. We can specify the cost of transport, which is defined as the order processing cost in this case:

$$^{KR}K^{MF} = \frac{\tau}{T^C} \cdot c^{SZ} \tag{2.5}$$

The storage costs in the given timeframe can also be calculated:

$$^{KR}K^{T} = \sum_{t=1}^{T^C} \sum_{\alpha=1}^{\delta(t)} \sum_{\beta=1}^{m(t,\alpha)} K_{p_{t,\alpha,\beta}}^{max} - K_{p_{t,\alpha,\beta}}^{act} \tag{2.6}$$

Knowing these two costs the objective function for minimizing the central warehouse total cost can be written in the following form.

$$^{KR}K = {}^{KR}K^{MF} + {}^{KR}K^{T} \rightarrow min. \tag{2.7}$$

Besides objective functions various restrictions and limitations need to be introduced. The first limitation defines that each route lengths have to be between minimum and maximum distance.

$$L_\alpha^J \leq L_{max}^J \text{ and } L_\alpha^J \geq L_{min}^J \tag{2.8}$$

Another important condition states that an object only can be served by one vehicle and one warehouse, so the P matrix is a permutation matrix.

The last function of the model is a limitation. It describes that the volume or weight that the route require cannot exceed the carrying capacity of the vehicle.

$$\sum_{\beta=1}^{m(t,\alpha)} K_{p_{t,\alpha,\beta}}^{max} - K_{p_{t,\alpha,\beta}}^{act} \leq K_\alpha^J \tag{2.9}$$

3. Distance measurement between variations

In the developed algorithm we examined the distance between the various versions of solutions defining metrics, as they affect the convergence of the algorithm. In the case of heuristic and metaheuristic algorithms, the best solution variants have to be found by optimization in different state spaces. Swarm intelligence algorithms types (ant colony algorithm, bee colony algorithm, firefly algorithm) needs different methods to measure the distance between individual solutions [12, 14]. These methods include the Hamming or the Difference distance or their normalized weighted forms and new metrics derived from them. If the solutions in the search space are binary-coded, the Hamming distance is a suitable metric. It is one of the simplest method [13], which uses the number of positions which are not identical with the elements of the two permutations:

$$d_{Ham}(s_1, s_2) = \sum_{i=1}^{n} x_i \text{ where } x_i = \begin{cases} 0, & \text{if } s_1(i) = s_2(i) \\ 1, & \text{else,} \end{cases} \tag{3.1}$$

where

- d_{Ham}: Hamming distance,
- s_1, s_2: different permutations,
- n: number of elements in permutation,
- i: positive integer.

4. The algorithm

In this chapter we will present an algorithm that can solve the above mentioned problem. The Firefly algorithm is a nature inspired metaheuristic algorithm, which has the basis of the behavior of the fireflies. The fireflies signaling system based on using a self created light at night in order to attract the opposite sex. Xin- She Yang created the first version of the algorithm in 2008, with the basic tenets of the algorithm:

- Every bug is unisex, so all of them attracted to each.
- The attraction is directly proportional to the degree of the bug's brightness. The brighter attracts less bright. However, the relative brightness is proportional with the distance.
- The brightest bug moves randomly.

For maximum search problems the brightness of the fireflies is proportional with the objective function, however a fitness function or something similar have to be used when minimum search needed.

The firefly algorithm is invented for solving continuous problems, but with special terms and interpretation it can be highly discreditable, so problems can be solved with simple permutation. The relation between two firefly bug movement (any x_i and x_j firefly movement in iteration $t+1$) can be identified as:

$$x_i^{t+1} = x_i^t + \beta_0 \cdot \exp(-\gamma \cdot r_{ij}^2) + \alpha_t \cdot \epsilon_t \tag{4.1}$$

$$\beta = \beta_0 + e^{-\gamma r} x_i = x_i \cdot (1-\beta) + x_i \cdot \beta + \alpha \left(rand - \frac{1}{2} \right), \tag{4.2}$$

where

- β_0: maximum attraction value,
- γ: absorption coefficient: usually a value between $0, 1, \ldots, 10$,
- r_{ij}: the distance between the i-th and the j-th firefly bugs,
- α_t: randomization parameter, gives us the step number,
- ϵ_t: randomization parameter, a random number.

The application of the algorithm is created with C# programming language. The program reads a data file for input parameters of the optimization problem: the coordinates of the objects or the transport route length matrix, the starting levels and daily level reductions. The steps between levels, the number of days, the number of iterations and the firefly population (versions) must be given. It is possible to set the starting percentage level. To verify the application a test run is required; we create a problem with basic parameters found in Table 1. The test case is derived from the general model and we can observe how efficient the firefly algorithm is in this case. The method now operates with one warehouse and only one vehicle to determine the optimal path and the vehicle capacity set to infinite. In the future we have a plan to expand the problem and the application to any kind of situation that we can determine with this model.

The optimization problem derived from the general model is a task where the goal is to optimize the scattered objects refilling process. In this case the objects are ATM terminals and their positioning is shown in Figure 3. The blue squares are the objects waiting for refilling and the red square is the central distribution warehouse, where every day the vehicles leaves and returns. The routes, in this case, are in flight distance to simplify the testing process. We have to insert the starting levels and the daily average reduction of each object, like we did in Table 2. When a test is made for long term we don't need the exact initial levels because it has minimal effect on the result, but in this case the test requires an accurate reduction measurement [15].

In addition, it is required to define the object's coordinates or transport route length matrix for the application. With the coordinates the program

```
Begin
Initial level (IL), daily average level reduction (DALR), coordinates
(X,Y,[Z]) or distance matrix (L) Specifying or calculation
specify: Step interval (S), iteration (I), number of days (D) and the
number of firefly population (X)
Define objective function: f(x)
for i=1:100/S
Calculate actual minimum: AM= 1+i*S
     for j=1:D
     Determination of the objects in the route:
         if (IL_j<AM),
          The object is in the route
         end if
      Generate Random route versions: SOL[]
       for k=1:object number in the route+1
       Specify route distance: M[]=L(SOL[k];SOL[k+1])
       end for k
       Definition of brightness function: M_ij, M_ij∝f(X) or simply M_ij=f(X)
       for l=1:I (iteration number)
             Select brightest (minimum) version
             Examination of the other version how many element is
             different from the brightest: A(X)
             Generate random: B=Rand(1:A(X)-1)
             In every version that different from the best, we need to
             exchange B time randomly selected numbers
             In the best version we have to exchange 2 randomly selected
             number
             Redefine the new brightness: M_ijl
      end for l
      Select best daily route: BDM_ij
      Redefine object actual level
  end for j
  The sum of all the daily minimum route distances for a specific alarm
  level:BDM_i=SUM[BDM_ij]
end for i
Select the alarm level with the least summarized distance
processing results, visualization;
end
```

Figure 2. The pseudocode of the application based on the modell and firefly algorithm

calculates the distance between two objects in flight path, but if we insert the actual transport matrix, the calculation will be more accurate.

After that it is possible to set the affecting parameters of the algorithm. The chosen step between percentages is 2. In this case, the program increases the critical percentage levels with two percent for each testing phase, according to the given time period. We chose the time period 1 year, so the program optimizes routes for the defined 365. The firefly population contains 10 specimens and with 100 iterations the application can easily serve such a small task. The obtained calculation results: the minimum delivery work can be achieved at 7% alarm level, but 23% and 35% also takes up local minimum of the chart.

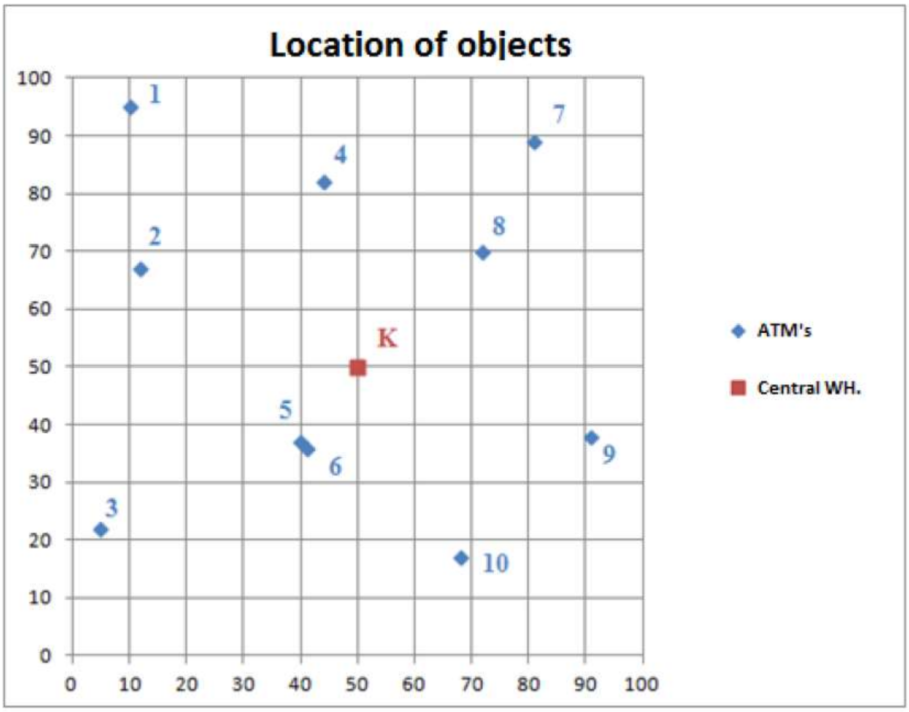

Figure 3. Location of objects

Moreover, the points can be matched very well to a polynomial curve, which shows that from 30% to 35% a low transportation work can serve the objects, and above this limit the transport distance jumps exponentially.

As the results of the processing also show the algorithm is well suited for solving the defined models problems. Of course, the model presented here is considered to be a basic model, further research is still ongoing and a number of challenges need to be taken for creating real conditions as much as possible.

5. Summary

The planning of service processes have to be solved by suitable models and algorithms. In the present research, a firefly-based heuristic optimization algorithm has been developed, that allows to optimize various network-based logistic service activities processes properly.

Objects name	X coordinate	Y coordinate	Starting level	Average daily reduction
K	50	50	100	0
1	10	95	47	9
2	12	67	12	25
3	5	22	83	11
4	44	82	75	7
5	40	37	40	23
6	41	36	61	18
7	81	89	32	22
8	72	70	47	16
9	91	38	25	14
10	68	17	56	8

Table 2. Initial parameters

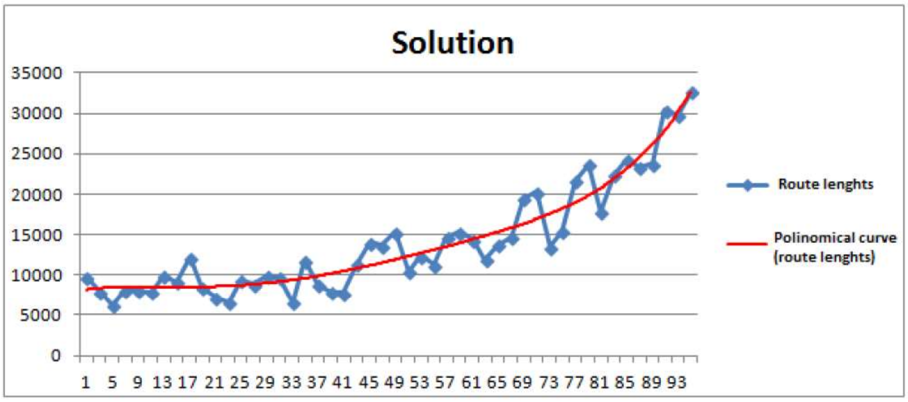

Figure 4. Transport routes lengths depending on the replenishment levels

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