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RESEARCH ARTICLE

State-Dependent Weighting in Fuzzy Signatures Optimizing Material Handling Management Problems

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Abstract: The scheduling of jobs in functional production systems (job shop scheduling) is a frequently researched area of the literature. However, the management of material handling in functional production systems receives little attention. Publications in connection with that can scarcely be found, even though in the case of small- and medium-sized companies the problem is definitely topical. For them, solving this problem can mean an opportunity for improvement. This paper presents an expert knowledge-based method that contains novelties and uses fuzzy signatures to solve this problem. The performance of the proposed method is compared with the performance of other methods which are common in the industry or in the literature (mixed-integer linear programming, priority dispatch rules, human decisions). We present the construction of the fuzzy signature-based method and the aggregations used. As a novelty, the method of selecting the proper weights for state-dependent dynamic weighting is presented.

Keywords: material handling, functional production system, fuzzy signature, state-dependent weighting, aggregation operators

1. Introduction

Functional production system or job shop production—typically used by small- and medium-sized enterprises—is a flexible production system suitable for small to medium batch production. Based on technology attributions, production machinery is grouped into workshops and work pieces are moved between those depending on the process of the production. One of the main advantages of such systems is the flexibility and the relatively low capital cost requirement. On the other hand, scheduling and organizing production logistics are considerably more complex tasks compared to the widely used and balanced process production system. Physical production logistics (or material handling) means the supply of raw materials for production machinery and the removal of finished goods, typically by universal material handling devices such as forklifts and pallet trucks, usually managed by logistics departments. The challenge of production logistics in such a system is the uncertainty of the material handling tasks; moreover, the logistics have a narrow time window for supplying the workplace or raw material movements. Otherwise, production systems will come to an idle state, which will have a significant negative financial impact on the company. According to Groover (2002), material handling problems cause 25% of production losses. Consequently, the improvement of logistical services may have significant effect on the efficiency of the company. Therefore, one of the main objectives of logistics in such a system could be to minimize (or avoid if possible) the negative effect of material handling on production. Since production machines which have to be served can have different economic importance, as they have different priorities in the production system, this factor also has to be considered. Due to the different priorities of machines, tardiness cannot be handled at the same level; therefore, delays are usually weighted in the calculations. In the literature, it is called weighted tardiness. The objective of logistics in such a system is to minimize the weighted tardiness of material handling tasks.

These critical material handling tasks can be described by the following key parameters:

- The deadline of the task
- The time required to complete the task
- The penalty cost of production delays
- The traveling time of the material handling equipment between the tasks
- The suitability of the material handling machinery, for example, if it is capable of lifting the material.

If there are many tasks to complete, it requires logistics operators to make continuous and complex decisions in narrow time windows. In practice, these decisions are typically made by shift supervisors or forklift drivers, potentially leading to inappropriate choices and resulting in severe stress to both the employees and the management. One component of those is the limitation of the human mind. Since scheduling with weighted tardiness is known as a complex, non-deterministic polynomial-time hard (NP-hard), problem that cannot be handled well by humans. Another may be the human factor, including the decision makers' experience which takes time to be developed, and motivation which may not be aligned with the company's interest. Consequently, instead of human-managed material handling activity, it seems to be more

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beneficial to develop a computer-based decision-making system that is able to determine the (approximate) optimum execution order of the tasks aligned with the company's best financial interest.

The automation of material handling seems to be less common in this functional production system because automated guided vehicles (AGVs) can barely fit into already existing factory layouts; therefore, human-driven forklifts remain in charge in the future, especially in small- and medium-sized companies.

The aim of our research is to develop and test computer-aided material handling management solutions that can be applied to the already existing environment of small- and medium-sized companies and can reduce the negative effect of the problems mentioned above. In this system, the forklifts are driven by humans, but the task management is done by a computer system, removing the human factor. As a result, the benefits of computer-supported decisions can be achieved without any structural changes.

This research is motivated by a real company, where there is no material handling task scheduling system used and the material handling cost is far from the optimum. Moreover, as the responsibility for the scheduling itself is of the employees on the lowest operational level, their stress level is extremely high. Although hardware solutions for computerized material handling management would be easily available, the company's management is not convinced of the practical applicability and the cost-effective usage of such a system. Since the literature slightly contains methods that can be implemented easily and without severe costs, we tried to develop an appropriate method. For this, we have identified the lowest set of parameters that influence the waiting cost, constructed a fuzzy signature-based model, developed a function for quantifying the state of the material handling situation, and proposed weights of parameters used in our model based on the quantified state as follows.

2. Literature Review

To date, there has been little research into the daily management of material handling in functional production systems, since this problem is usually solved on the given site by methods developed by local experts. In contrast, other issues like job shop scheduling or AGVs are paid considerable attention in scientific papers (Chaudhry & Kahn, 2016; Nageswararao et al., 2017; Murugesan, 2017). Therefore, it seems to be worth investigating whether these solutions may be applied in material handling problems.

According to Zhang et al. (2019), optimization strategies can be grouped into exact and approximate methods. The main difference between them is that the best possible mathematical solutions are achieved by exact methods, while approximate ones result in solutions good enough with significantly lower calculation efforts.

The first method of finding an exact result of a linear optimization problem is the simplex method, which was developed by Dantzig (2016). Finding the optimum using linear programming can be directly applied in cases where there is a linear connection between variables. These problems can be solved by specific computer software developed for this purpose. Linear programming was soon developed into mixed-integer linear programming (MILP) that can handle integer variables that are common in routing problems (Lee et al., 2010; Floudas & Lin, 2005; Murakami, 2020). Weighted tardiness as an objective was handled by integer programming by Liu et al. (2021).

Heuristic solutions are approximate methods, where rules and algorithms are formulated on previous experience. They are commonly used in practical problems because of their simplicity and low computational requirements (Zandin, 2001). On the other hand, their main disadvantages are that most of the effective heuristics are tailored to a specific problem (Chiang & Fu, 2007; Sculli & Tsang, 1990). Several simple and complex priority dispatch rules are available to handle weighted tardiness, but it has been found that the more complex are the rules, the more precise results can be achieved (Vepsalainen & Morton, 1987; Arik et al., 2022).

Metaheuristics are approximate, general-purpose methods that are able to handle complex, even nonlinear relationships. One of the main advantages of these methods is that they are capable of finding a reasonable result within an appropriate time frame irrespective of the complexity of the correlation between the variables and the final result (Davis, 2014; Falkenauer & Bouffouix, 1991). The principal idea behind genetic algorithm (GA)—which is the classical evolutionary algorithm, and still today one of the most commonly used metaheuristics methods—is based on the concept of natural selection. Based on the constant mutation of individuals, the method preserves the combination of variables that result in better outcomes. Since metaheuristics approaches can handle very complex, even nonlinear problems, they are also suitable for use in weighted tardiness problems (Besten et al., 2000), even in the case of multi-objective problems (Qiao et al., 2021).

Another advanced way of (approximate) optimization is based on machine learning, where computers can learn and adapt new information. It is capable of handling large data pools which are incomprehensible to the human mind. These systems can produce good approximate results and event forecasts; however, they need a large pool of preliminary examples (learning samples) which are sometimes scarce. However, these versatile systems, for example, neural networks or fuzzy systems based on adaptive calculations, can be applied in several scientific fields (Matsuoka et al., 2019; Zhao et al., 2012).

One of the disadvantages of the above solutions, especially that of exact ones and many of the metaheuristics approaches, is that they often require highly sophisticated mathematics and the logical connections between the input data play a fundamental role in the models. Consequently, if the circumstances change, the models may also require a significant change. In addition, these models are quite complex and require a special knowledge base as well as a specific computer software. Given their complexity, their practical application may not be implemented, because of the high computational resource intensity. Another drawback of these solutions is that due to their sophistication, users who are not highly qualified often do not understand these models' working and subsequently they do not completely trust in their decisions and results. In addition, providing highly qualified employees who are able to manage such systems can be financially unsustainable for small- and medium-sized companies. These disadvantages can prevent small- and medium-sized enterprises from modernizing their material handling processes.

To resolve these operational problems, a solution, similar to priority-based models, needs to be found. This solution must be efficient enough to handle the complex logistical needs of the functional production system without the above-mentioned drawbacks.

Computerized decision methods are usually based on human expertise which is hard to be algorithmized in traditional ways. Since experts' knowledge including subjective, uncertain, and nondeterministic components can be effectively implemented by modeling with fuzzy systems, this approach was chosen for use in our research.

3. An Overview of Fuzzy Systems

One of the features of fuzzy logic is its similarity to human thinking. Therefore, industrial experts' experience, knowledge, and their decision-making pattern and logic can be successfully algorithmized and converted into an easily usable and transparent computer program by applying fuzzy sets and fuzzy rule bases (Bilkay et al., 2004).

Fuzzy rule bases (Zadeh, 1973) are suitable for modeling inference and control systems with uncertain elements. An extension of the original fuzzy set, fuzzy descriptors with multiple and partly or entirely hierarchically arranged membership degrees can also give very easily manageable models of objects or phenomena with complex properties, containing sub-properties and operations between sub-properties. These latter fuzzy structures are called fuzzy signatures (Kóczy & Vámos, 1999). Graphically, these complex structures can be represented as tree graph structures where the overall or resulting property is represented by the root of the tree while the leaf nodes represent sub-properties. To all nonterminal nodes (the root, and the intermediate nodes) fuzzy aggregations are assigned. These can be unions, intersections, generalized (possibly weighted) averages, and further operations. This graph is a multilevel structure, where the fuzzy value of a "higher level" node is calculated from its corresponding sub-properties by executing the corresponding aggregation operator. The most frequently used aggregation operators in the nodes are the various norms and functions returning some kind of average of the sub-properties, for example, weighted relevance aggregation operator (WRAO) (Mendis et al., 2006). WRAO is traditionally used with constant weights, but recent works introduced an alternative usage with changing weights called state-dependent dynamic weighting, where the weights depend on the values of sub-properties (Bukovics et al., 2022; Sós & Földesi, 2022).

4. Research Methodology

The objective of this research was to find a material handling management (quasi-) optimization method that can be used under the specific circumstances of functional production systems. Some of the basic requirements for this method are better decisions than those that can be achieved by human operators, further, transparency and simplicity, that is, the method must be simpler to develop and to operate than MILP or GA-based systems.

For the case study of the research, we selected an existing company which is large enough to be a representative sample and which uses a functional production system. In the first step, we collected the available expert knowledge. We conducted interviews with local experts (forklift operators, shift leaders, production staff) and gathered information from valid work instructions. Based on this expert knowledge, the influential parameters (e.g., traveling distance, machines priority, processing time, forklift suitability) were collected and their logical relationships determined. This information was built into a tree structure, where the nodes were the influencing parameters, and the hierarchy was determined by their respective relations. To build a multilevel tree, the raw parameters were aggregated to higher level properties.

As handling logical connections between multivalued data is reasonably easy with fuzzy calculations, this dependency tree was transformed into a fuzzy signature. As all of the raw parameters were considered to be equally important by the experts, during the aggregations simple averaging (WRAO with constant weights of 1) was used in this fuzzy signature.

The calculation method was tested on several sets of material handling task. In the following part, we refer to these sets as scenarios. Since not enough samples were available, scenarios were created by real-life data based on our research. These data were used as input parameters for several methods (MILP, priority dispatch rules: earliest due date [EDD], shortest processing time [SPT]) besides the fuzzy signature-based calculations. A MILP model was created during the early stage of the research and was used as a proven optimal basis in order to evaluate the efficiency of our method while the results by the random selection (RND) method were used to determine the possible worst outcome of the optimization.

The test showed that the results of the fuzzy signature-based model were somewhat more efficient than those of applying simple priority rules like SPT or EDD, but still well approximating the optimum, with slightly different end results. These were published in Ferenczi et al. (2022).

In order to improve the efficiency of the method, we used different weights for the parameters. It resulted in much better outcomes. As this is the main focus of this paper, it will be detailed in the next section.

5. The Fuzzy Signature-Based Model

Finding a suitable execution order of material handling tasks starts from a set of tasks that can be executed at the same time. Based on the surveys of forklift drivers' decision-making processes, it has been concluded that one possible practical decision-making method is that the forklift driver evaluates the priority of each task based on the tasks' parameters and the relationships among them.

Since forklift drivers cannot make long-term plans due to the unpredictable activity of the shop, the basic idea behind their decision is that the task with the highest priority is the one where the following conditions are the strongest at the same time:

- the task can be finished in the shortest and at the earliest time,
- the earliest the deadline, or the machine has been stopped,
- the task belonging to the most important machine will be chosen,
- the forklift is able to handle it.

The first three parameters are in logical OR connection, while the fourth one is connected to them by AND. The forklift drivers use one of the first strategies according to their own decision. Based on their evaluation, the task with the highest priority is executed first. Once it is completed, the set of tasks is re-evaluated with the changed circumstances and the task with the highest priority is selected again. Since it is possible that in the meantime another task is added to the set, continuous re-evaluation (dynamic scheduling) is necessary

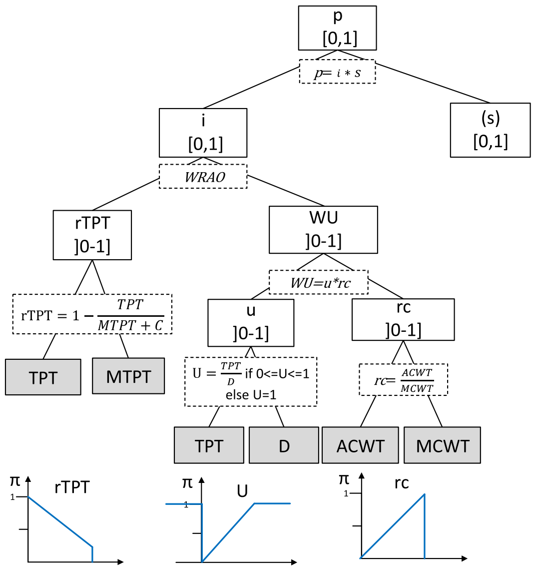
The fuzzy signature-based model copies this human decision-making algorithm. From the parameters listed in Section 1, the model uses total processing time (*TPT*), maximal total processing time (*MTPT*), deadline of the task (*D*), actual cost of waiting time (*ACWT*), and maximal cost of waiting time (*MCWT*) which are independent from one another.

The parameters were quantified from [0,1], WRAO and algebraic product were used as aggregation operators, so the priority (p) as the ultimate result was determined between 0 and 1.

The applied fuzzy signature and the membership functions can be seen in Figure 1, where the used properties are as follows.

Relative total processing time (*rTPT*) includes the *TPT* of the task and the time needed to travel to the task location from the current position of the forklift (*TPT*). Its quantification can be seen in the dotted line square where *MTPT* is the maximal processing time and travel time in the set. According to this, the task that can be finished within the shortest time is given the highest value. Weighted urgency (*WU*) shows how urgent the execution of a task is. It is calculated from two sub-properties, urgency (u) and relative cost (rc), and their aggregation operator

Figure 1
The aggregation functions and the relationships of the fuzzy signature with the membership functions



is the algebraic product. Urgency (u) is calculated from TPT and the deadline (D) of the task. There are two possible cases.

(a) The task can be executed before the deadline ($TPT <= D$). If TPT/D is close to one, urgency (u) is high. If it is close to 0, it means that extra time is available to complete the task. In this case u=*tPT/D*.

(b) There is no time to finish the task before the deadline ($TPT > D$). The value of urgency (u) is 1. It also contains the case when the machine has already stopped.

Relative cost (rc) is calculated by comparing the waiting cost of the actual machine ($ACWT$) with the highest waiting cost in the set ($MCWT$). The machine with the highest waiting cost gets the value of 1, whereas the one with the lowest gets proportionately less, but higher than 0.

Suitability (S) is a key parameter. If the task cannot be handled by the actual forklift, this value is zero; therefore, the final value of the priority is also zero and the task cannot be selected.

6. State-Dependent Weights

6.1. The value determining the state of a task set

In order to examine the possibility of improving the efficiency of the model, we studied the effect of using different weights in the aggregations. Deriving from the parameters considered to have the same weights by the experts, we tried to find a suitable method for calculating the weights.

It has been found that in the case of previously unknown important order of the parameters, the analytic hierarchy process (Peng, 2012), the Churchman–Ackoff process (Szentesi et al., 2018), and the Guilford process (Rodrigues et al., 2004) have been proposed by the literature. All of them are based on previously existing experience. It means that all three methods use experts to define the importance of parameters. In our case, the experts said that the importance order would depend on the actual state of the parameters, but they could not give consistent orders. However, examining the different states seemed reasonable.

Scenarios can be characterized by a novel value that we simply call state (s). The state is determined by the average deadline and the deadline threshold (DT). The average deadline ($\bar{D}$) is the average of the deadlines in the actual set. The DT is the fictional average deadline which enables the execution of all tasks without any idle time. (This is our own parameter, if it is higher than average deadline, then idle of machines is unavoidable.) We defined DT as it can be seen in (1)

$$DT = \frac{\frac{n+1}{2} * (\bar{P} + \bar{T})}{K} + 2(\sigma P + \sigma T) \quad (1)$$

where $\bar{P}$ is the average processing time, σP is the standard deviation of processing times, $\bar{T}$ is the average traveling time, σT is the standard deviation of traveling times, K is the number of forklifts, n is the number of tasks.

and s as it can be seen in (2)

$$s = \frac{\bar{D}}{DT} \quad (2)$$

Equation (1) was created in a way that besides giving a numerical representation of the state, it is also suitable to show how easy it is to find an order where there is no idle time. If s equals 1, there is high probability that at least one execution order can be found that results in no waiting cost. The higher its value, the more solutions without waiting can be found. Consequently, avoiding the waiting cost is much easier. However, if the value of s is less than 1, waiting cannot be avoided. The smaller the value of s, the higher the idling cost. (According to industrial practice, it is assumed that each of the forklifts is able to handle at least 90% of the tasks.)

Consequently, by knowing the state values, the examination of different weight combinations may become possible.

6.2. Determination of the parameters' weights

With the lack of preliminary information about weights of WU and $rTPT$, we examined the possible waiting costs of each scenario, in the case of all weight combinations. Since the experts said that the importance of parameters was equal, using weight ratios higher than 2:1 seemed to be unnecessary. For the investigation, we used weight values from 0.1 to 2.0, in 0.1 steps and the average waiting cost was calculated for each investigated state (st). This resulted in different costs. Presenting graphically these costs results in a surface for each state (an example can be seen in Figure 2).

The axes of $rTPT$ and WU are linear, while the axis of the total waiting cost is logarithmic in order to highlight the most interesting part of the graph. The best results (the lowest values) can be easily identified in the figure.

According to the results, we propose the following weight ratios for different states that can be seen in Table 1. The table contains that weight ratio for each state (st) that resulted the lowest (best) waiting cost.

7. Experimental Results

To compare various optimization methods, several tests were carried out on the same sets of data (the same 7 × 11 scenarios were used for each of the five methods).

We used the following data for testing: by random selection from the same dataset, 11 discrete scenarios were created for each examined state, including 8 tasks with 2 forklifts and the same distance matrix. (The distance matrix describes the distances as traveling times between the machines.) Since the state is defined by the ratio of the average deadlines and the average processing time, each scenario has nearly

Figure 2
Summarized waiting costs of the scenario sets belonging to $s = 0.7$ with different weights of *rTPT* and *WU*

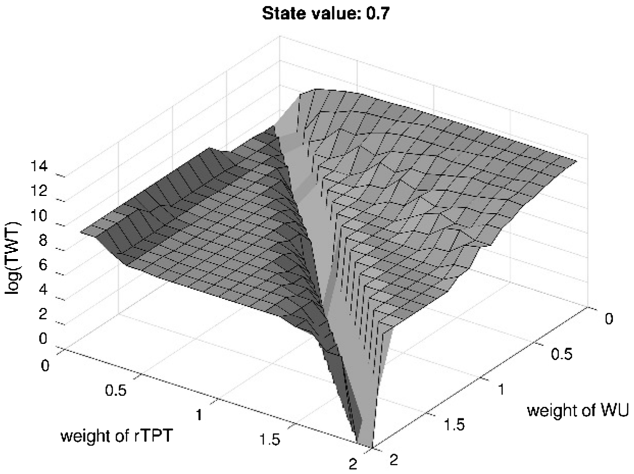


Figure 3
Average of the total waiting cost of the different optimization methods

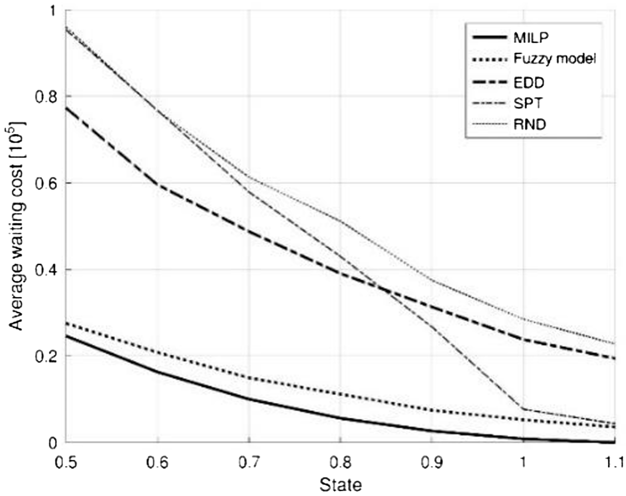
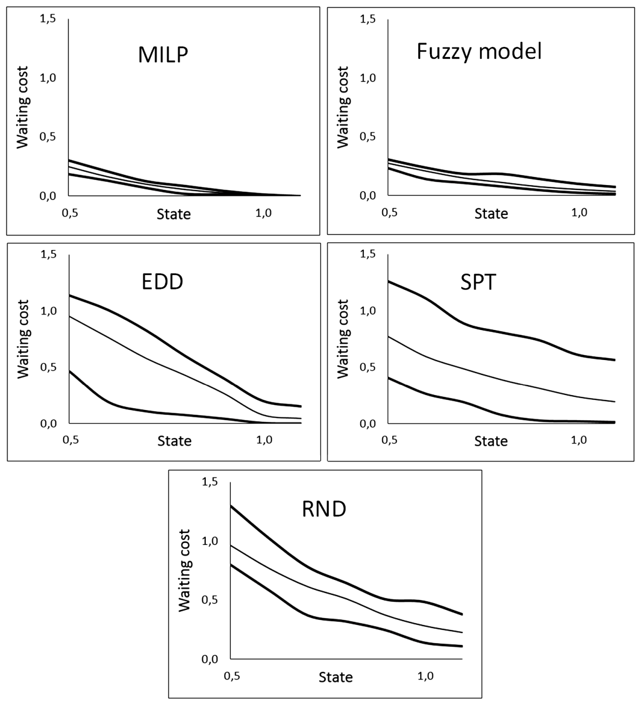


Table 1
The optimal weight ratios for specific states

State	Weight ratio rTPT/WU
0.5	1.25
0.6	1
0.7	0.95
0.8	0.75
0.9	0.65
1	0.5
1.1	0.5

Figure 4
State-dependent waiting costs of each optimization method. Each graph shows the maximum, minimum, and average values



the same state. The versions of the states were set up by systematically changing the deadlines in the original scenario. In this way, 7 sets of 11 different scenarios were constructed from state 0.5 to 1.1. So, each method was tested on all the 77 scenarios.

The following optimization methods were examined:

- MILP
- Priority dispatch rules
  - EDD, the task with the earliest deadline is always selected first.
  - SPT, the task with the SPT is executed first.
  - Randomized selection (RND). In this case, no selection rule was used. It is quite similar to those forklift drivers' decisions who have no training; therefore, the results can be handled as the worst possible outcome.
- Fuzzy signature-based model (proposed in this paper).

The results of the tests can be seen in Figure 3 where the *X* axis represents the state, and the *Y* axis is the average waiting cost of the test scenarios.

Four out of the five examined methods have consequent behavior. These are the MILP, the fuzzy signature, the EDD, the SPT, and the RND. The best—according to the expectations—is MILP, and the worst is RND for each state. The presented fuzzy signature-based model always has the second-best performance. It is important to note that its deviation from the performance of the MILP is almost constant, and considerably low. In addition to the benefits deriving from the original aim of the method, it has another advantage, namely the financial advantage of the fuzzy approach compared to MILP is well predictable; thus, it is definitely suitable for economical calculations.

The behavior of EDD is different from the others. Even if s is bigger and the performance is better, if $s < 1$, the results will dramatically decrease. If $s > 1$, its efficiency is almost the same as of the fuzzy signature-based model, yet its usage is risky. Hence, we propose the implementation of the fuzzy signature-based model, especially in cases when there is a shortage of material handling capacity. A significant deviation between the results given by the different methods can be observed in Figure 4.

It shows the maximum and the minimum waiting costs for the tested scenarios, and the average waiting cost was presented in Figure 3. While the results of RND, EDD, and SPT occupy a definitely wide domain, the fuzzy signature-based model and MILP results give a significantly narrow band. Besides the low average cost, this property of the fuzzy signature-based model makes it suitable for practical use.

The figure contains interesting information about s as well. As MILP gives the optimal solution, and it almost reaches 0 at $s = 1$, it can be stated that from this point, there is the possibility of avoiding waiting (cost); thus, s is a suitable state parameter.

8. Summary

The paper has investigated the material handling problem in functional production systems. The operative management of material handling in such production systems has not been dealt with in much detail so far; publications have rather tackled frequently applied solutions for similar but not exactly the same problems (AGV dispatching and job shop scheduling). We have described these methods and pointed out their limitations.

We have presented a novel, fuzzy signature-based method, which is able to effectively handle this problem with satisfying results. The performance of the proposed method was compared to the performances of the other presented methods. During the tests, it was revealed that our method's performance approximates the performance of the (optimal) MILP-based model, which was used as a reference. Furthermore, the deviation of the MILP and our fuzzy signature-based method is almost constant and rather small, and—what gives the key motivation for its use—the fuzzy signature-based model needs definitely less calculations and, thus, computing resources and is definitely easier to handle than the MILP model. According to our results, we propose using this model for small- and medium-sized companies with a lack of advanced logistics management and the possibility of high volume improvement. For them, our method can easily be applied without high investment and grants a significant improvement in their production efficiency.

During the construction of the model, the most appropriate weights had to be found. According to the fact that in this case, there was no possibility to use common expertise-based methods, the proper weights were experimentally determined. To do it, the possible states of the examined system had to be quantified. The method of this quantification is also novel. Both the proper weight ratios and the property of state have been first presented in this paper.

The limitations of the method are as follows. First, as the presented method selects only the task with the highest priority and does not set a whole execution order, it may happen that instead of optimal selection, the system finds a local minimum, which means that the forklift is placed in such a false position which influence affects adversely the total waiting cost. Another limitation is that it was not possible to test the method in a real-life environment, we had to use artificially created scenarios. However, the implementation of the method does not need specially educated personnel and high investment; the changes of the environment can be followed easily.

The direction of future research may include the practical implementation of the method in the corporate sector, as well as the creation of the exact mathematical formula for the state (input) and the weight (output) pairs for the broader application of the method.

Since the weights were determined by experiments, in the future we will investigate that artificial intelligence methods, like neural networks or fuzzy clustering, could provide better outcome.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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