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The Milk Collection Problem with Time Constraint: an Optimization Study Integrating Simulation

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Abstract

Transport management and vehicle routing problems play a strong role on a company's efficiency and competitiveness. In the food sector, the complexity of the problem grows because of strict constraints. This paper addresses the dairy transportation problem and in particular tries to optimize the milk collection process of a real company. A two-step approach has been proposed to test the current system and solve the routing problem. First, starting from the "As is" collection tours, a travel salesman problem has been modelled. Later, the Nearest Neighbor algorithm has been implemented in order to find a global optimal solution. Finally, a stochastic simulation model integrates the solutions of the previous step in order to test the feasibility of the outcomes, primarily in terms of their capability to meet the time constraints of the tours. Results show that the greedy approach allows less vehicles to be involved, with a good potential on annual cost saving. On the other hand, the simulation outcomes highlight a borderline case, which is not always in line with the time constraints of the problem.

Keywords: dairy transportation problem; vehicle routing problem; nearest neighbour algorithm; stochastic simulation model

1. Introduction

Supply chain management (SCM) and its optimization is an important topic widely discussed in literature. It includes different processes, which interact each other in different ways. Among them, procurement and the related logistic service is one of the most critical activity, having a strong influence on all the downstream processes of the chain. The need of flexibility and the increasing logistic costs can lead companies to externalize the transportation management, especially in food industry (Hsiao et al., 2010). The complexity of the problem has also led many academic researchers to study the topic and try to optimize real systems.

A common problem is the batching and collection management, in terms of quantity of raw material to procure per collection route (Das & Chowdhury, 2012). Another widely discussed topic is the routing problem, i.e. the identification of the best sequence of collection points that minimize travel distance, time or cost (Jozefowiez et al., 2008).

In the food sector, logistics and operations management are influenced by strict constraints and SCM plays a strong role on the company success. Transport management and efficient vehicle routing solutions become crucial for the competitiveness of the whole supply chain. Since years, researchers have started to study dairy company and they have tried to optimize dairy plants. Energy aspects and waste reduction are the most popular topics (Schnitzer et al. 2017; Marchini et al., 2014), and the current literature seems to have a gap on supply chain aspects in the dairy sector.

In this context, some authors have started to study the dairy transportation problem (DTP) that consists of determining the best routes to be performed for collecting milk from farms and delivering it to the processing plants (Lahrichi et al., 2015). Jouzdani and Fathian (2014) proposed a mathematical programming model combining facility location (FLP) and vehicle routing problem (VRP) in a dairy supply chain with the goal of reducing transportation costs. Such approach can solve small and medium sized problems in a reasonable amount of time. Because of the computational complexity, other authors have implemented heuristic or meta-heuristic approaches for large scale problems, which find a good solution in an acceptable time (Dooley et al., 2005; Tarantilis and Kiranoudis, 2007). Amorim and Almada-Lobo (2014) proposed a multi-objective framework to solve a VRP with perishability, inserting a freshness objective function to take into consideration the perishable nature of the product. Another current issue is the high variability and continuous fluctuation between milk supply and demand, which increases the complexity of the milk collection planning phase (Claassen and Hendriks, 2007). Masson et al. (2016) contribute to the DTP literature integrating weekly variations to better plan the routes and the assignment of routes to plants.

Only in recent years, authors have started to solve routing problems in food sector integrating simulation. In a variable context, simulation could be a great tool for determining the shortest route to transport fresh products. Wang et al. (2019) used numerical simulation to test the optimization algorithm presented. Calabrò et al. (2020) proposed a dynamic Ant Colony Optimization (ACO) algorithm implemented with a multi-agent simulation model to solve a capacity VRP with time window. Considering the variability of the traffic condition and the typical restrictions of the food sector, this paper proposes a two-step methodology for solving the dairy transportation problem and optimizing the milk collection process of a dairy company. First, the problem has been solved using both an analytic and a heuristic method, then the resulting solutions have been implemented in a stochastic simulation model. Thus, a first optimization has been performed starting from the current process: each vehicle visits fixed Pickup Points just choosing the sequence and a traditional multiple traveling salesman problem (MTSP) has been applied. Secondly, a greedy approach for solving a capacitated traveling salesman problem (CTSP) has been implemented in order to optimize the whole system, considering capacity constraints. This second solution starts from the assumption that each vehicle can visit each Pickup Point in accordance with its capacity. The Nearest Neighbor algorithm has been chosen because of its simplicity and its limited computational effort. Finally, in both cases, the resulting tours have been reproduced using a simulation model. Thus, the paper contributes to the current literature by combining mathematical, heuristic and simulation methods to find the most suitable solution. Moreover, considering the time restrictions of the food industry, the model becomes a useful tool able to support logistic operators in routing problems with uncertainty.

The rest of the paper is organized as follows: section 2 introduces the context. Section 3 explains the two-step approach proposed. Then, main results are shown in section 4 and some general conclusions and limitations are presented in section 5.

2. Context Analysis

The company involved in the study is a dairy company located in the north of Italy. Its business is focused on Parmigiano Reggiano cheese production. The product needs different raw materials, but obviously, the most important one is milk. Because of the need for flexibility and the high demand variability, transportation activities are outsourced. A logistics provider manages the raw material collection and its commission has been negotiated with the company considering the provided service and the specific constraints.

In fact, milk collection management depends on the rules that regulate the production of Parmigiano Reggiano. In line with these rules, two picks per day have to be performed, one in the morning and one in the evening. Moreover, the time elapsing from milking to cheese manufacturing must be lower than 4 hours. Thus, in order to respect the time constraints, six different tours are organized twice a day to reach 36 milk suppliers. Four different vehicles with various capacity are involved. The first four tours start at the driver's home and end at the dairy plant. The last two tours are carried out when the first two procurement processes have been concluded, always starting and ending at the dairy plant. Overall, the system consists of 5 different Starting Points, 1 End Point, and 36 Pickup Points.

As already introduced, the delivery quantity is highly variable and mainly depends on the season of the year. In fact, the animal well-being is fundamental and the milk production becomes strongly related to the climatic conditions. Spring is the most productive period, while milk production decreases to the lowest level in autumn. Table 1 shows the minimum, maximum and average amount of raw material (kg/week) provided by firms during the four seasons.

Table 1. Raw material amount (kg/week) provided by firms during a calendar year

Raw Material	Minimum quantity	Maximum quantity	Average quantity
Milk	624,121	729,756	679,869

Taking the specific context into consideration, the Logistics Provider applies a variable cost, due to the outsourcing service. Such cost has been determined in the form of a fixed rate due to the general service plus a variable rate reflecting the resources involved. A preliminary analysis has revealed that the variable rate mainly covers the travel distance, which accounts for approximately 85% of the total variable cost. The remaining 15% depends, instead, on the number of vehicles used.

Starting from the considerations above, the following costs have been determined: 13.25 € for each tour and 1.36 € for each km travelled.

3. Methodology

As already asserted, the proposed approach consists of two steps:

1. Shortest path search: this step consists of some sub-steps involving different resolution methods
   - "As is" analysis: the current milk collection system has been studied. The Provider manages fixed runs with fixed routes. All the Pickup Points are assigned to fixed tours.
   - First optimization: a first optimization has been performed starting from the "As is" scenario. For each fixed tour, a classic traveling salesman problem has been applied in order to identify the best route to be performed.
   - Second optimization: a greedy approach is implemented in order to optimize the whole system, considering capacity constraints. This second solution starts from the assumption that each vehicle can visit each Pickup Point in according with their capacity. Tours and routes are mixed with the aim of limiting the number of vehicles involved.
2. Time window constraint test: the solutions resulting from the previous step are reproduced using a simulation model, with the aim to test the practical feasibility of the solution taking into account the time constraints.

Three Key Performance Indicators (KPIs) have been calculated to evaluate and compare the different scenarios. For each v-th Vehicle and each r-th collecting tour, two strategic KPIs have been defined:

- The Vehicle Saturation Rate (%), calculated as the ratio between the total amount of milk transported by the vehicle (kg) and its capacity (kg).
- The Vehicle Efficiency (kg/km), computed as the ratio between the quantity transported (kg) and the distance travelled (km)

Moreover, a further economic KPI is computed:

- The Total Travel Cost (€/year) is the total cost payed for the procurement service, excluded the fixed service cost. It is computed as the sum of fixed and variable costs due to the travel distance and the number of vehicles involved.

3.1. Minimum path search

3.1.1. Sub-step 1: "As is" analysis

The first step of the analysis was the study of the current system ("As-is" system), which can be resumed as follows. Concerning the milk collection process, we have 6 fixed tours, performed 2 times a day for 365 days a year. All 36 Pickup Points are visited twice a day. All the distances and the travel time between two Points have been calculated using Google Maps. Even though the delivery quantity is variable and it depends on seasonal factors, annual average values have been considered in order to simplify the modelling and derive general considerations. Thus, for each Supplier, the specific situation has been analyzed considering all the deliveries of the year. Later, an average quantity provided for each fixed delivery has been obtained. Such data will be used as input data in all scenarios. Finally, the current runs have been reproduced following the current sequence of Points and the three KPIs have been computed.

3.1.2. Sub-step 2: Mathematical solution

Step 2 consists on the optimization of the current system by simply changing the sequence of the Pickup Points, keeping the fixed tours unchanged. The aim is to check if the system is already optimized; otherwise the shortest path for each tour will be identified.

The specific context involves a defined number of vehicles with different capacity. However, at this stage, the capacity is not taken into account, since the fixed run have been already defined considering the maximum amount of raw material that each vehicle can transport.

For such reason, a MTSP has been applied considering more vehicles characterized by fixed start and end points. For each vehicle, the mathematical model consists on the following formulation: in a graph $G = (V, E)$ where V is the set of n vertices (reflecting n Suppliers in our case) and E is the set of arcs (the routes that connect two different vertices), d_{ij} is the distance to be travelled from vertex i to vertex j. Taking x_{ij} as a binary variable which scores 1 only if arc (i,j) appears in the tour and zero otherwise, the problem can be modeled as follows:

$$\text{Min } z = \sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} d_{ij} \tag{1}$$

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad j = 1, \dots, n \tag{2}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \qquad i = 1, \dots, n \tag{3}$$

$$\sum_{i \in Q}\sum_{j \in V-Q} x_{ij} > 1 \qquad \forall\, Q \subseteq V, |Q| \geq 1 \tag{4}$$

Equations (2) and (3) form the assignment constraints and ensure that each node is visited only once. Equation (4) avoids sub tours.

As it is well known, there are no exact algorithms for solving the problem in general; the only way to find the global optimum path is enumerating all the possible tours. However, if the graphs consists of n nodes, there are *n!* possible paths. In the case under examination, because of the strict constraints, the "As is" fixed runs had been defined with a limited number of nodes to visit, i.e. up to 9. For such reason, thanks to the computational potential of Microsoft Excel™, all the possible combinations were tested, meaning that 6 fixed milk tours were solved by calculating all the possible paths. The best solution in terms of minimum path has been identified for each "As is" fixed tour.

3.1.3. Sub-step 3: Heuristic Approach

The last optimization phase rises from the consideration that the supplier assignment to a run has been defined following reasonable assumptions about the farm location. Moreover, the number of vehicles has been defined *a priori* too. For these reasons, starting from the list of all Suppliers, a heuristic algorithm has been implemented to find a better solution. Thus, the model redistributes the suppliers to the tours just maintaining the same start and end points of the previous step. Since all the milk suppliers have to be visited every day, the algorithm has been applied to the whole list of Suppliers. In fact, it is necessary to maintain the time and number of deliveries established with each firm.

The Vehicle routing problem analyzed consists of a set of vehicles, which have to visit multiple delivery points considering their capacity. Each point provides a fixed quantity of raw material. The aim is to assign each supplier to a vehicle minimizing the distance and the number of vehicles involved.

The nearest neighbor algorithm has been chosen because it is very easy to implement. It consists of a greedy approach, which tries to find a good global solution by connecting at each step the closest point. Thus, each time, the algorithm chooses the best local solution without considering the effect on next steps.

Once again, the computational potential of Microsoft Excel™ has been used to implement the logic of the algorithm. Such tool allows to simply insert all the logics using its VBA programming language.

The model input data are: maximum number of vehicles (V) with related capacity (Q_v), start Point and end Point; the list of suppliers (S=36) with relating delivery quantity per day (DQ_S), and distance between each point (d_{ij}). The VBA code has been written following a procedure delineated by the authors; because of the multiple vehicles, before assigning a supplier to a tour, a double check has been inserted.

The first check is shown in figure 1. For each vehicle, the model searches the nearest Delivery Point that respects the capacity constraint and the Supplier is temporary assigned to that tour.

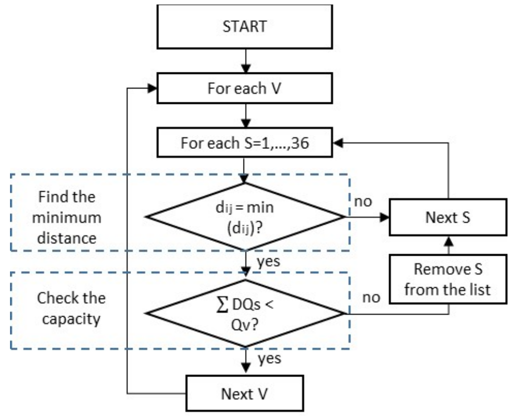

Figure 1. assignment phase; first check

Once the model has identified the closest feasible solution, a second control is made. For each vehicle, if the selected Delivery Point has been assigned just to it, the decision is confirmed and the Supplier is definitively assigned to that tour. Otherwise, if two or more vehicles choose the same Delivery Point, distances (d_{ij}) are compared and the Supplier is definitively assigned to the vehicle that registers the minimum distance. The remaining vehicles go back to the previous step and repeat the first check since a Supplier is assigned. Obviously, anytime a Supplier is definitively assigned to a tour, it is also removed from the list. Once all the Suppliers of the list have been chosen or if the capacity constraint can no longer be satisfied, the vehicle return to the end point.

Finally, in order to identify the minimum number of vehicles, the model was launched with V=6, which reflects the real case. Then, the remaining solutions were tested by decreasing the number of vehicles available. If was found that V=5 still returns a feasible solution, while V=4 does not generate feasible solutions as the capacity constraint is not met.

3.2. Simulation test

As explained in the previous section, the process of collecting the raw material daily depends on rules and constraints, which regulate the specific production of the finished product. The main restriction is due to the total collecting time, which must be shorter than 4 hours. The simulation phase aims at verifying whether the solutions found in the previous step also meet this constraint. For this purpose, the final tours proposed by each approach have been reproduced in a simulation model designed again using Microsoft Excel™. Stochastic times have been considered for taking into account the variability due to traffic conditions. For each scenario, 30 replicates were launched and the Total Time per Tour (minutes) was calculated as the sum of the travel times and the loading times resulting from all the Pickup Points of the tour. In turn, for each Point the travel time to reach a different Point was calculated starting from the estimate returned by Google Maps (*Tt*). In fact, the travel time has been modelled as a normal distribution with (Tt, 25%*Tt).

Since the milk loading time (*Tl*) is affected by a lower variability, it has been described as a normal distribution with (Tl, 5%*Tl) as suggested by the company owner. In each replicate, the simulation model provides different *Tt* and *Tl*, according with the normal distribution implemented. Finally, for each tour, an average result is computed and compared with the time constraint (4*60 = 240 minutes). All the numerical results are discussed in the next session.

4. Results and Discussion

A comparison between the three scenarios is presented in order to test the suitability of the current collection system. As already asserted, 6 milk collection tours are organized twice a day, one in the morning and one in the evening. Table 2 shows the results of the 6 fixed tours and compares the performance of the current sequence of Points with the best sequence found with the MTSP application. First findings are presented considering that the two scenarios start from the same defined and fixed assignment. For such reason, the Vehicle Saturation Rate (%) does not vary and it is not reported in Table 2.

Table 2. "As is" vs. MTSP scenario

Tour	KPIs	As Is	MTSP
1	Total distance (km)	28	
	Vehicle Efficiency (kg/km)	385	
2	Total distance (km)	57	**50**
	Vehicle Efficiency (kg/km)	128	**146**
3	Total distance (km)	68	**58**
	Vehicle Efficiency (kg/km)	146	**171**
4	Total distance (km)	38	
	Vehicle Efficiency (kg/km)	165	
5	Total distance (km)	31	**29**
	Vehicle Efficiency (kg/km)	255	**272**
6	Total distance (km)	33	
	Vehicle Efficiency (kg/km)	186	

For three out of six tours , the Logistic Provider applies the solution with the minimum path, and Tour 5 is quite close to the best performance. In all cases, the total distance of the tour is limited and such aspect could affect the result. In fact, when the distance increases (tour 2 or 3), a better solution is found, with a saving in the total distance of about 15%.

Otherwise, the third scenario consists in the identification of new tours with the purpose of finding better solutions. Since new tours are completely different, it is not always possible to compare them as shown in the previous analysis. Aggregated performance values are computed and compared considering the whole quantity collected in the morning milk runs. Table 3 shows that the most efficient solution is provided by scenario 2, while the other two solutions present similar performances. Since the amount delivered is the same, the best approach is the one with the minimum distance travelled.

Table 3. Vehicle Efficiency comparison (morning tours)

KPIs	As Is	MTSP	Nearest Neighbour
Total quantity (kg)		49,673	
Total distance (km)	254	**235**	253
Vehicle Efficiency (kg/km)	195	**211**	196

The vehicle efficiency does not take into account the number of vehicles involved in the tours. In fact, considering the vehicles fleet, the third scenario would become the best one. Thus, concerning the Vehicle Saturation Rate, the greedy algorithm provides the best solution; results are presented in Table 4.

Table 4. KPIs results (morning tours)

KPIs	As Is	MTSP	Nearest Neighbour
Total Vehicles	6	6	**5**
Vehicle Saturation Rate (%)	80%	80%	**97%**

As a first general conclusion, we can say that the algorithm generates a worse solution in terms of total distance because it employs less vehicles to visit all the suppliers of the list.

Finally, a cost comparison has been made. As already explained, the Logistic Provider applies a transport rate, which considers the resources involved. Table 5 presents the daily cost considering both the morning and the afternoon tours of the day. Fixed costs consider the number of vehicles, while the variable rate depends on the total travel distance.

Table 5. Economic performance (daily results)

Cost (€/day)	As Is	MTSP	Nearest Neighbour
Fixed Cost	79.50	79.50	66.25
Variable Cost	347.51	322.08	346.83
Total Daily Cost	854.02	**803.15**	826.15

Since the travel distance has a central importance, the most competitive approach remains the second one. Even though the remaining two solutions are almost equivalent in terms of travel distance, the nearest neighbour algorithm provides better performance in terms of the number of vehicles involved (5 vs. 6). For such reason, the "As is" scenario results to be the worst one. Moreover, considering that the daily tours are carried out every day of the year, the gap becomes relevant. Figure 2 shows the interesting annual savings that could be reached compared to the current solution.

Finally, the simulation outcomes are presented in terms of mean and standard deviation resulting from the 30 replications. The mean values are reported in Table 6. Moreover, results show a very low variability; in fact, the standard deviation varies from 0.02% to 0.05%, which demonstrates the stability of the outcomes.

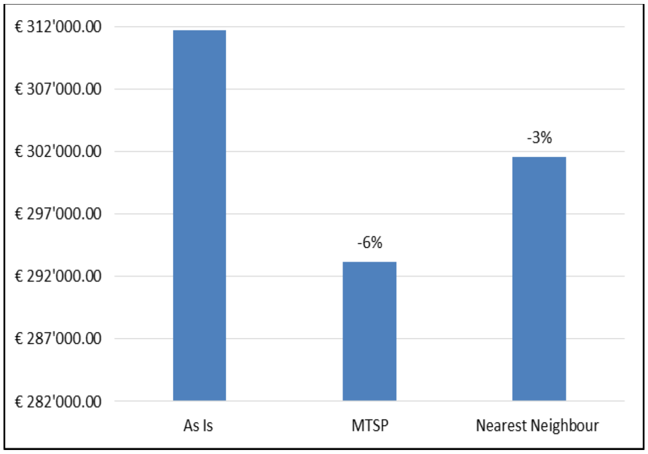

Figure 2. Total travel Cost (€/year)

Table 6. Average Total Time per tour (minutes)

Tour	As Is	MTSP	Nearest Neighbour
1	56	57	180
2	154	144	**238**
3	165	158	178
4	95	96	51
5	114	107	112
6	119	120	-

As shown, the Nearest Neighbour algorithm provides one critical result only. In fact, Tour #2 presents an average time lower than the time constraint (240 min), but very close to it. Such outcome turns out to be borderline and needs to be examined in detail. Thus, analysing each replicate, 14 times out of 30, the simulation model provides a Total Time out of bound, with a maximum score of 253 minutes.

5. Conclusions

The paper proposes a two-step approach for solving the milk collection problem. The aim is to check the performance of the current system and to try to find better solutions. First, the current tours have been reproduced to evaluate their efficiency. Then, a travel salesman problem has been modelled and the Nearest Neighbour algorithm has been implemented to find alternative solutions that could be improve the current process. Finally, the tours provided by each approach have been tested by means of a simulation model, in order to check the consistency with the time constraint.

In general, results show that the current system could be improved. In terms of travel distance, the MTSP returns the best performance. Anyway, the greedy algorithm allows to involve less vehicles respect to the other alternatives. Such aspect is relevant and could considerably change the annual cost. In fact, the applied transport rate assumes 6 vehicles to be involved at a time, while the new approach allows reducing this number. Thanks to such finding, the company could discuss and negotiate a new tariff in order to decrease the total cost. On the other end, the simulation outcomes reveal that one tour proposed by the algorithm is very critical; thus, the variability of the traffic conditions could involve some problems in respecting the time constraints. Nonetheless, the algorithm has room for improvement; in fact, the end point is never considered and the model usually leaves the farthest suppliers as the last points to visit. Thus, all the vehicles move away from the dairy plant and they have to travel high distance to return. In addition, further heuristic approaches could be tested to find better solutions and respecting the time constraints.

Finally, several future researches could be undertaken. As mentioned, the study considers an annual average quantity even though the monthly quantity is really variable and depends on natural factors. As a further research direction, the model could consider the seasonal fluctuations of the amount of milk collected. Thus, the integration of the two steps could help the milk collection planning and provide a dynamic outcome with a specific daily solution.

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