SIMULTANEOUS ROUTING AND LOADING METHOD FOR MILK-RUN USING HYBRID GENETIC SEARCH ALGORITHM

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Abstract − *Milk-run methodology is proposed to manage the procurement of orders from suppliers. The heuristic solution methods in the literature generally apply stepwise approach to route and load the vehicles. In this study we propose a hybrid genetic local search algorithm which simultaneous solves vehicle routing and order loading problems. This is the main contribution of the study. We consider volume and weight capacities (multi capacitated) of different types of transportation vehicles (heterogeneous fleet). Because of high adaptability and easy utilization, genetic algorithms are the most preferred approach of meta-heuristics. The chromosome structure of the proposed genetic algorithm is constituted by random numbers to eliminate infeasibility. The best chromosome of each generation is improved using local search method during the algorithm runs. We applied the algorithm to a real manufacturing company that produces welding robots and other process automation equipment. The results showed the effectiveness of the algorithm.*

Keywords −*Hybrid Genetic Algorithms, Local Search, Milk-Run, Total Transportation Costs*

1. INTRODUCTION

In today's business environment supply chain competitiveness is increasingly based on providing customers with consistent quality at reasonable low prices. Material procurement systems play a crucial role in order to achieve this goal because their effectiveness and efficiency directly contribute to make production and following processes smooth in order to avoid lateness, lack of materials, or line stops and thus minimizing operating expenses and enhancing the customer service level. Material procurement is mainly based on delivery methods which can be categorized as direct shipping, milk-run, cross docking and tailored networks [5]. If full truckload is used, then direct shipment will be required. But in general, for real world applications, less than truck load is used. So, in this situation the other three modes are implemented. In milk-run, a common vehicle utilization method is applied to collect the orders from different suppliers. So, it might be necessary to consider local suppliers. In cross docking, vehicle sharing between suppliers and customers is also possible. Additionally in cross docking, consolidation centers are used in order to decrease inventory levels. In the tailored networks approach, direct shipment, milk-run and cross docking can be used according to the conditions under consideration. It requires a high level of system coordination in order to prevent shortage. The complex transportation structures generally need to cover solutions about direct shipment and milk-run problem.

In particular, milk-run is a procurement method whose aims are delivering raw materials, work in process or finished goods using a fixed route and time schedule and consolidating products by the buyer [3, 4]. The milk-run problem is a special kind of vehicle routing problem with time windows and a limited number of vehicles [7]. It has been extensively adopted by the automotive industry but also the consumer electronic, electro-mechanical, and convenience good industries, and even third party logistics [21] have developed interesting applications of milk-run. There are multiple benefits of this strategy. First of all, milk-run yields a reduction in

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transportation costs due to load consolidation. Moreover, it allows synchronization between suppliers and customers that supports better production and inventory performance. Additionally, the milk-run approach improves vehicle load factors and shortens the total distance travelled. Finally, it reduces the risk of product quality since customers can promptly discover and inform the suppliers of any rising issue. In a word, milk-run helps achieving suppliers and customers coordination, agility and flexibility of supplies as well as responsiveness and system efficiency ([3]; [13]; [15]; [22]; [23]; [24]). However, it implies a certain level of complexity due to the strict coordination required to all the parties involved [1].

Two main forms of milk-run can be found both in literature and in practice: in-plant ([11]; [12]) and supplier milk-run ([5]; [15]). In-plant milk-run is usually applied by the shop floor of a company to supply different workstations and departments from a warehouse, while supplier milk-run is concerned with the distribution of goods from external suppliers to a customer.

This work focuses on supplier milk-run. Operations research has proposed a lot of mathematical and heuristics models for solving such problem under different conditions and finding optimal routes, quantities and vehicle loads. Most of them are focused on either the vehicle routing or the loading issue separately and very often consider just one type of vehicle and one kind of product. Therefore, a more general approach is required in order to provide solutions that effectively capture the interactions between vehicle routing and loading strategies and that can be applied in complex procurement systems characterized by multiple vehicles, different products and associated heterogeneous capacities.

In order to contribute to fill the research gap, the present paper develops a simultaneous routing and loading model for milk-run using a hybrid genetic search algorithm. This is a multi-capacitated model where various products and capacity constraints, together with a heterogeneous fleet of vehicles, are taken into account. The model has been applied to design a supplier milk-run system for Comau S.p.A, an Italian company producing robotized equipment. In particular, the plant located in Torino, Italy was considered. The benefits that can be achieved compared to the traditional material procurement system that is currently adopted were estimated.

The paper is organized as follows. Relevant literature is overviewed in Section 2, while Section 3 presents the model. Its first application is described in Section 4. Finally, benefits and limitations of the proposed approach as well as its implications and future research development are discussed in Section 5.

2. LITERATURE REVIEW

In the literature there are different types of studies about milk-run which are inspired by diverse logistic requirements. While some studies mainly focus on milk-run transportation costs, others consider cross-docking, time windows and/or inventory costs. Generally, their assumptions are different from each other. While this situation obstructs the possibility of comparing different algorithms, it gives real production companies the opportunity to use the algorithm which best fits their needs.

Cross-docking and milk-run logistics are frequently studied in the literature. Hosseini et al. (2014) developed an integer programming model for the problem. Because of the problem complexity, they also proposed a heuristic model that has a hybrid structure, using harmony search and simulated annealing algorithms. In the studied problem, all trucks had the same capacity [9]. Yildiz et al. (2010) proposed a Mixed Integer Programming (MIP) model to select subsets of suppliers and customers which were in the same location to combine their shipments on the same route. Consolidation centers were also considered in the study and it was investigated whether this type of change increases savings or not. Additionally, in this work cross-dock utilization was investigated besides routing problem [17]. Kallehauge (2008) presented a survey of effective exact algorithms about vehicle routing problem with time windows. In the study, the problem definition is made and different approaches on sub tour, path and resource inequalities are summed up. The author also gave methods to find lower bounds for the aforementioned problem [10]. Inventory costs were sometimes taken into account besides transportation costs. Özdemir et al. (2006) focused on collaborative supply methods which benefit from sharing stock amounts between locations (information pooling), thus minimizing total cost including stock holding and shortage costs. The authors proposed a linear programming (LP) model for the problem and considered the capacity of trucks [14]. Yun et al. (2010) analyzed the interaction between inventory and transshipment. In order to perform vehicle routing, they used genetic algorithms. Natural numbers were used in the encoding scheme. With the aim of balancing inventory cost and transportation cost, a stepwise iterative algorithm was applied to minimize total cost. Vehicles maximum load weights are considered in the problem [24]. In the study of Yokoyama (2002), the authors developed an integrated optimization model with stochastic demand that considers transportation, inventory and shortage costs. There were multiple distribution centers in the study and in order to simplify the model, a single item was considered. The authors also included time horizon. In particular, they developed two different models; the first one was a random local search model to determine target inventory levels. The second one was a genetic algorithm based method to test random local search methods. The target inventory levels of each distribution center constituted the chromosome structure [20]. Sadjadi et al. (2009) included due dates and inventory costs in their analysis. The waiting cost of a truck at each supplier was also taken into account (stopping cost). Authors considered pallet loads for each part. A mathematical model was proposed for the milk-run problem. Such mathematical model and a genetic algorithm approach, which was developed beforehand to determine optimal price discrimination [16], were used to solve the small scale problem which includes maximum ten suppliers and fifty parts [15].

The following studies are mainly focused on the milk-run problem with different assumptions. Bianchessi and Righini (2007) analyzed the simultaneous pick-up and delivery problem and presented heuristics algorithms in order to minimize the overall length of tours. In this problem type, each customer had either delivery or pick-up operation (or both) and vehicle capacity was determined. The authors presented several neighborhoods to be used in local search algorithms. They also applied tabu search for the mentioned problem and tested the set of instances that was generated randomly [2]. In the study of Guizzi et al. (2012), authors focused on reverse milk-run. In order to manage waste electrical and electronic equipment, the authors built a new model based on pull logic. They first analyzed and described the key features of the current system and introduced the main features of the new system by means of causal loop diagrams. Then, the authors used the System Dynamics approach to generate stock and flow diagrams. After analyzing the model, which aims to decrease inventory, effective results were obtained via a simulation software [6]. You and Jiao (2014) considered volume and weight capacities of vehicles and parts. There was one type of vehicle in this study and fixed costs and transportation costs were determined. A mathematical model was developed for the mentioned problem and in order to solve large scale problems an improved saving algorithm was presented. The algorithm, including six successor steps, was then applied to a courier company [23].

In our study, we consider multi capacity vehicles (volume and weight capacities) and a heterogeneous fleet (small and big vehicles) to increase flexibility and decrease costs. We also consider a multi-product structure to comply with the requirements of real systems. None of the examined studies provides all these assumptions together. However, it is important to understand how vehicles with different capacities and products with diverse characteristics simultaneously influence both routing and vehicle loading strategies in the milk-run problem. This enables a better use of available resources and an optimization of tours, thus increasing efficiency. That is the main contribution of the study. Another point is that the proposed hybrid genetic algorithm is inspired from our previous algorithms related to the scheduling problem [18] and the open vehicle routing problem (OVRP) [19]. The algorithm outperformed Ant Colony Optimization heuristic- whose performance was better than other heuristics- for scheduling problems. For OVRP, comparisons with mixed integer programming models were done to show the strength of the algorithm. We do not only adapt the chromosome structure to the milk-run problem, but also improve the code which is written in C# to get faster and more accurate results. In order to get better parameter values the design of experiment method is used which will be explained in the subsequent sections.

3. HYBRID GENETIC SEARCH ALGORITHM

Genetic algorithm -which was introduced in 1975 by Holland [8] - is a heuristic search algorithm based on evaluation theory which makes natural selection to strengthen the next generations. The population contains a number of different chromosomes which have different objective function results. Chromosomes are constituted by genes. In our study, we used random numbers to represent genes in order to get feasible chromosomes after each crossover operation. In our previous studies we succeeded to overcome the difficulties that are caused by utilizing a local search algorithm in genetic algorithm [18, 19]. In the present work the algorithm was adapted to the milk-run problem by using assumptions that were determined by Comau S.p.A. The hybrid genetic search algorithm is presented in the next sub-sections.

3.1. Encoding

In the developed genetic algorithm, chromosome is designed by random numbers that are generated between 0 and 1. Random numbers determine the route of each vehicle type. A sample chromosome structure of the example is shown in Figure 1. According to this structure, chromosome involves *n* (number of suppliers) sections. Each section is divided into two sub-sections, which show the different vehicle types. According to example that illustrated in Figure 1, we have 3 suppliers and 2 vehicle types. For $Supplier_A$, we will select the vehicle that has the smallest random number between the two numbers generated for $Supplier_A$. This value is 0.20 which means, products of $Supplier_A$ will be carried by $VehicleType_1$. Similarly, the products of $Supplier_B$ will be carried by $VehicleType_0$ and the products of $Supplier_C$ will be carried by $VehicleType_1$. The selected numbers in chromosome are shown in bold in Figure 1.

Supplier	A		B		C	
Vehicle Types	0	1	0	1	0	1
Random Keys	0.99	**0.20**	**0.30**	0.54	0.80	**0.44**

Figure 1. Chromosome Structure

3.2. Fitness Function and Genetic Operators

For the example that considers three suppliers and two vehicle types, Table 1 and Table 2 show transportation costs between stated nodes for $VehicleType_0$ and $VehicleType_1$ respectively.

Table 1. Transportation Cost for $VehicleType_0$ (unit of currency)

	$Supplier_A$	$Supplier_B$	$Supplier_C$
Manufacturer	20	30	40
$Supplier_A$	-	10	20
$Supplier_B$	30	-	50
$Supplier_C$	40	30	-

Table 2. Transportation Cost for $VehicleType_1$ (unit of currency)

	$Supplier_A$	$Supplier_B$	$Supplier_C$
Manufacturer	40	60	80
$Supplier_A$	-	20	40
$Supplier_B$	60	-	100
$Supplier_C$	80	60	-

According to the chromosome structure in Figure 1, $VehicleType_0$ will carry the products of $Supplier_B$. And $VehicleType_1$ will carry the products of $Supplier_A$ and $Supplier_C$. The sequence in which suppliers are visited will be determined by increasing order of the selected random numbers (0.20; 0.44). So, $VehicleType_1$ will first take the products of $Supplier_A$ and then the products of $Supplier_C$. Transportation costs of $VehicleType_0$ and $VehicleType_1$ will be 30 and 80 respectively as it shown in Figure 2. The objective value at this moment is minimizing the maximum transportation cost. We selected this objective value at this stage associated with "makespan" logic in scheduling problem [18] that the proposed algorithm in this study is inspired from. For each specific chromosome, the local search algorithm explained in the next section will be applied to find better transportation cost. After getting the best route for this chromosome, the products of each supplier need to be loaded onto the predetermined type of vehicle. The outline of this process is described in Figure 3. According to the load assignment flowchart in Figure 3, if the demand of suppliers for each product is bigger than a full vehicle load, direct shipment from the supplier is performed. For the remaining loads, orders of different suppliers are combined according to aforementioned routes to minimize the total transportation cost. At this point, capacity constraints and maximum number of stops for each vehicle constraints are considered. For the application in Comau S.p.A., the maximum number of stops for each vehicle is determined as ten suppliers- which will be explained in detail in the next sections-. The stopping cost is considered as 20€ for small vehicles 30€ for big vehicles. After determining the number of vehicles and their final routes, the objective function of chromosome (total transportation cost) will be ready. The number of different chromosome structures and objective function values will be determined by the population size (P_{size}).

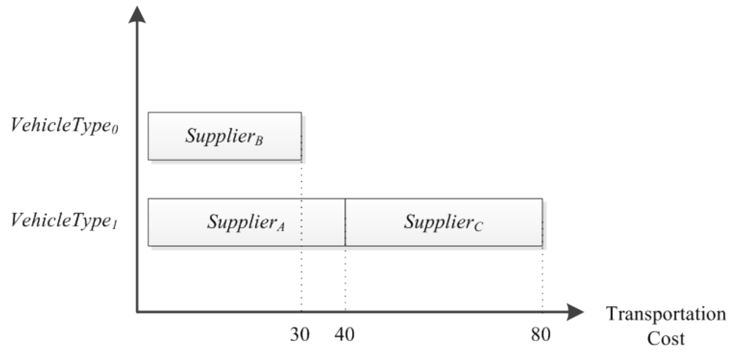

Figure 2. Resulting Routes For Chromosome in Figure 1

After getting the initial population, selection, crossover and mutation operators need to be applied to achieve better subsequent generation. Brief explanation of these processes is as follows. For further information the previous applications can be examined [18], [19].

- Selection: in the presented hybrid genetic search algorithm, mom and dad (parent) chromosomes are selected randomly from the population into mating pool.
- Crossover: crossover operation is applied to selected parent chromosomes. The crossover rate (P_c) determines the quantity of crossover operations in the population. A single point crossover operator is applied in the presented algorithm. The crossover operator randomly choses the point of crossing, and exchanges the genes between mom and dad in order to create offspring. The next generation will include the best two chromosomes out of mom, dad and two new offsprings.
- Mutation: mutation operation is used to prevent convergence to local optimum. The multiplication of population number and mutation rate (P_m) defines the number of chromosomes that will be mutated. The value of the randomly selected gene will be replaced with the new random number for each selected chromosome in this operation. The fitness value might be the same, better or worse after applying the operator.

3.3. Local Search

In order to obtain lower transportation costs, the local search method is implemented in genetic algorithm. Our aim is searching all possible alternatives in a chromosome. There are three types of change in this algorithm.

- Inter-vehicle change of adjacent suppliers: if the suppliers at issue are consecutive in the same vehicle route, transportation costs differences are calculated in case of changing these two suppliers in the route. If a better result is obtained, the route of the vehicle is changed according to the new sequence of suppliers.
- Inter-vehicle change of non-adjacent suppliers: the logic is similar to the adjacent supplier case but additional transportation cost differences are considered during the calculation. Because some other transportation costs between non adjacent suppliers need to be included.
- Intra-vehicle exchange: this time the decision about supplier change between vehicles is given. The number of calculations is increased in this step, but this is the most important search type to get lower costs.

The chromosome structure we used in the algorithm is consisting of random numbers. So, after each interchange or exchange decision of suppliers in vehicles, the new routes need to be reflected to chromosome.

The algorithm that provides the required route by changing the minimum number of random numbers on the chromosome in this application is similar to our previous study about scheduling [18]. Jobs are converted to suppliers; machines are converted to vehicle types in this study. The required adaptations are made for the milk-run code which is written in C# language.

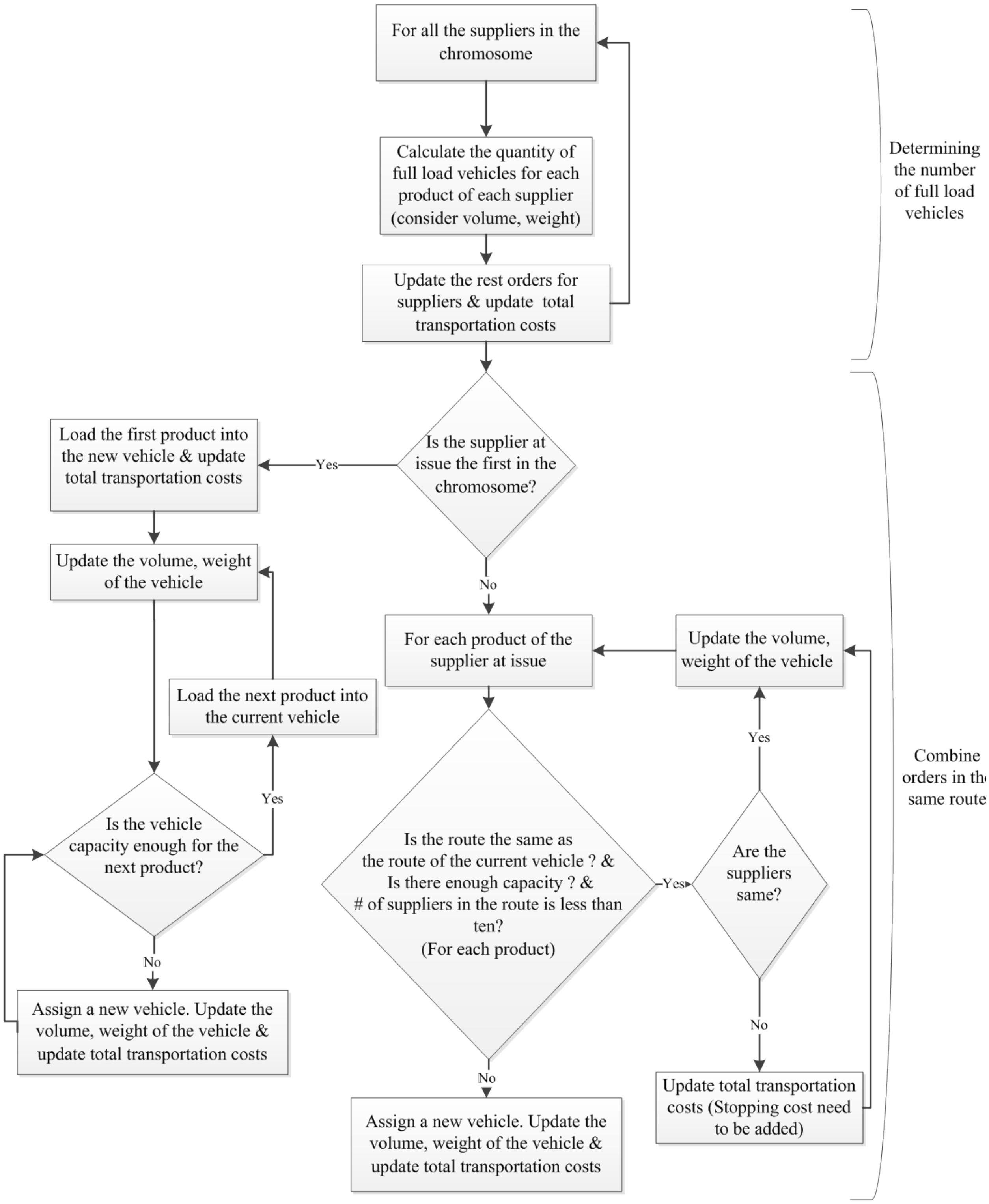

Figure 3. Load Assignment Flowchart

4. EXPERIMENTAL DESIGN AND APPLICATION IN COMAU S.P.A.

The parameter tuning of the presented algorithm will be done using real application data in the first sub-section. In the second sub-section, the input data that was used in the application will be introduced. In the third sub-section the computational results will be analyzed.

4.1. Experimental Design The main parameters of hybrid genetic local search algorithm P_{size}, P_c, P_m are selected as 100, 1, and 0.2 respectively that conform to our previous study of scheduling [18]. The current algorithm was run using these values and the results were effective. The transportation costs are registered for every 100 generations up to 500 generations. The algorithm could not give improved results after 100 generations. So, the number of generations is fixed to 100. The configuration of the other factors that are specific to the milk-run problem is done by Design of Experiments (DoE) methodology. Volume and weight constraints of the selected vehicle types need to be compatible with the structure of orders. That's why vehicle type's factor is important in this study. In this real application, two types of vehicle will be used and we are trying to determine which will be used by DoE. Stopping cost effects total transportation cost. So, deciding maximum stop quantity for vehicles is another important factor. The associated factors (parameters) and levels are summarized in Table 3. Each combination is replicated five times to improve the significance of experimental results. According to Figure 4, when the value of the maximum stop quantity parameter is set to the level of 10 and the vehicle type parameter is set to the level of Pick-up van; Truck, the algorithm gives better transportation costs. It would be worth noting that there is no interaction between the two parameters according to interaction plot that is shown in Figure 5.

Table 3. Parameters And Levels For DoE

Parameters	Levels	
1. Vehicle Type	Truck ; TIR	Pick-up van; Truck
2. Maximum Stop Quantity	10	5

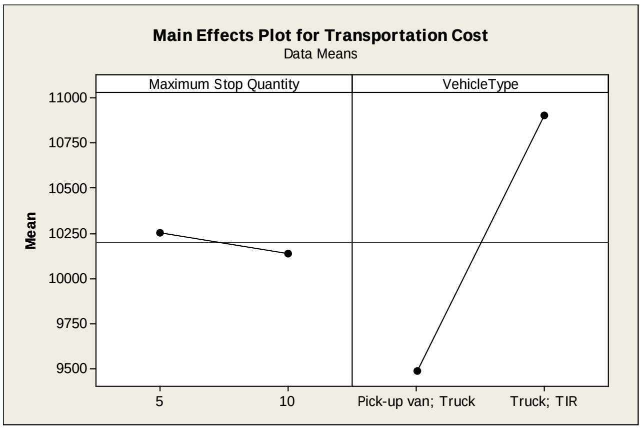

Figure 4. Main Effects Plot of Two Parameters

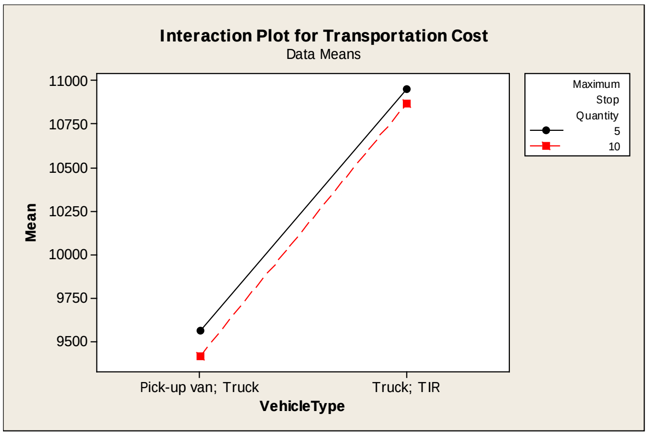

Figure 5. Interaction Plot

4.2. Input Data

The developed algorithm is run using one week production order- which will be delivered from Italy - of Comau Robotics. All orders are considered without making any classification analysis such as ABC analysis. Note that, some of the applications in real life do not consider C group materials of ABC analysis that needs simple control. There are two types of input data that the algorithm requires. The first one includes materials, quantities, unit weights, unit volume, suppliers and location information for each ordered material. Table 4 shows a selection of this data. The most of robotic materials are heavyweight, that's why the volume constraint is overshadowed in many materials. So, volume data is obtained only for high volume parts. The second data is the distance between locations. Table 5 shows a section of this distance matrix which is not symmetric. For example, the distance from $Location_1$ to $Location_2$ is different than the distance from $Location_2$ to $Location_1$ according to Table 5. Number of parts, locations and suppliers are 536, 29, and 36 respectively for the considered case. Total number of parts that will be carried in milk-run is 40,788. For this real application, all input data can be found in [25]. For confidentiality reasons the name of parts, suppliers and locations are symbolized. Volume and weight constraints of pick-up vans and trucks are, 17m^3, 45m^3, 3,500kg, 15,500kg respectively.

Table 4. Input Data for Materials

Material	Quantity	Unit Weight [kg]	Unit Volume [m^3]	Suppliers	Location
0001	2	50.00	0.65	18	13
0002	5	50.00	0.65	18	13
0003	4	38.00	0.11	20	18
…	…	…	…	…	…
0534	33	0.01		14	2
0535	5	0.01		17	26
0536	10	0.01		22	17

Table 5. Input Data for Distances

TO LOCATION

FROM LOCATION

Distances Between Locations [km.]	1	2	3	4	5	…	27	28	29
1	10	74	928	360	36	…	780	18	29
2	63	10	889	321	43	…	741	75	44
3	930	889	10	618	897	…	216	928	903
4	362	321	619	10	329	…	452	360	335
5	36	42	10	328	10	…	749	34	8
…	…	…	…	…	…	…	…	…	…
27	782	741	216	451	749	…	10	780	755
28	18	73	926	358	34	…	779	10	38
29	29	43	900	332	8	…	753	39	10

4.3. Computational Results

The developed algorithm was run utilizing input values of the above mentioned problem. The registered elapsed time was 47 seconds for this instance. According to the proposed model, all of the orders are carried using 9 pick-up vans and 3 trucks. Each vehicle's utilization rate, route, total material quantities (item) that was carried and total distance information is summarized in Table 6. Utilization was computed for both weight and volume constraints. The maximum value of these two utilization rates gives the values of the variable "Vehicle Utilization Rate" in Table 6. Average utilization rate is 70% for this application. The location of the Torino Comau plant is coded with the number 26. That's why all of the vehicles leave from 26th location and turn back the same place. As it can be seen in Table 6, vehicles are visiting maximum ten locations, which is one of the algorithm's parameter that was investigated in experimental design section. Stopping costs for pick-up vans and trucks are assumed equal to 20€ and 30€ per stop respectively. The value of the variable Total Material Quantity for each vehicle is also shown in Table 6. The loading details of vehicles can be seen in the Output_Load page of the aforementioned link [25]. The total travelled distance is 5,691 km. Suppliers are transshipping their orders themselves to Comau according to the current supply method. There is not any data of the current utilization rates to compare with the average data of milk-run.

But, when the suppliers bring orders themselves and the customer allows supplier to dispatch orders that more than required planning period, high vehicle utilization causes high inventory costs. This is another subject of study that includes inventories. For the studied problem, the ratio of milk-run total transportation costs to total material costs is calculated as 1.5%. As a result, the proposed hybrid genetic algorithm outperformed by a considerable margin the supply method currently adopted by Comau. The applied milk-run method managed consolidating the orders of different suppliers on the same way. This method not only decreases transportation costs but also saves the environment. We do not give here the values of the unit cost of transportation, expressed in €/km, for each vehicle type in order to protect the rights of the company.

Table 6. The Result of The Examined Problem

Vehicle	Vehicle Utilization Rate	Route of Locations	Total Material Quantity	Total Distance [km]
Pick-up van 1	97%	26-23-26	16	78
Pick-up van 2	59%	26-6-4-20-26-13-12-10-26	34,005	1,119
Pick-up van 3	81%	26-23-26	20	78
Pick-up van 4	55%	26-23-26	18	78
Pick-up van 5	90%	26-23-9-26	31	84
Pick-up van 6	72%	26-9-2-29-26	2,602	126
Pick-up van 7	99%	26-29-5-3-27-8-5-26	963	1,050
Pick-up van 8	28%	26-5-26-26-16-1-28-21-7-1-19-26	1,376	189
Pick-up van 9	19%	26-25-14-17-13-26-26	960	273
Truck 1	84%	26-11-17-15-18-22-24-26	665	1,396
Truck 2	99%	26-24-26	50	610
Truck 3	54%	26-24-26	82	610
Average	**70%**	**Total**	**40,788**	**5,691**

5. CONCLUSIONS

The present work develops a hybrid genetic local search algorithm to solve both vehicle routing and loading problems in supplier milk-run. The main advantage of the proposed approach is that it addresses different products and vehicles with diverse capacities, thus allowing taking into account the mutual interactions among such factors while determining the best route and loading strategy. The application to the design of a milk-run system for Comau S.p.A. brought benefits in terms of vehicle utilization and optimization of distance travelled, thus leading to a significant reduction in non-value-added transportation costs. The developed methodology has both theoretical and practical implications. On the one hand, it suggests researchers an effective way to combine the vehicle routing and loading problems in a multi-capacitated and multi-product environment, thus overcoming the limitation of current literature that usually looks at one or few products and kinds of vehicle. On the other hand, it provides the focus company and other potentially interested organizations with a structured method to design a milk-run system that fits the characteristics of complex material procurement processes.

However, the proposed approach still needs an appropriate validation. In fact, its claimed benefits are theoretical in nature and should be checked with the actual implementation of the milk-run system by Comau. Also, the methodology should be applied to different settings in order to assess its robustness. Another validation method might be formulating MIP model and evaluate the hybrid genetic local search algorithm for some instances.

Future research will be mainly addressed towards extending the application of the algorithm to various manufacturing environments to test its suitability and foster the necessary improvements. Other constraints, such as inventory costs, could be incorporated into future research.

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