



Optimizing Milkrun Routes: Heuristic Approach for Minimizing Transportation Loops

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Abstract: Milkrun systems serve as the backbone of material supply for multi-line or parallel manufacturing production, ensuring synchronized and efficient logistics. Despite their importance, route optimization is still largely done manually, leading to inefficiencies. If too few routes are used, transportation time increases, and individual vehicles become overloaded, which is a common issue in current practices. Finding the optimal number of routes is a complex NP-hard problem, requiring advanced computational approaches. While assignment matrices are often available and useful for direct transport allocation, they are not used for optimizing milkrun loops. To address this, a heuristic-based model has been developed that optimizes the number of routes while considering travel length and vehicle capacity. The model and case study integrates genetic algorithms to explore feasible solutions efficiently, balancing the trade-off between too many and too few routes. The proposed approach improves both cost-effectiveness and service reliability in production logistics.

Keywords: assignment problem; heuristic optimisation; milkrun; production logistics; route planning

1 INTRODUCTION

In today's fast-paced manufacturing environment, the efficiency of logistics and supply chain operations has become more critical than ever. Complex manufacturing systems that rely on the movement of materials in a scheduled order with vehicle support, often referred to as milkrun systems, are vital for ensuring smooth and synchronized material supply across multiple production lines or parallel manufacturing processes. These systems help maintain a steady flow of materials to production areas while minimizing delays, reducing costs, and improving overall productivity [1]. The design and optimization of milkrun routes, however, remain a complex challenge that many manufacturing systems still face. Although these systems are integral to manufacturing, route optimization is often carried out manually, leading to inefficiencies in logistics operations. The traditional approach can cause various problems, such as excessive transportation time or overloading of vehicles, which in turn, undermines the potential for cost savings and resource utilization [2].

One of the most significant challenges in optimizing milkrun systems lies in determining the ideal number of routes required for efficient material transportation. This task is classified as an NP-hard problem, meaning that finding the optimal solution is computationally demanding, especially as the number of production lines and logistics variables increases [3]. With too few routes, transportation times may increase, and vehicles can become overloaded or too long to handle, which can lead to delays and decrease service reliability. Conversely, too many routes can result in underutilized vehicles and higher operational costs. Therefore, a balance must be found that optimizes vehicle capacity while minimizing travel time, making the process a delicate one.

To address these challenges, a new approach is created based on the assignment or transportation problem. Traditional methods, most likely drawing on a layout, and using manual greedy optimisation approaches often useful for transport allocation but fall short when it comes to

optimizing the routes for milkrun loops considering different material needs of multiple products, capacity and sizes of boxes and trays. The lack of an efficient and systematic approach to route optimization has improved the development of more sophisticated techniques. A heuristic-based model has recently been introduced that focuses on finding the optimal number of routes while considering factors such as vehicle capacity and travel length. This approach integrates genetic algorithms, a type of evolutionary algorithm that mimics the process of natural selection to explore feasible solutions more efficiently.

The application of heuristics to optimize milkrun systems represents a significant advancement in solving this problem [4]. The genetic algorithm offers a flexible and powerful tool for tackling complex optimization task, which is widely integrated into various software platforms and programming languages, making them easily accessible and adaptable across different industries. This flexibility allows it to be applied to a broad range of optimization problems, including route optimisation and assignment problem.

In the following chapter, a literature review will be provided to explore the existing research in the field of milkrun system optimization and how others have approached similar problems. The third chapter will explore the basis of the problem and the methodology for solving it using a genetic algorithm. The fourth chapter will present a case study, showcasing the application of the proposed model in a constructed scenario. The results of this case study will be analyzed, demonstrating the effectiveness and potential of the model. Finally, the last chapter will summarize the findings of the paper, draw conclusions on the success of the proposed approach, and suggest future directions for research in milkrun system optimization.

2 LITERATURE REVIEW

In today's fast-paced manufacturing environment, the efficiency of logistics and material handling plays a vital role in ensuring uninterrupted production flow and cost-effectiveness. Milkrun logistics has become an essential

strategy in modern supply chain and manufacturing systems, especially for industries like automotive, where timely and efficient part delivery is critical. The concept, which originates from the Just-In-Time (JIT) philosophy introduced by the Toyota Production System, involves collecting materials from multiple suppliers and delivering them to a central point or production line in a single, circular route [5]. This approach helps reduce transportation costs, minimize inventory, and improve overall efficiency. Over the years, milkrun systems have grown more complex, now involving challenges such as multi-stop routing, reverse logistics, and diverse vehicle and packing constraints [6]. Solving these problems using exact optimization methods can be time-consuming and impractical for large-scale operations. As a result, heuristic and metaheuristic approaches - such as Ant Colony Optimization, Genetic Algorithm, Simulated Annealing, and tailored routing strategies - have become increasingly popular. These methods provide fast, near-optimal solutions and are highly effective in handling real-world logistics challenges where flexibility and speed are key [7].

Ranjbaran and his team worked on improving how auto parts are delivered and returned using a milkrun system. Their mathematical model considered real-life constraints like truck size, pallet packing, order compatibility, and even the return of empty pallets. To solve large, complex problems quickly, they developed heuristic methods that found good solutions and showed clear cost savings [8].

Salleh and her team focused on reducing transport distance and improving truck space usage in milkrun routes. They found nearly half the truck space was going to waste and showed that this could be reduced to just 3% using optimization methods like Tabu Search and Ant Colony Optimization. Their approach supports the Just-In-Time delivery model by encouraging smaller, more frequent shipments with better efficiency [9]. Sipahioğlu and his team also looked at in-plant milkruns but added autonomous vehicles into the mix. With complex delivery needs and timing, they used Simulated Annealing to plan both routes and delivery periods effectively [10]. Uygun and Rustemaj compared traditional Mixed Integer Programming with Ant Colony Optimization for solving milkrun routing problems. While both used vehicle space efficiently, the ant colony method created better delivery routes, showing that nature-inspired algorithms can offer strong alternatives in logistics planning [11].

Bányai offered a simpler method using Excel Solver to plan milkrun routes within factories, helping decide how many carts are needed and where they should go. His method is flexible and works well in different manufacturing setups [12]. In a more recent and advanced study, the same researcher also investigates a hub-based milkrun supply system, showing that integrating warehouse handling with production can significantly reduce service and transportation times. His work presents a new mathematical model that compares traditional milkrun methods with a hub-based approach in the automotive industry. The analysis reveals that a hub-based system can boost efficiency by reducing total service time by about 13% and transportation

time by up to 45% in the component warehouse [13]. Roberto Murillo-Ramirez and partner use Bayesian networks to address uncertainty in milkrun systems, quantifying both optimistic and pessimistic scenarios. Their research provides insights into how delays in component deliveries can lead to financial losses in assembly lines [14]. Hashini and Nishal explore vehicle routing models for milkrun deliveries of fresh produce, highlighting the challenges faced by third-party logistics providers. Their study demonstrates that an automated routing solution can cut total costs by 26% and reduce overall travel distance by 40% [15]. The research emphasizes the impact of factors such as vehicle capacity, departure times, and route assignments on overall efficiency. Grzegorz Bocewicz, Izabela Nielsen, and Zbigniew Banaszak examine cyclic systems for in-plant milkrun delivery by looking at both routing and scheduling decisions [16]. Hosseini and partners employ a cyclic scheduling approach to minimize both vehicle downtime and production takt time. Their declarative model synchronizes cyclic flows using a recursive constraint satisfaction method to manage congestion effectively. To solve the NP-hard problem, a hybrid Harmony Search-Simulated Annealing algorithm is developed, which outperforms traditional solvers like GAMS/CPLEX in both cost reduction and computational efficiency, particularly in large-scale scenarios [17].

Each of these studies highlights the value of heuristic and optimization methods in addressing the complex logistics challenges found in milkrun systems. While studies [8–11] rely heavily on metaheuristics without incorporating simpler methods, studies [12–17] combine heuristic approaches with additional deterministic algorithms (like Linear Programming), offering more balanced solutions. Notably, studies [12], [13], and [15] make use of assignment matrices, though only as supportive tools rather than primary optimization methods. Bányai's contributions [12–13] have had a strong influence on my research in this area.

Collectively, this body of literature demonstrates how smart planning, and advanced computational techniques can significantly improve supply chain performance. Bányai's contributions have had a strong influence on my research in this area.

3 MODELLING MILKRUNS WITH ASSIGNMENT MATRICES

Milkrun logistics systems aim to optimize the collection and distribution of goods along predefined, often cyclic, delivery routes. One effective way to represent and manage the decision-making in such systems is using assignment matrices.

3.1 Assignment Matrices in Logistics

These matrices are structured grids, usually binary, where rows represent delivery points (e.g., suppliers or customers) and columns represent vehicles or routes. A value of 1 in a cell indicates that a particular point is assigned to a specific vehicle, while 0 indicates no assignment. This structure allows for a clear and organized formulation of

route allocation, facilitating the modelling of key logistics decisions such as who serves whom and in what order.

When transitioning from simple assignment problems to more complex transportation problems, the assignment matrix can be adapted to include capacity constraints, delivery time windows, and route continuity. This transforms the matrix from a pure allocation model to a more dynamic structure that supports cost-based optimization. In this context, cost matrices become essential, incorporating not only time and distance but also factors such as human labour and machine resources, administrative overhead, installation costs, and other relevant parameters. These matrices feed into the cost function, typically aiming to minimize total distance travelled, fuel consumption, or delivery time.

To solve these models, deterministic methods are preferred when feasible. Linear Programming (LP) and Mixed Integer Linear Programming (MILP) formulations allow for precise optimization, especially when the problem size is moderate, and all parameters are known. These approaches are particularly suitable for industrial applications where predictability and reliability are prioritized over computational speed.

In more complex or large-scale systems where, exact solutions are computationally expensive, minimal heuristic approaches may be introduced - often not as a replacement for exact methods, but as supporting tools. For instance, assignment matrices may be pre-processed using greedy or clustering techniques to reduce the problem size before applying LP or MILP solvers. In other cases this is often solved using heuristic methods, especially in cases with a large number of parameters, multiple objectives, or weighting, since one of the key requirements of linear programming is that the relationships between parameters must be linear.

3.2 Assignment Matrices in Logistics

In this chapter, a model is introduced for optimizing milkrun routes using assignment matrices. The first step involves determining which materials are transported from various warehouses, storage locations, or supermarkets to specific destinations. This task can be solved efficiently and accurately using basic linear programming, producing optimal or near-optimal solutions. This process is demonstrated in the first table of the case study, where Excel Solver's built-in Simplex LP function was used.

The minimum number of required milkruns can also be calculated easily based on a perfectly constructed assignment matrix. In such cases, the minimum is determined by the smaller number between the matrix's rows or columns, for example a 4×7 matrix the exact number of assignments is 4. However, in transportation problems, adjustments are needed, since a single destination, such as a production line, may be served by multiple milkruns if one vehicle cannot fulfil the demand alone, or if the cost matrix yields a more efficient configuration. These decisions are driven by material demand and vehicle capacity constraints.

A distinctive feature of the model lies in its ability to reduce the number of milkruns by identifying and merging

destinations and starting points visited by multiple originally assigned routes. Through this consolidation, redundant routes can be eliminated, improving overall efficiency and lowering transportation costs.

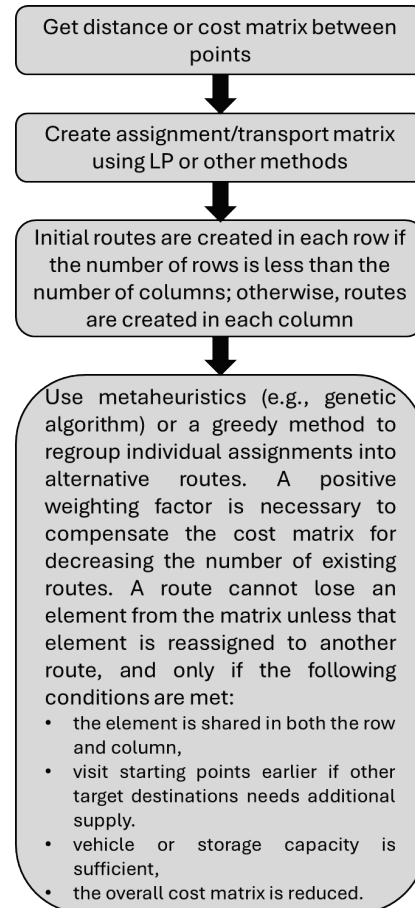


Figure 1 Schematic Description of the Model

The schematic operation of the algorithm is shown in Fig. 1. Since no new development or proposal has been made from a mathematical or algorithmic standpoint, this part will not be discussed in detail. Using the distance and cost matrices - derived from the positions and other characteristics of the points - it is possible to construct the actual assignment matrix through relatively simple methods such as LP or MILP. This matrix remains unchanged afterward. As mentioned earlier, the initial number of routes will equal the minimum of the number of rows and columns. The upper part of Figure 2 illustrates this: it displays a 4×7 matrix where the rows represent four suppliers (starting points), and the columns represent seven consumers (destinations). Since the number of suppliers is smaller, we start with four initial routes, shown in yellow, red, green, and blue. The pale-coloured cells indicate no delivery, because no connection was established by the LP algorithm - while the more vivid cells represent active assignments.

Considering the lower part of Fig. 2, many assignment or transport tasks can be reallocated in such a way that a milkrun can not only connect destinations but also include other starting points in its route, if delivery is required from those

points to the target destination. This redistribution can be optimized using heuristic, metaheuristic, or greedy methods. While greedy methods can sometimes yield optimal solutions in smaller problems, for larger instances, the chances of reaching a perfect solution are considerably lower.

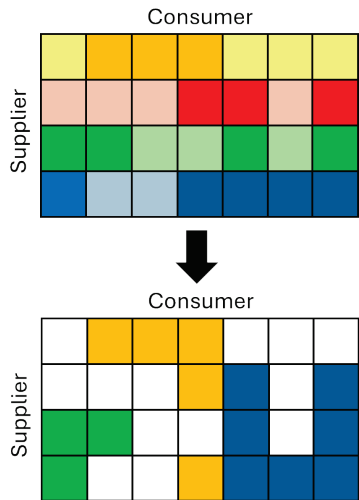


Figure 2 Visual representation of milkrun routes regrouping

Since the process involves extending routes - by including starting points that, under the original setup, were not meant to be part of the route network - it is almost inevitable that the resulting routes will be longer compared to the original multiple-route configuration. This can be compensated by assigning a high reward weight in the cost matrix whenever an existing route is eliminated. Unfortunately, determining the appropriate value of this weight is largely based on practical experience. If the goal is to strongly encourage the reduction of routes, a reward for eliminating a route should be roughly the same order of magnitude to the total cost of the original cost matrix.

A simple and practical approach to define the weight of a single route is to take the total cost of the original distribution and divide it by the number of routes. This can be represented as a function of: Summarized cost + n(route) × weight(route). In this case, the weight would be roughly on the same scale as the original total cost, but removing a route would still result in a significant value change, justifying it. Of course, this weight can be increased, but doing so would diminish the importance of optimizing the internal routing network, shifting the focus purely to reducing the number of routes. On the other hand, lowering the weight would emphasize the optimization of the internal network structure rather than simply reducing the number of routes. This is just a recommendation, but it is also applied this way in the current research.

When designing and configuring higher-level algorithms, special attention must be paid to several critical limitations. The most important of these is that a route cannot lose an element from the assignment matrix unless that element is reassigned to another route, and only if the following conditions are satisfied:

- the element appears in both a common row and column (i.e., there is an overlap),

- the vehicle or storage capacity is sufficient,
- visit other starting points earlier if multiple destinations still have demand from them,
- the overall cost matrix is reduced as a result with the weight of the route elimination.

Heuristic algorithms generally run until they can no longer improve the current solution for a significant number of iterations, and this is the approach recommended here as well. However, in large-scale problems - where matrix sizes may reach into the hundreds - there is a high chance that long periods go without any improvement. In contrast, running a greedy algorithm across various initial swap configurations can often yield good solutions early in the optimization process.

4 CASE STUDY ON SIMPLE TASK

The actual operation of the model and algorithm will be demonstrated on a relatively small, artificially created problem. According to the task description, a manufacturing company operates 7 product line and has 4 available storage points. The actual distances between them are shown in Tab. 2. The storage locations have different capacities, while the production lines have varying demands, represented by unit quantities. These demands, along with the distances, are displayed in the upper table of Fig. 3. For simplicity, the capacity of each milkrun is set to 200 units. In the middle table of Fig. 3, the assignment was solved using Excel Solver with the Simplex LP method, resulting in the formation of four groups starting from the four storage points. Also visible in Figure 3, the middle table shows the optimal distances between these points, and the bottom table displays the optimal route alongside the cost function. In this case, the total distance covered is 579.6 meters, and all demands have been fully satisfied.

Table 1 Distance matrix of task production

Distance (m)	S1	S2	S3	S4	PL1	PL2	PL3	PL4	PL5	PL6	PL7
Storage 1	0	37.5	87.3	155.4	6	67.2	136.3	35.6	71.9	118.9	142
Storage 2	37.5	0	64.8	132.9	43.3	79.9	149.4	14.3	51.6	98	119.5
Storage 3	87.3	64.8	0	101.5	81.3	48.5	118	51.7	20.2	66.6	88.1
Storage 4	155.4	132.9	102	0	149.4	112.4	43.3	119.8	83.5	36.5	13.4
Product Line 1	6	43.3	81.3	149.4	0	61.4	130.5	29.6	65.9	112.9	136
Product Line 2	67.2	79.9	48.5	112.4	61.4	0	93.9	65.6	28.9	75.9	99
Product Line 3	136.3	149.4	118	43.3	130.5	93.9	0	135.1	97.8	51.4	29.9
Product Line 4	35.6	14.3	51.7	119.8	29.6	65.6	135.1	0	38.5	84.9	106.4
Product Line 5	71.9	51.6	20.2	83.5	65.9	28.9	97.8	38.5	0	48.6	70.1
Product Line 6	118.9	98	66.6	36.5	112.9	75.9	51.4	84.9	48.6	0	23.1
Product Line 7	142	119.5	88.1	13.4	136	99	29.9	106.4	70.1	23.1	0

By applying the described algorithm, it was not only able to reduce the number of milkrun routes by one, but also managed to lower the total distance - without the need to define any additional weighting factors. This result was achieved by merging the two routes originating from S1 and S4 through their shared point PL3, using Excel Solver's built-in evolutionary algorithm, which also determined the optimal sequence. As a result, the total combined distance was reduced to 555.2 meters. This can be seen on Fig. 4.

Distance (m)	PL1	PL2	PL3	PL4	PL5	PL6	PL7	Service capacity (pcs)
Storage 1	6.0	67.2	136.3	35.6	71.9	118.9	142.0	140
Storage 2	43.3	79.9	149.4	14.3	51.6	98.0	119.5	100
Storage 3	81.3	48.5	118.0	51.7	20.2	66.6	88.1	170
Storage 4	149.4	112.4	43.3	119.8	83.5	36.5	13.4	80
Demands (pcs)	40	100	70	60	50	20	70	

Assignment matrix (pcs)	PL1	PL2	PL3	PL4	PL5	PL6	PL7	Utilized capacity (pcs)	Optimal distance (m)
Storage 1	40		60					100	272.8
Storage 2				60				60	28.6
Storage 3		100			50	20		170	191.6
Storage 4			10				70	80	86.6
Delivered (pcs)	40	100	70	60	50	20	70		579.6

Cost matrix	PL1	PL2	PL3	PL4	PL5	PL6	PL7	Utilized capacity (pcs)	Optimal route
Storage 1	240		8178					100	S1-PL1-PL3-S1
Storage 2				858				60	S2-PL4-S2
Storage 3		4850			1010	1332		170	S3-PL5-PL2-PL6-S3
Storage 4			433				938	80	S4-PL3-PL7-S4
Delivered (pcs)	40	60	70	60	50	20	70		

Summarized Cost 17839

Figure 3 The initial solution provided by the LP method

Assignment matrix (pcs)	PL1	PL2	PL3	PL4	PL5	PL6	PL7	Utilized capacity (pcs)	Optimal distance (m)
Storage 1	40		60					100	335.0
Storage 2				60				60	28.6
Storage 3		100			50	20		170	191.6
Storage 4			10				70	80	
Delivered (pcs)	40	100	70	60	50	20	70		555.2

Cost matrix	PL1	PL2	PL3	PL4	PL5	PL6	PL7	Utilized capacity (pcs)	Optimal route
Storage 1	240		8178					180	S1-PL1-S4-PL7-PL3-S1
Storage 2				858				60	S2-PL4-S2
Storage 3		4850			1010	1332		170	S3-PL5-PL2-PL6-S3
Storage 4			433				938	80	
Delivered (pcs)	40	60	70	60	50	20	70		

Summarized Cost 17839

Figure 4 The final solution by applying the proposed algorithms

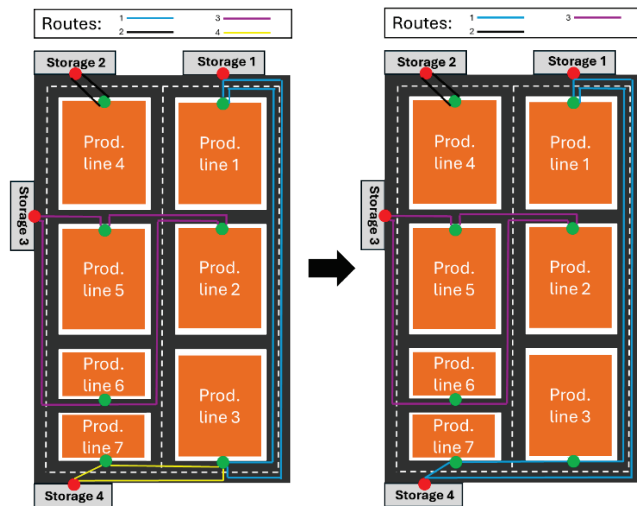


Figure 5 Visual solutions of the two phases of proposed algorithm

Fig. 5 shows how the algorithm slightly modified the route, along with the layout of the facility, from which the point locations were accurately scaled and the distances calculated.

5 CONCLUSION

The research presented in this paper offers an efficient solution to one of the most challenging aspects of milkrun logistics: determining the optimal number of delivery routes

while maintaining cost-effectiveness and service reliability. While milkrun systems are widely adopted for supplying multi-line or parallel production in manufacturing, route planning is still frequently performed manually, which often leads to overloaded vehicles, inefficient transport loops, and increased operational costs. Recognizing this, the developed model builds on the structure of assignment matrices - commonly used for transport allocation - but extends their function to optimize full milkrun loops.

Using Linear Programming and Excel Solver's Simplex LP method, the initial assignment matrix is generated based on distance and cost matrices derived from scaled layout data of a production facility. In the test scenario, a manufacturing environment with 7 production lines and 4 storage points was analysed. The base LP solution initially assigned four routes, one per storage location, with a total transportation distance of 579.6 meters. However, through the application of heuristic optimization—using Excel Solver's evolutionary algorithm—the number of routes was successfully reduced from four to three. This was achieved by merging the routes from S1 and S4 through a common delivery point, PL3, resulting in an optimized transport sequence with a reduced total distance of 555.2 meters.

The proposed model is applicable to any scenario where an assignment or transport matrix can be constructed, making it highly versatile across different logistics systems and manufacturing environments. However, there is still room for further improvement, particularly in the first phase of the algorithm. A known limitation of this initial phase is that it can only handle a limited number of variables effectively. This becomes especially problematic when the relationships between parameters are non-linear or not appropriately weighted. In such cases, even the assignment step may no longer be solvable by traditional means and must instead rely on heuristic approaches to generate feasible solutions. Another issue can be the size and complexity of the problem. When dealing with larger matrices or multidimensional constraints (e.g., time windows, variable capacities, or compatibility rules), the algorithm may not be able to run efficiently.

In summary, this research demonstrates how a structured and flexible model based on assignment matrices and heuristic algorithms can significantly improve route optimization in milkrun logistics. By combining mathematical precision with algorithmic adaptability, the model contributes a valuable tool for enhancing efficiency in modern production supply chains.

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