APEM journal
Advances in Production Engineering & Management **ISSN 1854-6250**
Volume 13 | Number 2 | June 2018 | pp 169–178 Journal home: apem-journal.org
https://doi.org/10.14743/apem2018.2.282 Original scientific paper

A robust hybrid heuristic algorithm to solve multi-plant milk-run pickup problem with uncertain demand in automobile parts industry

Wu, Q.[a], **Wang, X.**[a,*], **He, Y.D.**[a], **Xuan, J.**[b], **He, W.D.**[c]

[a]College of Mechanical Engineering, Chongqing University, Chongqing, P.R. China
[b]College of Computer Science, Chongqing University, Chongqing, P.R. China
[c]College of Computer Science, Chongqing University of Posts and Telecommunications, Chongqing, P.R. China

A B S T R A C T

Considering the actual situation of China's automobile industry, this paper pioneers the discussion of the multi-factory milk run pickup problem with uncertain demand and frequency (MFMRPP-UDF). Considering the balance between inventory cost and distribution cost, a mixed-integer programming model was built for the problem, and converted into a robust optimization model by the Chernoff-Hoeffding theorem; then, the adaptive genetic algorithm (AGA) and local search (LS) were combined into a general hybrid heuristic algorithm (AGA-LS) to solve the problem. Then, the proposed algorithm was run 10 times and contrasted with the standard GA. The results show that the AGA-LS outperformed the standard GA in the reduction of the overall cost. This research provides important insights into the cost efficiency of inventory and delivery in the automobile parts industry.

© 2018, PEI, University of Maribor. All rights reserved.

A R T I C L E I N F O

Keywords:
Milk-run pickup problem;
Optimization;
Uncertain demand;
Hybrid heuristic algorithm;
Adaptive genetic algorithm;
Local search

**Corresponding author:*
wx921@163.com
(Wang, X.)

Article history:
Received 21 February 2018
Revised 29 May 2018
Accepted 31 May 2018

1. Introduction

The advent of the Internet has enabled customers to place orders and specialize requirements online. With the increasingly individualized demand, automobile enterprises are competing to implement small-batch and multi-frequency customized production [1]. The ensuing changes of the later stages of the supply chain throw down major challenges to production and logistics, creating the need for lean manufacturing, just-in-time (JIT) production, and production-centred logistics [2-5]. Facing the constantly changing customer demand, automobile enterprises should also maintain the supply of parts at a suitable level to lower the inventory cost. All of these developments call for a good logistic strategy customized production with uncertain demand that can balance inventory cost and distribution cost.

One of the viable strategies is the milk run logistics system. Being a mature and popular distribution strategy [6], the milk run logistics system enables suppliers located close to each other to transport goods to assembly plants at a lower cost and faster speed [7]. In this way, the system can reduce both inventory cost and distribution cost, and thus decrease the product price.

Considering the actual situation of China's automobile industry, this paper pioneers the discussion of the multi-factory milk run pickup problem with uncertain demand and frequency (MFMRPP-UDF). In the logistics system, there are many assembly plants and numerous part suppliers located close to each other. The suppliers collect the parts and transport them to the assembly plants in the small-batch and multi-frequency mode, aiming to balance the inventory cost and distribution cost under uncertain demand.

The remainder of this paper is organized as follows: Section 2 reviews the relevant studies on our topic; Section 3 puts forward the mathematical formulation; Section 4 designs a detailed solution to the problem; Section 5 explores a specific case of the problem; Section 6 wraps up this paper with meaningful conclusions.

2. Literature review

In the automotive parts industry, the milk run problem can be considered as a special vehicle routing problem (VRP) [7]. So far, many variants of the VRP have been developed, but few of them tackle the balance between the VRP and transport frequency under uncertain demand.

Luiz *et al*. [8] were the first to introduce the milk run strategy to cut the number of cycles in lean manufacturing. Following the strategy, these scholars saved over 80 % of the inventory cost, and diverted the labour force on parts unpacking to production building, creating a truly smooth material flow. Sadjadi *et al*. [6] proposed a mixed-integer milk run method for supply chain problems, and designed a customized metaheuristic for a special case in the automobile industry. Jiang *et al*. [9] developed an optimization-based routing approach for a small-batch, multi-frequency JIT supply system, and presented a tabu search problem to solve the problem. Nevertheless, their approach only minimizes inventory cost and distribution cost of suppliers, failing to benefit the assembly plants or fulfil the uncertain demand. Lin *et al*. [10] applied a two-phase heuristic algorithm to handle the single-plant milk run pickup problem. As the name suggests, the algorithm merely considers a single assembly plant under certain demand. Focusing on a real-time milk run-based vehicle routing problem, Du *et al*. [11] proposed the best fit algorithm for initial vehicle dispatch and the 2-point crossover algorithm for inter route improvement, and determined the parameters of the problem through comprehensive experimental design. Klenk *et al*. [12] laid down various peak handling strategies to ensure the efficiency and stability of in-plant milk run systems.

In addition, some scholars have explored the dynamic milk run routing problem. For instance, Antonio *et al*. [13] investigated the milk run JIT production problem with occasional over-congestion, created a dynamic alternative for vehicles to perform extra tasks, and predicted urban traffic surges by probabilistic sequential analysis. Guner *et al*. [14] discussed the dynamic milk run routing with stochastic time-dependent networks, in which the travel times are stochastic and time-dependent due to the recurrent congestion. Specifically, these scholars generated dynamic routing policies through stochastic dynamic programming, and obtained the travel time distribution by simulation. Despite the consideration of uncertain factors, these studies take not account of the relation between inventory cost and distribution cost.

Cho *et al*. [15] introduced the inventory factor into vehicle route planning, creating the inventory routing problem (IRP). In pursuit of the minimum system cost, the IRP only attaches importance to inventory quantity and vehicle routing. Jiang *et al*. [9] probed into the common frequency routing (CFR) problem, aiming to minimize inventory cost and distribution cost. Focusing on frequency and routing, their solution only allows a vehicle to pay a single visit to each supplier, which is obviously irrational for the case of multiple assembly plants. Considering uncertain inventory, Jafari-Eskandari [16,17] developed a robust optimization solution to milk run system with time window, minimized the distribution cost for all inventories in a given bounded uncertainty set, and optimized the routes from the perspective of suppliers and logistic service providers (LSPs).

From the above analysis, it is clear that the MFMRPP-UDF problem has not been given much attention. To make up for this gap, this paper attempts to study this problem considering the balance between inventory cost and distribution cost. Specifically, a mixed-integer programming model was built for the problem, and converted into a robust optimization model by the Chernoff-Hoeffding theorem; then, the adaptive genetic algorithm (AGA) and local search (LS) were combined into a hybrid heuristic algorithm (AGA-LS) to solve the problem.

3. Problem formulation

3.1 Mathematical model

The MFMRPP-UD can be defined as directed graph $G = (V, E)$, where $V = D \cup N$, with $D = \{1, 2,..., m\}$ being the set of assembly plants and $N = \{1, 2,..., n\}$ being the set of part suppliers, and $E = \{(i, j): i, j \in V, i \neq j\}$ is the set of routes [18]. Let q_d, α_d, $[0, T]$ and β be the uncertain demand, unit inventory cost, operation period, and unit distribution cost, respectively, where $d \in D$. Besides, let c_{ij} and t_{ij} be the distance and travel time from i to j, respectively. For the part supplier $i \in N$, it is assumed that the load time is t_i, and the supply quantity is s_i. Let $K = \{1, 2,..., k\}$ be the set of the vehicles, each of which has a capacity of Q. In addition, let us define f_k as the pickup frequency for the vehicle $k \in K$, and $p_{ik} = s_i/f_k$ as the part quantity picked up by the vehicle $k \in K$ at the supplier $i \in N$.

Then, the following decision variables were defined before setting up the mix-integer programming model:

$$x_{ijk} = \begin{cases} 1 & \text{the truck k travels from node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_{dk} = \begin{cases} 1 & \text{the truck k is assigned to depot } d \\ 0 & \text{otherwise} \end{cases}$$

$$z_{ik} = \begin{cases} 1 & \text{the truck k picks up at part supplier } i \\ 0 & \text{otherwise} \end{cases}$$

Thus, the model was constructed as:

$$\min \left\{ \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{ijk} c_{ij} f_k + \sum_{k \in K} \sum_{i \in V} \sum_{d \in D} \alpha_d p_{ik} z_{ik} y_{dk} \right\} \tag{1}$$

$$\sum_{d \in D} \sum_{j \in V} \sum_{k \in K} x_{djk} \leq K \tag{2}$$

$$\sum_{k \in K} \sum_{j \in V} x_{ijk} = \sum_{k \in K} \sum_{j \in V} x_{jik} = 1, \forall i \in V \tag{3}$$

$$\sum_{i \in D} \sum_{j \in D} x_{ijk} = 0, \forall j \in V, k \in K \tag{4}$$

$$\sum_{i \in V} x_{idk} y_{dk} = \sum_{i \in V} x_{dik} y_{dk} \leq 1, \forall d \in D, k \in K \tag{5}$$

$$\sum_{d \in D} y_{dk} = 1, \forall k \in K \tag{6}$$

$$\sum_{i \in V} z_{ik} = 1, \forall k \in K \tag{7}$$

$$\sum_{j \in V} x_{ijk} = z_{ik}, \forall i \in N, k \in K \tag{8}$$

$$\sum_{i \in V} x_{ijk} = z_{jk}, \forall j \in N, k \in K \tag{9}$$

$$\sum_{i \in V} p_{ik} z_{ik} = Q_k, \forall k \in K \tag{10}$$

$$\sum_{i\in V} t_i z_{ik} + \sum_{i\in V}\sum_{j\in V} t_{ij} x_{ijk} \leq T, \forall k \in K \tag{11}$$

$$\sum_{i\in V}\sum_{k\in K} p_{ik} z_{ik} y_{dk} = q_d, \forall d \in D \tag{12}$$

$$x_{ijk}, y_{dk}, z_{ik} \in \{0,1\}, \forall i, j \in V, d \in D \tag{13}$$

In the above formulation, Eq. 1 minimizes inventory cost and distribution cost; Eq. 2 limits the total number of vehicles; Eq. 3 and Eq. 4 stipulates that a vehicle visits each part supplier only once; Eq. 5 requires that each vehicle must leave from and return to the same assembly plant; Eq. 6 guarantees the one vehicle is only assigned to one assembly plant; Eq. 7-9 defines the value of z_{ik}; Eq. 10 specifies the capacity of each vehicle; Eq. 11 sets out the operational period; Eq. 12 lays down the demand of each assembly plant; Eq. 13 provides the decision variables.

3.2 Robust optimization

Despite the uncertainty in the volume and time of the demand from assembly plants, the suppliers always expect the demand to be fulfilled at the minimum inventory cost and distribution cost. Thus, it is necessary to prepare a robust schedule according to the actual conditions. In light of this, Eq. 12 was transformed to depict the uncertain demand by means of a chance-constrained stochastic program based on possibility measure:

$$pr\left\{q_d - \sum_{i\in V}\sum_{k\in K} p_{ik} z_{ik} y_{dk} \geq 0\right\} \geq \varepsilon, \forall d \in D \tag{14}$$

where ε is the pre-set level of confidence. Then, the Chernoff-Hoeffding theorem [20, 21] was introduced to transform Eq. 14 into a robust constraint:

$$r_d = \left\{1 - 2exp - 2\left[q_d + E(\rho_d) - \sum_{i\in V}\sum_{k\in K} p_{ik} z_{ik} y_{dk}\right]^2 \div (u_d - l_d)^2\right\}, \forall d \in D \tag{15}$$

where $E(\rho_d)$ ($d \in D$) are the expected values of uncertain variables; $[u_d, l_d]$ ($d \in D$) are the internal values of uncertain variables.

4. Proposed methods

To solve the NP-hard MFMRPP-UDF problem, the AGA and the LS were combined into a hybrid heuristic algorithm (AGA-LS). The AGA is good at solving NP problems thanks to its robustness and global search ability [21, 22] while the LS is a desirable way to process diverse population and prevent local optimum trap [23-27].

4.1 Representation of solutions (coding)

The solution was represented as a double-layer chromosome coding program. The first layer contains the assembly plants, and the second layer stands for the routes. First, r routes were generated by greedy strategy (GS). For example, suppose there exists a solution involving 2 assembly plants and 12 suppliers with 4 routes r1 1-3-5-6-1, r2 1-9-11-13-1, r3 2-4-7-8-2, and r4 2-10-12-14-2 (Fig. 1). On each route, the vehicle leaves from and returns to assembly plants 1 and 2, respectively (Fig. 1).

4.2 Initial solutions

The initial solutions can be generated as follows described by Algorithm 1:

Algorithm 1: Initial solution generation
Input: Population size P; the set of unserved suppliers N'.
Output: Initial solution S

```
For count ← 1 to P do
S ← ∅, N' ← N
  if N' ≠ ∅ do
     Insert a supplier i selected randomly into the route of vehicle k by the GS
     N' ← N\i
   end
   S ← s
End
```

4.3 Improved 2-point crossover

In light of the features of multiple assembly plants, a 2-point crossover operation was designed below (Fig. 2):

- Select two chromosomes according to the crossover probability;
- Select two random gene positions $g1$ and $g2$ from chromosome $P1$;
- Switch the places of genes $g1$ and $g2$ with the genes $g3$ and $g4$ in the same position of chromosome $P2$;
- Switch the places of other genes in $P1$ in a similar way;
- Switch the places of other genes in $P2$ in a similar way.

Next, the adaptive crossover probability was used to select individuals:

$$p_c = \begin{cases} p_{c1} - \frac{(p_{c1}-p_{c2})(f'-f_{avg})}{f_{max}-f_{avg}}, & f' \geq f_{avg} \\ p_{c2}, & f' < f_{avg} \end{cases} \tag{16}$$

where f_{avg} is the mean fitness of the current population; f_{max} is the maximum fitness of the current population. Usually, $p_{c1} = 0.9$ and $p_{c2} = 0.6$.

4.4 Mutation operation

The author designed a simple mutation operation as follows (Fig. 3):

- Select a chromosome according to mutation probability;
- Remove a random gene from the chromosome;
- Insert the gene into another position of any other route randomly.

The adaptive mutation probability was adopted:

$$p_m = \begin{cases} p_{m1} - \dfrac{(p_{m1}-p_{m2})(f_{max}-f)}{f_{max}-f_{avg}}, & f' \geq f_{avg} \\ p_{m2}, & f' < f_{avg} \end{cases} \tag{17}$$

where $p_{m1} = 0.1$ and $p_{m2} = 0.01$.

Assembly plant	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
Route	1	3	5	6	0	9	11	13	2	4	7	8	0	10	12	14

Fig. 1 Double-layer solution representation

						cp1				cp2						
P1	1	3	5	6	0	9	11	13	2	4	7	8	0	10	12	2
P2	1	6	4	9	0	8	11	12	2	7	5	10	0	13	3	2
O1	1	3	5	6	0	8	11	13	2	7	4	9	0	10	12	2
O1	1	6	7	8	0	9	11	12	2	4	5	10	0	13	3	2

Fig 2 An example of 2-point crossover operation

Assembly plant	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
Route	1	3	5	6	0	9	11	13	2	4	7	8	0	10	12	2
Assembly plant	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2
Route	1	3	5	6	0	9	13	2	4	11	7	8	0	10	12	2

Fig. 3 An example of the muation operation

4.5 Selection

The individuals of relatively high fitness were copied to the next generation. Here, the roulette wheel method is employed for the selection of these individuals. During the iteration, some infeasible solutions may occur, which helps to explore better solutions. Hence, the objective function was combined with a penalty function into the fitness function below:

$$F_{fit}(I) = F(I) + W(I) \tag{18}$$

where $F(I)$ is the objective function; $W(I)$ is the penalty function:

$$W(I) = \alpha_1 w_1 + \alpha_2 w_2 \tag{19}$$

$$w_1 = max\left\{\sum_{i \in V} p_{ik} z_{ik} - Q_k, 0\right\} \tag{20}$$

$$w_2 = max\left\{\sum_{i \in N} t_i z_{ik} + \sum_{i \in V}\sum_{j \in V} t_{ij} x_{ijk} - T, 0\right\} \tag{21}$$

4.6 Local search

The LS can promote the quality of global search, and enhance the final solution [28]. In light of our problem, two neighbourhood structures were created to search for new solution spaces:

- Exchange operation: Select any chromosome and switch the places of any two genes on the chromosome;
- 2-opt: Reverse the order of any two genes in a random chromosome.

5. Case Study: Results and discussion

This section applies the proposed formulation in a real case using Python. The application was run on a computer (1.8 GHz Intel Core, 4 GB RAM). The CMAL, a third-party logistic provider for automobile enterprises, was taken as the object of the case study. The CMAL currently serves two assembly plants. The basic parameters are as follows: vehicle size is 2.4 × 2.4 × 9.6 m^3, unit distribution cost is 4.7, and inventory cost is 2. The data on demand and location of assembly plants are listed in Table 1, and the data on supply and location of suppliers are listed in Table 2. For assembly plant 1, the uncertain demand obeys normal distribution in [0, 9] and the expected value is 911.16; for assembly plant 2, the uncertain demand also obeys normal distribution in [0, 9] and the expected value is 782.62. The maximum and minimum values of uncertain variables were determined by the 3 σ rule.

The AGA-LS is run 10 times with the frequency 6, 7, 8, 9 and 10 when the demand is certain, the largest and smallest frequency numbers are obtained according to the production planning. The cost changes as follows in Table 3.

We can find that the cost is lowest when the frequency is 6. In this case, the inventory cost is 564.6, and the transportation cost is 2491.5. when the frequency increases from 6 to 10, the transportation cost also increases from 2491.5 to 3435.1, but the inventory cost decreases from 564.6 to 338.8. we can conclude that the transportation cost increases more than the inventory cost as the frequency increases. The cost change of the Instance 1 with the iteration is seen in Fig. 4. We can find that our proposed algorithm has a high convergence speed where a better solution is obtained when the iteration reaches no more than 60. In addition, when the iteration ranges from 0 to 60, the solutions are improved greatly and fast, which validates the superiority of the algorithm on solving the problem.

Table 1 Data about 2 assemble plants

ID	Demand	Coordinate_x	Coordinate_y
1	911.16	106.538078	29.677212
2	782.61	106.596291	29.68965

Table 2 Data about suppliers

ID	Supply	Coordinate_x	Coordinate_y
1	90.04	106.514381	29.669697
2	226.10	106.515114	29.664557
3	135.39	106.508034	29.667334
4	5.29	106.502769	29.666943
5	85.48	106.499321	29.664776
6	84.66	106.498947	29.666237
7	61.62	106.531982	29.683313
8	85.40	106.535172	29.681656
9	63.87	106.534164	29.680086
10	31.74	106.592857	29.675314
11	18.42	106.599693	29.679518
12	23.50	106.591721	29.678984
13	17.66	106.594559	29.68322
14	34.42	106.596855	29.685228
15	38.49	106.587585	29.684204
16	124.62	106.601219	29.691582
17	87.04	106.601578	29.694155
18	90.91	106.597221	29.694084
19	170.53	106.600243	29.698023
20	85.48	106.59433	29.6973
21	133.11	106.589554	29.696985

Table 3 Cost changes with different frequencies

	Frequency				
Instance	6	7	8	9	10
1	2864.5	2806.1	3733.8	3433.0	4042.0
2	2980.8	3443.2	3837.1	4227.3	3436.0
3	3263.7	3455.9	2884.0	3909.8	3986.0
4	2990.4	3158.2	3686.2	3867.9	3337.0
5	3156.0	3358.8	3564.9	3139.5	3475.5
6	3245.1	2884.8	3816.4	4133.1	3425.8
7	3082.0	3026.5	3264.0	3879.5	4539.0
8	2913.6	3520.7	3348.1	3121.5	3880.1
9	2803.1	2852.5	3657.8	3229.6	4174.4
10	3261.4	3523.2	3558.6	3244.7	3443.5
Average cost	3056.1	3203.0	3535.1	3618.6	3773.9

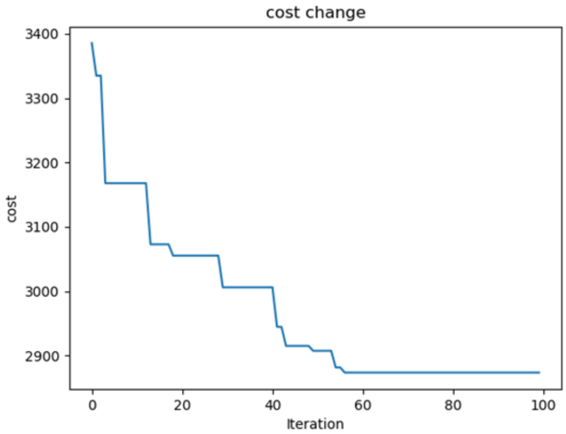

Fig. 4 the cost change with the frequency 6

Next, the AGA-LS is compared with the standard GA at the frequency of 6. The results are shown in Table 4.

We can conclude that we can get a better solution with total average cost 3056.1 by means of AGA-LS, and the total cost is 3786.7 obtained by the means of GA, the savings is over 20 % on average, which demonstrates the superiority of our method.

For the robust optimization model, defining the values of robust levels is important. However, schedulers cannot determine exactly the values of these variances. In this paper, we assume the robust level is 0.8. According to above analysis, the total cost is lowest when the frequency is 6. We can get following transportation schedules that is seen in Table 5.

According to the probablity distribution of uncertain demand, we generate 10 isntances with uncertain demand (the demand ranges from 902.16 to 920.16 at the depot 1 and from 773.61 to 791.61 at the depot 2) to evaluate the solutions. There are 10 routes on each schedule. As a result, we find 27 of 100 routes cannot satisfy the demand of corresponding assembly plant on the optimal schedule, while only 10 of 100 routes cannot satisfy the demand of corresponding assembly plant on the suboptimal schedule. We can concluside that the suboptimal schedule is a more stable one though its total cost is higher. Therefore, the manager can do that trade off between schedule stability and schedule cost according to obtained results and their production plan, e.g. they can apply the stable schedule for the sale season and the low cost schedule for the slow season.

Table 4 Performance analyze between AGA-LS and GA with the frequency 6

	Instance										
	1	2	3	4	5	6	7	8	9	10	Average
AGA-LS	2864.5	2980.8	3263.7	2990.4	3156.0	3245.1	3082.0	2913.6	2803.1	3261.4	3056.1
GA	2957.4	4471.2	3590.1	5382.7	3534.7	3991.5	3236.1	3117.6	3215.6	4370.3	3786.7

Table 5 Comparison of Optimal and suboptimal schedules

Transportaton schedule	Route		Objective value	Acceptable degree
Optimal schedule	Depot1 : D1-3-5-6-D1 D1-7-18-19-17-16-10-D1 D1-1-2-D1 D1-9-D1 D1-8-D1	Depot2 : D2-9-D2 D2-21-17-16-11-14-13-D2 D2-15-12-D2 D2-7-4-3-D2 D2-18-19-20-D2	2803.1	73/100
Suboptimal schedule	D1-5-6-D1 D1-7-9-D1 D1-1-3-2-D1 D1-8-D1 D1-18-19-17-16-10-D1	D2-17-16-11-D2 D2-18-20-21-D2 D2-14-3-D2 D2-9-7-D2 D2-15-12-13-14-19-D2	2933.1	90/100

6. Conclusion

This paper developed a novel model for milk run pickup problem on the distribution of automobile parts. Considering the complexity of the problem, the AGA-LS solution method was developed through the integration of the AGA and the LS. The proposed algorithm was run 10 times and contrasted with the standard GA. The results show that the AGA-LS outperformed the standard GA in the reduction of the overall cost.

This paper marks the first-ever research into the VRP on milk run pickup problem with uncertain demand and frequency, considering the balance between inventory cost and distribution cost. Our solution method is of important practical significance for logistics enterprises and automobile enterprises to make plan. The research findings also lay a solid foundation for the survey on stochastic travel time and the time windows, which will be the further research direction to make our proposed solution method more practical. In addition, order to guide operations of enterprises, we will develop a vehicle dispatch platform.

References

[1] Brabazon, P.G., MacCarthy, B.L. (2017). The automotive order to delivery process: How should it be configured for different markets?, *European Journal of Operational Research,* Vol. 263, No. 1, 142-157, doi: 10.1016/j.ejor.2017.04.017.

[2] Huminic, G., Huminic, A. (2017). Numerical analysis of hybrid nanofluids as coolants for automotive applications, *International Journal of Heat and Technology,* Vol. 35, No. 1, 288-292, doi: 10.18280/ijht.35Sp0139.

[3] Huang, Z.D., Liu, X.J., Tan, Y.S. (2016). An empirical study: Integrating relative coordinates with simulated annealing to solve a traveling salesman problem, *Mathematical Modelling of Engineering Problems,* Vol. 3, No. 4, 175-178.

[4] Kim, S.-L., Ha, D. (2003). A JIT lot-splitting model for supply chain management: Enhancing buyer-supplier linkage, *International Journal of Production Economics*, Vol. 86, No. 1, 1-10, doi: 10.1016/S0925-5273(03)00006-9.

[5] Su, J., Li, C., Tsai, S.-B., Lu, H., Liu, A., Chen, Q. (2018). A sustainable closed-loop supply chain decision mechanism in the electronic sector, *Sustainability,* Vol. 10, No. 4, 1295, doi: 10.3390/su10041295.

[6] Sadjadi, S.J., Jafari, M., Amini, T. (2009). A new mathematical modeling and a genetic algorithm search for milk run problem (an auto industry supply chain case study), *The International Journal of Advanced Manufacturing Technology*, Vol. 44, No. 1-2, 194-200, doi: 10.1007/s00170-008-1648-5.

[7] Hosseini, S.D., Shirazi, M.A., Karimi, B. (2014). Cross-docking and milk run logistics in a consolidation network: A hybrid of harmony search and simulated annealing approach, *Journal of Manufacturing Systems,* Vol. 33, No. 4, 567-577, doi: 10.1016/j.jmsy.2014.05.004.

[8] Pesce, L.F., Frazão, C., Civinskas, J., Pires, M. (2000). The next step for a lean production: Milk run, In: *International Mobility Technology Conference and Exhibit,* São Paulo, Brasil, doi: 10.4271/2000-01-3230.

[9] Jiang, Z., Huang, Y., Wang, J. (2010). Routing for the milk-run pickup system in automobile parts supply, In: Huang, G.Q., Mak, K.L., Maropoulos, P.G. (eds.), *Proceedings of the 6th CIRP-Sponsored International Conference on Digital Enterprise Technology*, *Advances in Intelligent and Soft Computing*, Vol 66, Springer, Berlin, Heidelberg, Germany, 1267-1275, doi: 10.1007/978-3-642-10430-5_97.

[10] Lin, Y., Xu, T., Bian, Z. (2015). A two-phase heuristic algorithm for the common frequency routing problem with vehicle type choice in the milk run, *Mathematical Problems in Engineering*, Vol. 2015, Article ID 404868, 13 pages, doi: 10.1155/ 2015/404868.

[11] Du, T., Wang, F.K., Lu, P.-Y. (2007). A real-time vehicle-dispatching system for consolidating milk runs, *Transportation Research Part E: Logistics and Transportation Review,* Vol. 43, No. 5, 565-577, doi: 10.1016/j.tre.2006.03.001.

[12] Klenk, E., Galka, S., Günthner, W.A. (2015). Operating strategies for in-plant milk-run systems, *IFAC-PapersOnLine,* Vol. 48, No. 3, 1882-1887, doi: 10.1016/j.ifacol.2015.06.361.

[13] Novaes, A.G.N., Bez, E.T., Burin, P.J., Aragão Jr, D.P. (2015). Dynamic milk-run OEM operations in over-congested traffic conditions, *Computers & Industrial Engineering,* Vol. 88, 326-340, doi: 10.1016/j.cie.2015.07.010.

[14] Güner, A.R., Murat, A., Chinnam, R.B. (2017). Dynamic routing for milk-run tours with time windows in stochastic time-dependent networks, *Transportation Research Part E: Logistics & Transportation Review,* Vol. 97, No. 251-267, doi: 10.1016/j.tre.2016.10.014.

[15] Cho, K.K., Chung, K.H., Park, C., Park, J.C., Kim, H.S. (2001). A spatial scheduling system for block painting process in shipbuilding, *CIRP Annals,* Vol. 50, No. 1, 339-342, doi: 10.1016/S0007-8506(07)62135-0.

[16] Jafari-Eskandari, M., Aliahmadi, A.R., Khaleghi, G.H.H. (2010). A robust optimisation approach for the milk run problem with time windows with inventory uncertainty: An auto industry supply chain case study*, International Journal of Rapid Manufacturing,* Vol. 1, No. 3, 334-347, doi: 10.1504/IJRAPIDM.2010.034254.

[17] Jafari-Eskandari, M., Jalali-Naiini, S.G.H., Aliahmadi, A.R., Sadjadi, S.J. (2010). A robust optimization approach for the milk run problem with time windows under inventory uncertainty – An auto industry supply chain case study, In: *Proceedings of the 2010 International Conference on Industrial Engineering and Operations Management*, Dhaka, Bangladesh, 1-7.

[18] Su, J., Yang, Y., Zhang, N. (2017). Measurement of knowledge diffusion efficiency for the weighted knowledge collaboration networks, *Kybernetes,* Vol. 46, No. 4, 672-692, doi: 10.1108/K-09-2016-0229.
[19] Hoeffding, W. (1963). Probability inequalities for sums of bounded random variables, *Journal of the American Statistical Association*, Vol. 58, No. 301, 13-30, doi: 10.1080/01621459.1963.10500830.
[20] Ni, L., He, Y.D., Zhou, L., Deng, L. (2015). Robust control optimization of triple-echelon closed-loop pallet pool system in multi-uncertain environment, *Journal of Information and Computational Science,* Vol. 12, No. 7, 2635-2645.
[21] Mirandola, A., Lorenzini, E. (2016). Energy, environment and climate: From the past to the future, *International Journal of Heat and Technology,* Vol. 34, No. 2, 159-164, doi: 10.18280/ijht.340201.
[22] Baker, B.M., Ayechew, M.A. (2003). A genetic algorithm for the vehicle routing problem, *Computers & Operations Research,* Vol. 30, No. 5, 787-800, doi: 10.1016/S0305-0548(02)00051-5.
[23] Ho, W., Ho, G.T.S., Ji, P., Lau, H.C.W. (2008). A hybrid genetic algorithm for the multi-depot vehicle routing problem, *Engineering Applications of Artificial Intelligence,* Vol. 21, No. 4, 548-557, doi: 10.1016/j.engappai.2007.06.001.
[24] Su, J., Yang, Y., Zhang, X. (2016). A member selection model of collaboration new product development teams considering knowledge and collaboration, *Journal of Intelligent Systems,* Vol. 27, No. 2, 213-229, doi: 10.1515/jisys-2016-0078.
[25] He, Y., Wang, X., Lin, Y., Zhou, F., Zhou, L. (2017). Sustainable decision making for joint distribution center location choice, *Transportation Research Part D: Transport and Environment*, Vol. 55, 202-216, doi: 10.1016/j.trd.2017.07.001.
[26] He, Y., Wang, X., Lin, Y., Zhou, F. (2016). Optimal partner combination for joint distribution alliance using integrated fuzzy EW-AHP and TOPSIS for online shopping, *Sustainability*, Vol. 8, No, 4, 341, doi: 10.3390/su8040341.
[27] Song, D. (2017). Decision-making process and information, *NeuroQuantology,* Vol. 15, No. 4, 31-36.
[28] Sen, G.D., Sharma, J., Goyal, G.R., Singh, A.K. (2017). A multi-objective PSO (MOPSO) algorithm for optimal active power dispatch with pollution control, *Mathematical Modelling of Engineering Problems,* Vol. 4, No. 3, 113-119, doi: 10.18280/mmep.040301.