BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 72(1), 2024, Article number: e146407
DOI: 10.24425/bpasts.2023.146407

SPECIAL SECTION

The solution of MRSLP with the use of heuristic algorithms

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Abstract. Improving production processes includes not only activities concerning manufacturing itself, but also all the activities that are necessary to achieve the main objectives. One such activity is transport, which, although a source of waste in terms of adding value to the product, is essential to the realization of the production process. Over the years, many methods have been developed to help manage supply and transport in such a way as to reduce it to the necessary minimum. In the paper, the problem of delivering components to a production area using trains and appropriately laid-out carriages was described. It is a milk run stop locations problem (MRSLP), whose proposed solution is based on the use of heuristic algorithms. Intelligent solutions are getting more and more popular in the industry because of the possible advantages they offer, especially those that include the possibility of finding an optimum local solution in a relatively short time and the prevention of human errors. In this paper, the applicability of three algorithms – tabu search, genetic algorithm, and simulated annealing – was explored.

Keywords: in-plant logistics; milk run; heuristic algorithms; assembly line; genetic algorithm; tabu search; simulated annealing.

1. INTRODUCTION

Logistics processes are an integral part of the implementation of production in any company. However, transport is one of the most important sources of waste, no matter how necessary it is. Therefore, many methods have been developed to help manage supply and transport in such a way as to reduce it to the necessary minimum. One of these is the milk run method, which can be applied to any logistics process where it is necessary to deliver items from one place to another. The continuous improvement of production processes has forced the search for better solutions for the implementation of internal transport tasks. Increasingly, these solutions include the use of intelligent methods, such as heuristic algorithms. Intelligent solutions are an integral part of Industry 4.0, increasingly used because of the range of advantages they offer. One crucial advantage is the reduction of the influence of the human factor, which makes the methods used more error-proof. Furthermore, heuristic methods allow satisfactory results to be achieved in a relatively short time. They are most often solutions involving a local optimum and, although they do not guarantee finding the best solution in a global sense, research confirms their high effectiveness in the context of improving production processes. This paper describes the problem of delivering components to a production line area using trains, and the proposed solution is based precisely on the milk run method and the use of algorithms including tabu search, genetic algorithm and simulated annealing.

This paper is organized as follows. Section 2 summarizes the characteristics of the milk run concept and literature review in the context of problems and their solutions considered by other researchers. Section 3 describes a new problem, defined by the authors as the milk run stop locations problem (MRSLP). The analysis and selection of algorithms and formulation of the problem are presented in Section 4. Section 5 is devoted to presenting solution variants and analysing the performed calculations. Conclusions and recommendations for future researchers are presented in Section 6.

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Manuscript submitted 2023-03-31, revised 2023-06-13, initially accepted for publication 2023-06-16, published in February 2024.

2. MILK RUN IN PRODUCTION AND LOGISTICS IMPROVEMENT

The milk run is a method based on a milk runner course which consists of efficiently delivering items to destination points along a loop, involving a certain number of points at each course [1,2]. It can be used at any of the levels considered by Lean Logistics: inbound logistics (from supplier to factory), in-plant logistics (in the factory) and outbound logistics (from factory to the customer) [3,4]. The method in the area of inbound logistics processes within manufacturing companies is to deliver components from a central warehouse [5] or supermarket system [6] to workstation deposit points (Fig. 1) frequently but in small quantities [7,8].

The method is based on the just-in-time (JIT) rule [10] and the deliveries can be made using a kanban system (for cyclical deliveries) or based on trip plans (for sequential deliveries). In this type of internal transport, logistics trains are often used, as well as the standardization of batch sizes, replenishment programmes, and reusable containers or pallets [11].

Studies show that proper implementation of the milk run method facilitates the achievement of [1,11–16]:

- Transport distance and time reduction;
- Delivery flow and control improvement;

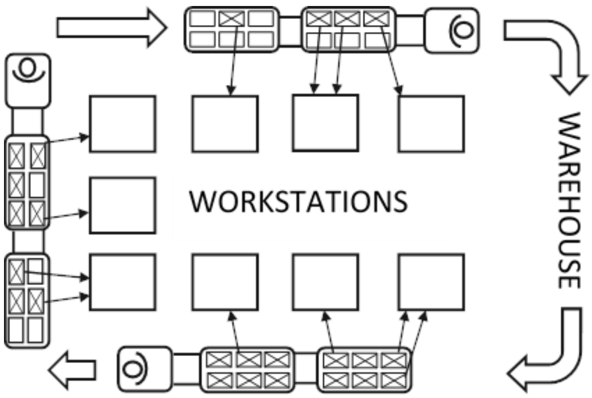


Fig. 1. Milk run concept [9]

- Inventories and storage area reduction;
- Throughput and efficiency increase;
- Empty runs and traffic congestion minimization;
- Cost reduction;
- Work ergonomics improvement.

Because of the many advantages of the method, a lot of attempts are made to develop a way to maximize its potential [5, 6, 11, 17, 18].

Research of the possibilities of optimizing processes using the milk run method often includes the traveling salesman problem (TSP), the vehicle routing problem (VRP), and related methods [11, 19–24]. Both of them are the NP-hardness type of problems, therefore obtaining an optimal solution in a reasonable time often requires the use of intelligent methods [5, 11, 17].

The issue was introduced to the scientific literature in the mid-20th century [25–27], while research development gained momentum in the 1990s due to the wider availability of computers and the development of meta-heuristics [28]. In the late 1990s, the possibility of solving VRP-type problems using various algorithms was explored, including genetic algorithms, neural networks, tabu search, and simulated and deterministic annealing [29]. With the passage of time and a relatively high level of interest in the issue from researchers, several different forms of VRP have evolved, including [11, 19, 30]:

- Capacitated vehicle routing problem (CVRP): considering a finite number of vehicles with limited capacity.
- Open vehicle routing problem (OVRP): excluding a return to the initial storage after the task has been completed.
- Vehicle routing problem with time windows (VRPTW): considering a runtime constraint.
- Vehicle routing problem with pickups and deliveries (VRPPD): assuming materials can be picked up and transported to subsequent destinations.
- Just-in-time vehicle routing problem (JITVRP): finding applications in JIT systems.
- Multiple depots vehicle routing problem (MDVRP): allowing for multiple central depots.
- Periodic vehicle routing problem (PVRP): assuming a certain frequency of delivery.
- Split delivery vehicle routing problem (SDVRP): allowing for split deliveries.

Several papers can be found about optimization based on the milk run method. The majority of these are based on the area of distribution at the supply chain level [19, 31–35]. The positive effects of using different optimization methods, and their modifications or combinations have been demonstrated, including methods such as:

- Genetic algorithm [33, 34, 36, 37];
- Mixed-integer programming [2];
- Robust linear optimization [19];
- Ant colony algorithm [9, 38–40];
- CW saving algorithm [41];
- Traveling salesman algorithm [42];
- Tabu search [20, 32, 40, 43];
- Hopfield neural networks [20];
- Stepwise iterated algorithm [36];
- Greedy algorithm [31, 43];
- Simulated annealing [20, 31];
- Scan algorithm [34].

Parameters were adopted as constraints depending on the case under consideration, with the objective of not only shortening delivery times [2, 33, 34, 37, 38, 41] or reducing costs (transport, storage, possible penalties) [19, 20, 31, 32, 42], but also reducing stock levels [19, 40], shortening the longest delivery times [38, 39], or selecting appropriate modes of transport [43].

Despite many studies in the area of optimizing logistics processes, only a few have focused on internal transport in a manufacturing environment [5, 18, 44]. Although as early as the 20th century, attention was drawn to the need to improve the entire manufacturing system, including the internal flow of materials [45]. In response to these needs, research began to be conducted more widely, using intelligent methods to plan the most beneficial journeys [46, 47]. With the development of methods to optimize the flow of in-plant transport processes [48], the benefits of implementing a milk runner course system for line supply were investigated [47], as well as the use of logistics trains as a means for such transport [49]. Similarities were observed between the milk runner course problem in the production area and the classical VRP at the level of supply chains [3, 18]. However, scientific papers on the topic of the milk runner course within the factory are still scarce [3], although the method itself is of considerable interest and widely used in many manufacturing companies [5].

The aims of these studies were set on not only shortening delivery times [2, 33, 34, 37, 41] or reducing costs (transport, storage, possible penalties) [19, 20, 31, 32, 42], but also reducing stock levels [19, 40], shortening the longest delivery times [38], or selecting appropriate modes of transport [43].

So far, the studies optimizing the milk run route have mainly been undertaken to determine the best possible routes, to reduce the number of means of transport [6, 11], to reduce costs (inventory maintenance [5] and transport [18]), or to minimize load variability [6]. Successful attempts were also made to select the optimal path, reducing travel time and the number of means of transport, with dynamic plan variability [17]. Heuristics and meta-heuristics were mainly used for research.

Analysing existing studies, it can be seen that they mainly focus on planning travel routes at given stop locations [50, 51].

This paper considers the case where the route is fixed, and the aim is to determine the stopping points of a logistics train on the route.

None of these studies examined the milk run route with the consideration of the stopping points for the logistics train on the route and its impact on system efficiency. The logistics train follows a fixed route, stopping at locations defined as stops, from which its operator manually transports the components to several nearby storage points. In this paper, we use intelligent algorithms to examine the efficiency, interactions, and impact of the milk runner course with the defined stopping points on a selected assembly line.

3. MILK RUN STOP LOCATIONS PROBLEM (MRSLP)

In the research performed in this case, the train travels along the production line and stops at several locations, from which its operator manually transports the required components to several nearby storage points. The potential to optimize the course of the milk runner by appropriately selecting the stop locations was previously verified using the example of an assembly line for series production [9]. Although simulations based on real data had already been carried out in the prototype, at that time the model was greatly simplified. The satisfactory results obtained for the base model prompted attempts to apply an improved solution to a more complex, and therefore much more realistic case. In this paper, the focus is primarily on the form of a logistics train with a certain number and length of carriages, with a standard place for transporting given groups of components. The aim is to realize a milk runner loop, aiming to reduce transport time as much as possible, and so the case studied relates to some extent to the issues presented at the beginning of the chapter. The main difference with VRP (off-fixed route) is that only 1 vehicle is used, and the problem of component allocation is considered in relation to stops instead of means of transport. In addition, the need to analyse the available capacity is excluded, as the loading of the train is predetermined. It may seem that the case under study is, therefore, closer to TSP, but extended to include the possibility of planning stopping places along a specific route, the form of a logistics train, and mixed transport (partly by the vehicle, partly by its operator). The problem considered here can be named the milk run stop locations problem (MRSLP).

In the research, the company implemented new methods for supplying components to workstations shortly before the collaboration began. However, with successive attempts to improve the flow of technological operations resulting in shorter production times, only an increase in wasteful waiting was noted. Many of the potential benefits of these improvements were limited by the mismatch between the rate of material delivery and faster production rates. Opportunities to improve the processes were observed on batch production assembly lines with components supplied by the milk run method. A scheme of the production line used as an example to solve the optimization task is shown in Fig. 2.

The production line consists of 15 workstations, each with at least two racking storage areas. The semi-finished products are transported between the workstations by conveyor belts. The materials are delivered to the racking fields by the milk runner, who has a logistics train (Fig. 3) with three double-decker (a), carriages (b).

The milk runner supplies the workstations with the relevant components from the central warehouse, according to the received course plan. The plan provides for 6 different courses within the production line. The logistics train follows a fixed route, stopping at locations defined as stops, from which its operator manually transports the components to several nearby storage points.

4. HEURISTIC ALGORITHMS SELECTION AND PROBLEM FORMULATION

The model built for the research is based on real data from the manufacturing company. The problem is how to deliver the components to the corresponding storage points, located at the workstations of the production line. The optimization problem consists of selecting the number and locations of the stops of the logistics train in such a way as to achieve the shortest possible loop time. The model considers the conditions arising

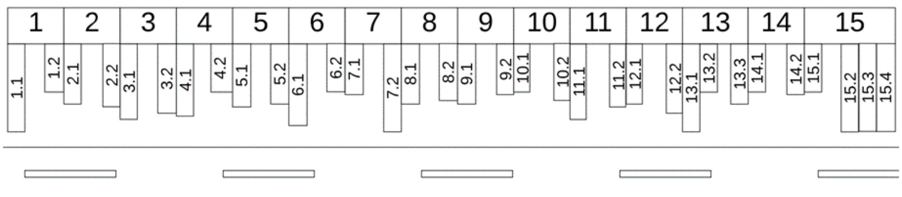
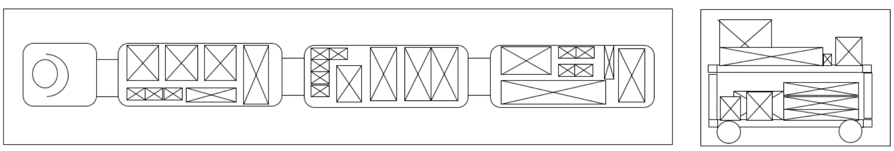


Fig. 2. Production line scheme [9]



(a) (b)

Fig. 3. Logistic train scheme [9]

from the actual constraints of the process implementation in the production company. The constants for the case considered are:

1. The location of the workstations: there is no possibility of changing the workstations' location due to the close dependence on the course of the production processes in progress, but also on the weight and dimensions of the equipment.
2. Distance of the storage points from the transport route: The storage point for the milk runner is always at the end of the field, because of the roller racks, which also enforce a FIFO queue.
3. The speed and start and stop points of the logistics train are based on the capacity of the available vehicle.
4. The speed of movement of the milk runner: The average speeds of delivering batches of components from the carriages to the storage points were determined, depending on their weight and dimensions. The average speed of return to the train, either unloaded or with empty cartons, was also determined.
5. The allocation of components to the storage points: adapted to the operations at the stations.
6. Distance of the locations of the individual component groups on the carriages from the start of the logistics train: The locations of the components are standardized in such a way that loading at each entry to the depot is as efficient as possible.
7. Component delivery plans: Several plans can be distinguished, and the differences between them are mainly due to the different sizes of the transport batches of components, which affects the frequency of their demand.
8. Stopping points: These are marked, using visual management tools, to standardize the milk runner route and thus increase control over the process. Thus, despite the different schedules on a given route, the stops should be set to allow the lines to be efficiently irrigated at each possible crossing and to allow the fastest total crossing of all routes.

The assumptions mentioned in items 2, 5, 6, 7, and 8 may change over time and then be standardized for the next period of time due to significant changes in product designs, technological processes, or production schedules.

The described problem was considered using three algorithms: tabu search, simulated annealing, and a genetic algorithm. Each of them was used successfully in many optimization problems, and each seeks the best solution in a different way, which affects their accuracy and speed, and provides a good basis for comparing results.

Tabu search

This algorithm replicates the natural search process performed by a human – it starts at a random or defined solution, checks all neighbouring solutions (best improvement strategy), then selects the best one and, starting from it, repeats the procedure. To avoid stopping at a local optimum and entering a cycle, the algorithm has a list containing information about solutions and/or moves made in previous iterations, the so-called taboo list [52]. Based on the list, the set of all neighbouring solutions is divided into two subsets: forbidden and not-forbidden solutions. From the set of forbidden solutions, a solution is selected which becomes the source of searches in the next iteration (Fig. 4). The operation of the algorithm ends after a certain number of iterations or with the fulfilment of another condition set by the user, for example after 10 iterations without improvement.

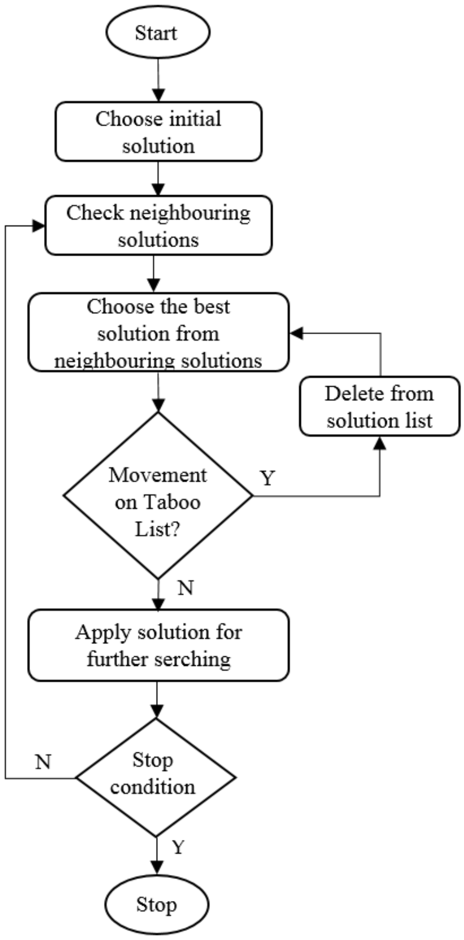


Fig. 4. Tabu search diagram

Simulated annealing

The algorithm starts from a certain (random or defined) solution and checks only one randomly selected neighbouring solution. If the checked solution is better than the current one, the algorithm proceeds to it, if not – the algorithm proceeds to it with a given probability, thus facilitating the transition to the worse solution, and from it the search continues in the next iteration of the algorithm. The probability of accepting the inferior solution depends on the difference in the value of the objective function of the solution being checked and the current solution. It also depends on the current temperature, expressed by the formula:

$$p = \exp(-\Delta T), \tag{1}$$

where Δ is the difference in the value of the objective function of the solution checked and the current solution, and T is the current temperature. The temperature in each iteration decreases, thus reducing the probability of accepting inferior solutions, and the temperature change function is experimentally tuned for the problem under analysis. In the following section, 4 cases are presented, and for each of them, the temperature change function of the simulated annealing algorithm is the same. Figure 5 shows a diagram of how the simulated annealing algorithm works.

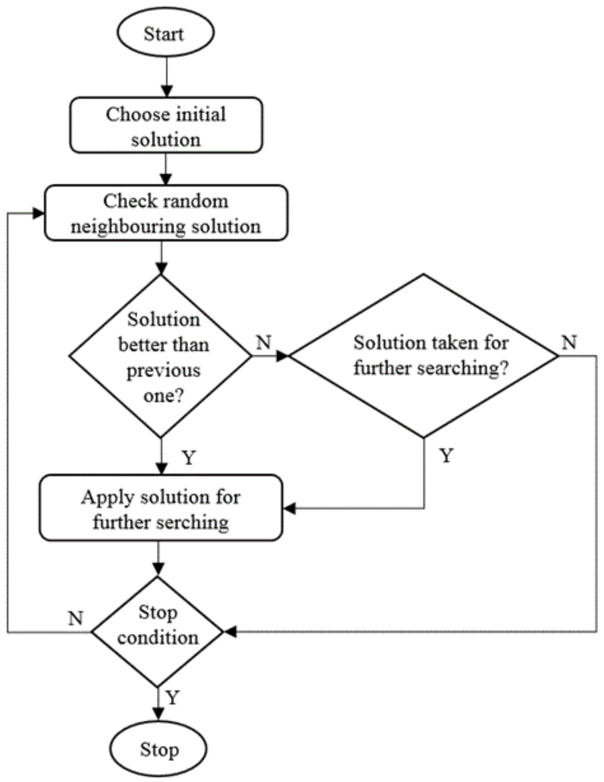


Fig. 5. Simulated annealing diagram

Genetic algorithm

Genetic search (GS), which is a base of genetic algorithms (GA), assumes that the implicit goal of evolution is to optimize the fit between individuals and the environment, while the transmission of traits between generations follows Darwin's theory of evolution [53, 54]. Figure 6 shows a diagram of how a genetic algorithm works.

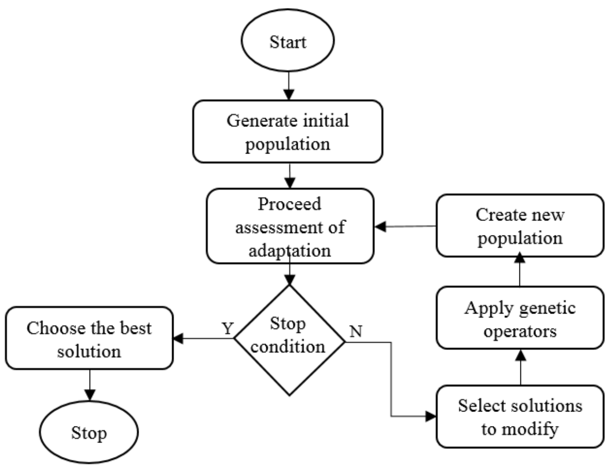


Fig. 6. Genetic algorithm diagram

It starts its operation not with a single solution, but with a selected population, for example, a group of solutions. To generate successive solutions (the next population), the algorithm uses crossover and mutation (introducing a random change). Thanks to crossover, the algorithm finds better and better solutions, while mutation guarantees the diversity of solutions and prevents convergence to a local optimum [54, 55].

5. VARIANTS OF SOLUTIONS

Referring to the needs of the company, calculations were conducted for 4 cases:

Case 1. One route

One route for all 6 courses – the same number of stops and at the same locations of stops regardless of the course being run. The results for this case are shown in Table 1.

Table 1
Results of Case 1

Method	Time [s]	Number of stops
Tabu search	414	9
Simulated annealing	423	10
Genetic algorithm	411	9

Each of the algorithms presented was required to generate a single route for all 6 runs. All runs have equal weights, so the objective function is the minimum time for the sum of the 6 runs using the same route each time.

The results proposed by the different algorithms are close to each other. The difference between the shortest time and the longest time is 3%. The time was proposed by the genetic algorithm (411 seconds) while making 9 stops.

Case 2. Two routes

Each course is assigned a green or blue route, which is a low level of logistical complexity. The results for this case are shown in Table 2.

Table 2
Results of Case 2

Method	Tabu search		Simulated annealing		Genetic algorithm	
	Time [s]	No. of stops	Time [s]	No. of stops	Time [s]	No. of stops
Blue route (1, 3, 5)	253	7	243	7	257	7
Green route (2, 4, 6)	374	9	382	9	405	10

Establishing two types of routes, each of the proposed algorithms unanimously proposed a "blue route" for routes 1, 3, and 5 and a "green route" for routes 2, 4, and 6.

The results proposed by the algorithms are also similar, with (especially for the longer route) the shortest time covered by the tabu search algorithm (374 seconds), where the solution proposed by the genetic algorithm requires 405 seconds, which is more than 8% longer.

Case 3. Three routes

Three routes (*long*, *medium*, and *short*), where the short route is contained in the medium route and the medium route in the long route. This means that eliminating selected stops from the long route will give a medium route, and eliminating specific stops from the medium route will give a short route. All stops of the short route are also stops of the medium route, and all stops of the medium route are also stops of the long route. Such a requirement increases the complexity of the problem while reducing the logistical complexity. The results for this case are shown in Table 3.

Table 3
Results of Case 3

Method	Tabu search		Simulated annealing		Genetic algorithm	
	Time [s]	No. of stops	Time [s]	No. of stops	Time [s]	No. of stops
Long route (6)	387	9	387	10	389	9
Medium route (2,4)	327	9	325	9	331	8
Short route (1,3,5)	278	7	2 69	7	275	7

Three routes were used here: a long route for run 6, a medium route for runs 2 and 4, and a short route for runs 1, 3, and 5, under the condition that the shorter route must be contained within the longer one (it is only possible to miss one or more stops).

The times proposed by the algorithms are similar (maximum difference of 3.3% for the short route), and the shortest time was achieved using simulated annealing. The tabu search algorithm presented a solution where the long route and the medium route are the same (they have 9 stops each), so the solution was reduced to 2 routes, where one short-circuits the other.

Case 4. Independent routes for each of the courses

Case 4 is the least restrictive and allows the best flexibility to choose the parameters for each course independently. However, the enterprise has a more rigid and simpler timetable, which will be provided for Cases 1, 2, and 3. Case 4 will serve as a reference for comparing the feasibility of individual route planning with cases where the individual courses are correlated with each other. The results for this case are shown in Table 4.

By treating each route separately, some of the constraints can be eliminated and as expected, the calculated route times are shorter than in the other cases. The differences in times between the algorithms are at most 4%. Out of 6 runs, simulated annealing proposed the shortest time for 4 cases, making a strong argument to be the best for individual route consideration.

Table 4
Results of Case 4

Method	Tabu search		Simulated annealing		Genetic algorithm	
Routes	Time [s]	No. of stops	Time [s]	No. of stops	Time [s]	No. of stops
1	234	6	231	6	233	6
2	272	8	263	7	266	8
3	229	6	229	5	217	6
4	302	7	294	8	289	7
5	218	7	226	7	217	6
6	368	8	354	8	369	7

The running time of the algorithms was limited to 5 minutes.

6. CONCLUSIONS

The paper presents a new problem, not studied so far in the literature, and its solutions with the use of intelligent algorithms. Further research could include:

- Extending the algorithms to include the possibility of increasing the number of milk runners supporting the production line.
- Adapting the algorithms also to plan the milk runner route with a predetermined loop time (adjusted to the production rate and the assumed stock level at production stations) in order to keep the production flow, while following the JIT principle.

Figure 7 shows a summary of the shortest time for each run for each of the cases considered.

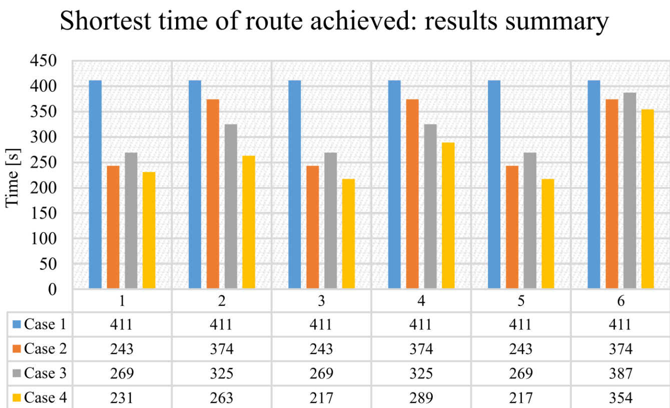


Fig. 7. Results summary

In Case 1, the shortest time (411 seconds) was proposed by the genetic algorithm; in Case 2, the shortest time for the green route (routes 1, 2, 3) was proposed by the simulated annealing algorithm, and, for green routes 2, 4, and 6, by the tabu search algorithm. In Case 3 for both the long, medium, and short routes, the shortest time was proposed by the simulated annealing algorithm. In Case 4, the best algorithms are: run 1 – SA, run 2 – SA, run 3 – GA, run 4 – GA, run 5 – GA, run 6 – SA. The conclusion is, in this case, the best are simulated annealing and genetic algorithms.

Following the criterion of shortest time, it can be seen that the use of one general route generates significant time wastage. The differences between Cases 2 and 3 (2 routes or 3 routes included) are negligible, and it is not possible to decide whether Case 2 or 3 is clearly better. It can also be seen that reference Case 4 has a significantly shorter time only for route 2. For the other route, the difference is insignificant, and, knowing the needs of the company, it will be more profitable to reduce the logistical complexity and choose Case 2 or 3. Adding up the times of all 6 routes for Cases 2 and 3, the difference is 7 seconds in favour of Case 2, a gain of 0.3%.

The results of the study indicate the validity of using heuristic methods in solving problems involving the milk run method. Further research may include extending both the algorithms used and the variety of processes in which they will be used.

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