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Innovative System for Scheduling Production Using a Combination of Parametric Simulation Models

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Abstract: The article deals with the design of an innovative system for scheduling piece and small series discrete production using a combination of parametric simulation models and selected optimization methods. An innovative system for solving production scheduling problems is created based on data from a real production system at the workshop level. The methodology of the innovative system using simulation and optimization methods deals with the sequential scheduling problem due to its versatility, which includes several production systems and due to the fact that in practice, several modifications to production scheduling problems are encountered. Proposals of individual modules of the innovative system with the proposed communication channels have been presented, which connect the individual elements of the created library of objects for solving problems of sequential production scheduling. With the help of created communication channels, it is possible to apply individual parameters of a real production system directly to the assembled simulation model. In this system, an initial set of optimization methods is deployed, which can be applied to solve the sequential problem of production scheduling. The benefit of the solution is an innovative system that defines the content of the necessary data for working with the innovative system and the design of output reports that the proposed system provides for production planning for the production shopfloor level. The DPSS system works with several optimization methods (CR—Critical Ratio, S/RO—Slack/Remaining Operations, FDD—Flow Due Date, MWKR—Most Work Remaining, WSL—Waiting Slack, OPFSLK/PK—Operational Flow Slack per Processing Time) and the simulation experiments prove that the most suitable solution for the FT10 problem is the critical ratio method in which the replaceability of the equipment was not considered. The total length of finding all solutions by the DPSS system was 1.68 min. The main benefit of the DPSS system is the combination of two effectively used techniques not only in practice, but also in research; the mentioned techniques are production scheduling and discrete computer simulation. By combining techniques, it is possible to generate a dynamically and interactively changing simulated production program. Subsequently, it is possible to decide in the emerging conditions of certainty, uncertainty, but also risk. To determine the conditions, models of production systems are used, which represent physical production systems with their complex internal processes. Another benefit of combining techniques is the ability to evaluate a production system with a number of emerging problem modifications.

Keywords: parameterization; simulation models; production scheduling; sustainable engineering; innovative system; communication channels; production planning; production system; optimization method

Citation: Micieta, B.; Staszewska, J.; Kovalsky, M.; Krajcovic, M.; Binasova, V.; Papanek, L.; Antoniuk, I. Innovative System for Scheduling Production Using a Combination of Parametric Simulation Models. *Sustainability* **2021**, *13*, 9518. https://doi.org/10.3390/su13179518

Academic Editor: Fabio De Felice

Received: 7 July 2021
Accepted: 20 August 2021
Published: 24 August 2021

1. Introduction

From the realized knowledge and study of the researched area [1–3], the potential in the problem of sequential production scheduling (JSSP) was found because its versatility includes several manufacturing companies and at the same time because it is possible to meet several modifications to scheduling problems in practice, for example, the selection of machines, limited quantities of intermediate warehouses, etc. The problem of sequential [4,5] scheduling belongs to piece and small series production, where there is very often complex material flows over the whole production system, which causes several other problems.

Production scheduling [6] is detailed planning at the highest level. Orders that are released in production must be translated into tasks with appropriate deadlines. These tasks must be processed using the available resources in the given order or sequence.

Job processing [7] can sometimes be delayed if some stations are busy, and situations can occur when high-priority jobs reach busy machines. It is also necessary to consider unforeseen events in the workshop such as machine failures or longer processing times than expected, as they can have a major impact on schedules. In such an environment, developing a detailed schedule of tasks helps maintain efficiency and control of operations [8].

Scheduling provides the greatest advantage when one or more of the following conditions are present [9]:

- in custom manufacturing, where orders are created to meet the demand of a particular customer entity and not for a simple market situation;
- in a more complex warehouse production environment that produces multiple products with significant changes, leading to production sequences that significantly affect throughput;
- when product delivery to customers on time is a key performance indicator;
- when the manufacturing process is expensive and, as a result, you have a limited resource system with orders competing for equipment assignment;
- in situations where you make several products at once and each product flows through the system differently; and
- when unplanned but probable failures—such as machine failures or late arrival of materials—require scheduling.

Scheduling decisions can vary greatly from company to company, but they all have common features. In this, certain features will be described to help us understand how to achieve a certain degree of abstraction that can help us formulate a general framework suitable for different societies. These properties are [10]:

- Comprehensive decisions because they involve the development of detailed plans for allocating tasks to resources over time.
- Planning decisions at short intervals to be taken repeatedly. The average lifetime of the schedule is very short and requires constant updating of the schedule based on the current state.
- Although a short-term decision, planning is relevant to the company's financial results because it determines delivery times and product costs, which in the long run affects the company's service level as well as its ability to compete on production costs and delivery times.
- As a decision-making process at the core of manufacturing company operations, the constraints and goals affecting planning are extremely specific to that company. The nature and use of resources in a chemical commodity plant have little to do with the production of ball carriers or the assembly of highly customized electronic devices.
- Scheduling is a relatively structured decision. Its operational nature means that scheduling requires relatively well-defined data, constraints, and objectives.

Given the wide variety of aspects and features that can occur in manufacturing systems, it is not surprising that a large number of different scheduling models can be found in the literature. Each of them describes a way to solve the problem of production scheduling using various methods, whether mathematical programming, boundary programming, heuristics and meta-heuristics, or hybrid methods. The predominant part of the literature consists of hybrid methods that solve various problems of production scheduling. Here, some of the mathematical methods or constraint programming are mostly combined with heuristic or meta-heuristic methods. The second most used combination is optimization algorithms with heuristics.

Leading software for production planning and detailed planning systems uses heuristics and meta-heuristics, especially the genetic algorithm [11,12], the bottleneck heuristics, dispatching rules, and constraint programming, while the task of heuristics is mainly to quickly find a possible solution and add genetic algorithms. These planning systems do not mention the possibility of optimizing the generated schedule [13,14], because their main goal is to generate a feasible production schedule in the shortest possible time. Due to the application of these planning systems in various industries, methods are also emerging that do not have many applications in practice [15].

The proposed innovative system should include, compared to the production solution such as PREACTOR or ASPROVA and others, especially the creation of a production system automatically, then complete the proposed system to the required level of detail and use applied optimization methods to obtain more initial production schedule solutions, from which statistics evaluate the production schedule that shows the best results for the production system. Finding the optimal solution in the field of scheduling piece to small series production is not always easy due to the complexity of the problem [16,17], while the rule of change applies only in the order of execution of individual customer orders [18–20].

The task of the proposed system is to create possibilities and functionalities that will be summarized into one comprehensive platform. When acquiring a new solution, no tool is needed, by means of which the production schedules will be obtained, and subsequently, the resulting sequences of processing the operations of individual tasks with subsequent evaluation of the production schedule will be verified in the simulation software. The given system will create various variants of schedules from the acquired data based on applied optimization methods directly in the proposed system with the evaluation of each variant of the production schedule.

2. Materials and Methods

When solving task attributes for a single-machine model, it is useful to distinguish between information that is known in advance and information that is generated because of planning decisions. Input information [21]:

- p_j—processing time required by task j;
- r_j—release date. The earliest time when job j can start its processing; and
- d_j—required completion/completion date.

The information that is generated because of planning decisions is the output of the planning function, and capital letters are usually used to indicate this type of data. Planning decisions form the most basic part of the data to be used when evaluating plans:

- C_j—task completion time j.

Quantitative measures to evaluate schedules are usually a function of task completion times. The two important quantities are:

- F_j—flowtime (time that task j spends in the system ($F_j = C_j - r_j$));
- L_j—lateness (time deviation from the planned end time ($L_j = C_j - d_j$). L_j can acquire both positive and negative values);
- $T_i = \max\{0, L_j\}$—delay of task j (tardiness); and
- $E_i = \max\{0, -L_j\}$—advance of the problem j (earliness).

Schedules are generally assessed as aggregated quantities that include information on all tasks, leading to one-dimensional performance measures. Schedule fulfillment rates are usually a function of the set of completion times in the schedule. For example, suppose n tasks are scheduled. There are several performance indicators [22]:

- $F = \sum_{j=1}^{n} F_j$—the total time spent in the system;
- $T = \sum_{j=1}^{n} T_j$—total tardiness;
- $F_{max} = \max_{1 \le j \le n} \{F_j\}$—the maximum time the task stays in the system;
- $T_{max} = \max_{1 \le j \le n} \{T_j\}$—maximum tardiness;
- $U = \sum_{j=1}^{n} \delta(T_j)$—number of tardy jobs or total unit penalty, where $\delta(x) = 1\ if\ x > 0$ and $\delta(x) = 0$ otherwise; and
- $C_{max} = \max_{1 \le j \le n} \{C_j\}$—maximum completion time.

According to the these basic assumptions, $C_{max} = F_{max} = p_j$, and this quantity is also known as the total processing time of all tasks (makespan). However, these three performance indicators may not be the same for a different set of assumptions. Thus, it is possible to label the minimization of the total stay of tasks in the system as the F-problem and similarly for the T-problem, C_{max}-problem below.

2.1. Approaches Used for Scheduling

Reliability scheduling algorithms can be divided into exact and approximate. Precise algorithms can create the optimal variant of solving the problem and can guarantee that no other schedule will work better than the one obtained concerning the desired goal. There is no guarantee in the approximate algorithms and their performance is determined by experience. The advantage of approximate algorithms is the possibility of solving more complex sequence problems in a relatively short time with the achievement of the most satisfactory solution, which is not guaranteed optimally, but can usually meet the goal.

2.1.1. Precise Design Algorithms

Precise design algorithms use the specific features of the planning model to create a solution that is guaranteed to be optimal. There are several causes for which finding exact algorithms is quite simple. For example, for a single-machine model to reduce C_{max}, each plan will produce the same result if all operations are shifted to the left on the timeline. For a single-machine model to minimize total completion time, sorting jobs according to the shortest processing time rule (SPT dispatching rule) provides the optimal solution. Similarly, it is possible to solve the problem with one machine at specified completion dates to minimize the maximum delay Lj by sorting the tasks according to the earliest due date (EDD) rule. Known exact algorithms include:

- Johnson's algorithm (Johnson, 1977) [23];
- Lawler's algorithm (Lawler, 1993) [24];
- Linear Programming (Tseng, 2004) [25];
- Mixed Integer Programming (MILP) [26]; and
- Constraint Programming (CP), [27].

2.1.2. Approximate Algorithms

Approximate algorithms, also called heuristic and metaheuristic methods, are used for more complex cases where it is not possible to apply precise methods. They are also able to work with incomplete information. Bertrand divides heuristic methods into construction methods (including the shifting bottleneck heuristics method and priority rules) and local search methods [28].

Shifting Bottleneck heuristics can be assigned to the most powerful heuristics of custom manufacturing because it was the first method that solved the FT10 problem (sequential problem with 10 machines and 10 products) [29].

The local search method is simple, but also the least effective heuristic method. Local search is based on probably the oldest optimization method: trial and error. The neighborhood of a given solution is a set of feasible solutions that are in some way like the given solution. This means that similar elements and values of purpose functions do not differ much [30].

2.2. Dispatching Rules

The general dispatching rules (priority rules), (Table 1) perform a simple calculation for all tasks in the list and send the tasks to the system according to the result of this calculation, which is sometimes referred to as a priority. Dispatching rules can be divided into static and dynamic—the result of the dispatching rule depends on the time in which it is applied. Static priority rules always return the same priority index, regardless of schedule status or task list. Conversely, the rules of dynamic dispatching depend on the moment (i.e., at which they are calculated), and thus on the information obtained from the sub-schedule derived to time t. Bonami [31] and Brucker [32] in their work created a comparison of selected priority rules for the job shop scheduling problem.

Table 1. Basic static and dynamic priority rules.

No.	Rules	Description	Type
1	FIFO	First In First Out	Static
2	LIFO	Last In First Out	Static
3	SPT	Shortest Processing Time	Static
4	LPT	Longest Processing Time	Static
5	SPS	Shortest Process Sequence	Static
6	LPS	Longest Process Sequence	Static
7	STPT	Shortest Total Processing Time	Static
8	LTPT	Longest Total Processing Time	Static
9	ECT	Earliest Creation Time	Dynamic
10	LCT	Longest Creation Time	Dynamic
11	SWT	Shortest Waiting Time	Dynamic
12	LWT	Longest Waiting Time	Dynamic
13	LTWR	Least Total Work Remaining	Dynamic
14	MTWR	Most Total Work Remaining	Dynamic

2.3. Metaheuristic Methods

A metaheuristic is a set of concepts that can be used to define heuristic methods that can be used for a wide variety of different problems [33].

Metaheuristics can be understood as a general algorithmic framework that can be applied to various optimization problems with a relatively small number of adjustments to adapt to a specific problem.

Several problem-specific heuristic methods have been developed to solve production scheduling problems [34–46]. The most popular production meta-heuristics include:

- Evolutionary computational algorithms, which fall into three main categories: genetic algorithms, evolutionary strategies, and evolutionary programming;
- Ant colony optimization (ACO) [47–49].
- Explorative local search represented by greedy random adaptive search procedure (GRASP), variable neighborhood search (VNS), and iterated local search (ILS);
- Hill climbing—HC [50];
- Tabu search—TS [51];
- Simulated annealing (SA);
- Neural networks (NN) are advanced artificial intelligence technologies that simulate “brain learning” and the decision-making process; and

- Threshold algorithms accept a transition if the difference between the current solution and the neighbor's solution is less than the given threshold.

As a general algorithmic framework, metaheuristics consist of a set of concepts that can be used to define or guide specific heuristic methods used for a wide range of different problems. These are mainly the following concepts [52–55].

- representation of the problem or solution;
- initialization;
- definition of neighborhood [56–58];
- local search process [59–64];
- admission criteria [65–67]; and
- completion criteria [68–71].

2.4. Proposal of a General Approach to the Creation of a Scheduling System

For the successful design of a scheduling system based on computer simulation [71–73], a general procedure for project implementation is proposed (Figure 1):

- Creation of the parametric simulation model itself [74];
- Update input parameters;
- Generating the initial variant of the schedule;
- Schedule optimization [75];
- Evaluation of the schedule [76]; and
- Implementation [77–81].

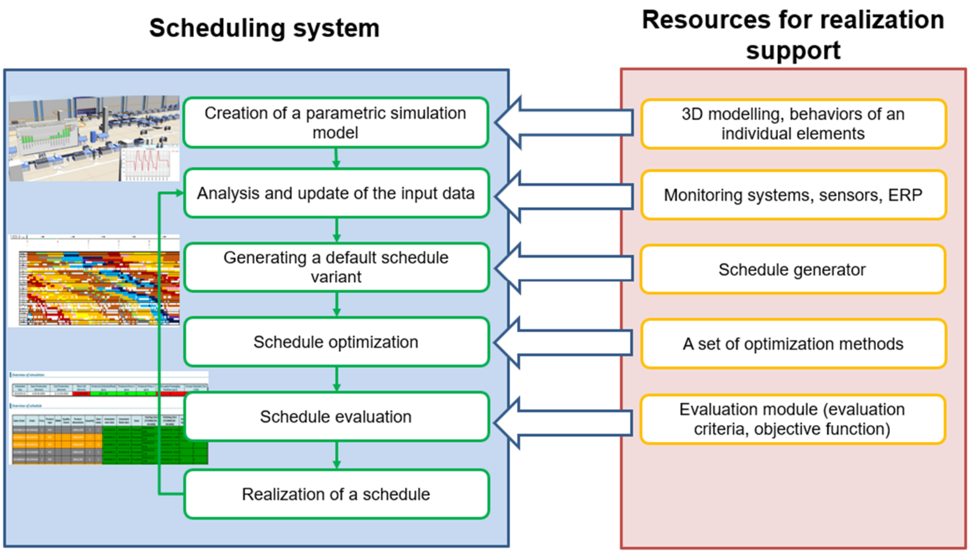

Figure 1. General approach to the creation of a scheduling system.

3. Results

The methodology of the innovative system using simulation and optimization methods deals with the sequential scheduling problem (JSSP) due to its versatility, which includes several production systems and due to the fact that in practice, several modifications to production scheduling problems are encountered. The innovative system was called DPSS—dynamic production scheduling system. The solution of the innovative system consists of several parts or modules, which are shown in Figure 2.

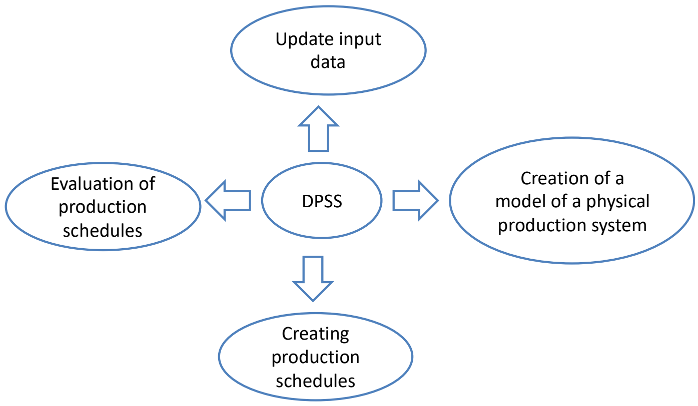

Figure 2. DPSS—dynamic production scheduling system.

Before the design part of the DPSS system concept, it is necessary to define the requirements and the purpose for which the proposed system is to be built as a matter of priority. The proposed innovative system should be able to create solutions for both robust production systems and smaller production systems where resources will be limited. Therefore, the following characteristics that will form the basis of the proposed innovative production scheduling system called DPSS are essential:

Property number 1: Variability—the influence of variability is the most important part of production scheduling to achieve the complexity of the solution because increasing variability reduces the performance of the production system. It is necessary to understand the limits and limitations of the production system so that the processes can be properly sequenced.

Property number 2: Variation—this type of system property can influence not only the long-term but also the short-term behavior of any production system, which results in a direct impact on the creation of acceptable production schedule solutions. The task that this feature contains is ignored in many advanced planning and scheduling (APS) tools, especially when creating a production schedule daily. This feature of the system will ensure the functioning of comprehensively designed production systems, which are full of differences and uncertainties.

Property number 3: Modularity—this represents the compilation of a model of a physical production system as well as the method of reading and updating data in the proposed solution. Of course, it also includes access to the user who will use the system. Therefore, it is a matter of setting up the system and individual applications to the extent of the detail and elaboration that will be necessary and required.

Property number 4: Possibility of connection—this is a basic pillar of the proposed DPSS system. It is necessary to connect the system with system databases, which record and evaluate input data directly from the production workshop, and ultimately also serve to evaluate and compare the resulting deviations in the created model of the physical production system with the real production system.

Property number 5: Possibility of evaluation—this is used to evaluate and compare the resulting summary of statistics obtained based on analyses performed in the created model of the physical production system. It is necessary to identify key indicators that will be the same for all created solutions for the simplification and clarity of individual solutions of production schedules. For use in daily deployment, it is also necessary to automatically create an output report of individual variants of solutions with a recommendation for the selection of an acceptable solution for the physical production system.

Property number 6: Possibility of control—this is indirectly connected with modularity, solution evaluation, and connection with other database systems, which means setting up the proposed innovative system not only to work with it, but the ability to interact with other modules of the proposed solution.

The Concept of the Proposed DPSS Solution

The concept of the DPSS design is shown in Figure 3, which also shows the individual modules as well as the information flow between the individual modules.

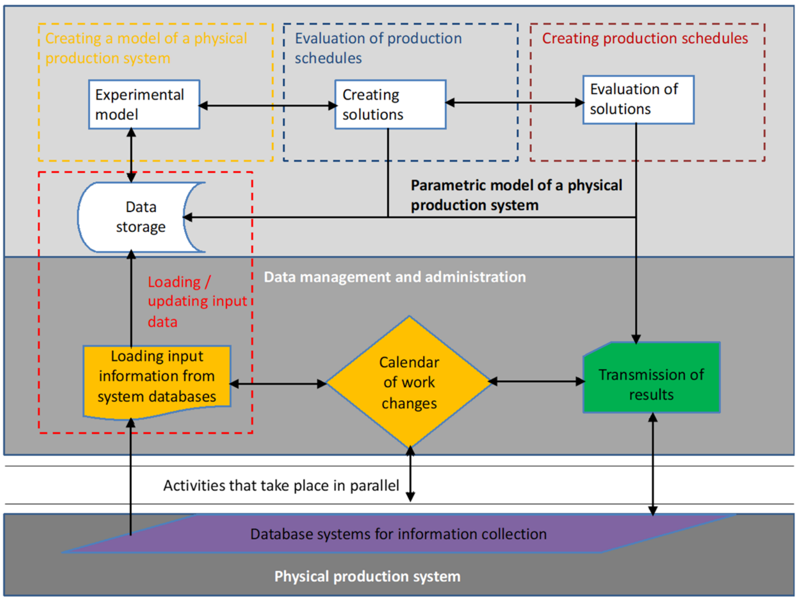

Figure 3. The concept of the DPSS.

The information flow is represented by solid black lines with arrows at their ends according to the direction of the information flow and the individual modules represent dashed lines with color differences.

In the proposed DPSS system, communication takes place between the physical production system, control, and management of input–output data of the physical production system, the activities of which are directly affected by the parametric model reflecting the behavior of the physical production system. The task of the created parametric model of the physical production system is to create solutions of production task schedules that will not only be satisfactory for the physical production system, but will reflect the real state in the processing of individual tasks going through its internal processes.

The first step of the proposed solution is to read the input data or update them due to the availability of consistent data, which are necessary for the created model of the physical production system. If ERP (enterprise resource planning), MES (manufacturing execution system) or SCADA (supervisory control of data acquisition) systems are used in each production system, it is possible to draw information about the production system from their databases and regularly update them to obtain more accurate estimates of emerging states. The data update takes place before the initialization of the production system model to obtain consistent data with the physical production system.

The second step is to create a model of a physical production system that emulates the behavior of a real system. For this step, it is necessary to have enough information in the input database of the simulation software. These data enter the created model in the simulation software, with the help of which a model of a real production system is created. To create a model, it is necessary to know which data are the same or similar for an individual production system and to create a model corresponding to reality from this data, while the user does not have to know about working in simulation software.

The third step is to create variant solutions of production schedules. It is necessary to use not only the created model of the physical production system and data obtained from the physical production system, but also other data such as production orders, which enter the production system. This information is initialized directly in the model of the production system, after which various solutions of production schedules are created according to the selected optimization criterion. The criteria can be combined in the concept thus compiled to create such acceptable solutions for the production system, which will have the least impact on its key indicators.

The fourth step is the evaluation of variant solutions of production task schedules for the physical production system. The evaluation of the production system model takes place according to the proposed purpose function. Its role in the proposed DPSS system is to select from the variants of possible solutions a solution in which suitable conditions (determination of certainty or risk) for the physical production system arise. Subsequently, the selected possible solution is exported for data management and administration. Based on these outputs from the model of the physical production system, these departments can gradually release tasks into the production process, and thus manage the processes at the level of the production workshop.

By closing the cycle of these four modules, it is possible to evaluate the accuracy of the estimates of the created model of the physical production system with the physical production system and to identify non-compliance with the created solution of the production schedule. Non-compliance with the schedule occurs due to the occurrence of an unexpected situation in the workshop, and it is necessary to find a new acceptable solution for this situation, in which the optimization criteria of individual orders change due to a change in assignment of individual production tasks and factory management settings.

Based on this fact, the ability arises to accurately model the details in the assembled model of the physical production system and to address the necessary risks arising from the uncertainties within this system. Thus, the proposed DPSS system can achieve results that fully correspond to all flows of moving elements in the physical production system.

Based on the above properties and individual parts of the proposed DPSS solution, it is desirable to list several modules entering directly into the proposed parts of which the proposed DPSS system consists (Figure 4).

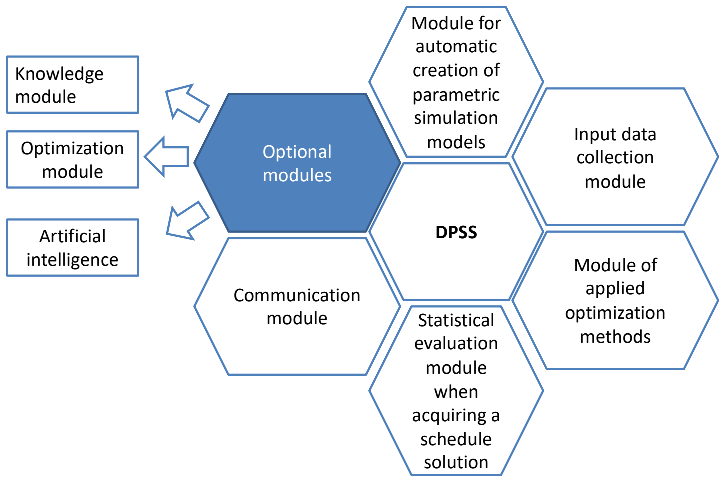

Figure 4. DPSS—optional modules.

4. Discussion

The verification was performed on two examples:

Fictitious production system—an example is a solution to the most widely used problem of sequential production scheduling, which is compiled in the range of 10×10 (where 10 different types of products are used, the individual operations of which are to be performed on 10 production facilities).

Real production system—in the example, it focuses mainly on creating a simulation model of a physical production system, which represents a real production system, and apply the problem of sequential scheduling of production. The example represents a solution to the 177 x 8 problem (177 production facilities are used to process eight final products), with eight final products consisting of 200 to 300 products entering one final product.

The examples use products that are either simple (no parts list required) or assembled products (parts list required). Using the compiled examples, it is tested the proposed innovative DPSS system so that it is possible to identify whether the use of such a system can be applied to both smaller and larger solutions to the problems of sequential production scheduling.

4.1. Testing of an Innovative DPSS System on a Fictitious Production System

The aim of the experimental verification set up in this way is to compare the proposed innovative DPSS system with other already designed systems, which have been compared with each other. The verification of the proposed DPSS system took place on the example in the range of 10 × 10 (where 10 different types of products are used, the individual operations of which are to be performed on exactly 10 production facilities).

The input data for the compiled experimental verification are fictitious products and their associated technological procedures, and fictitious production equipment with their parameters. The data entering the innovative DPSS system are given in Tables 2 and 3.

Table 2. Task operations assigned to individual production facilities.

Products	Available Production Equipment									
	M1 Operation Number	**M2 Operation Number**	**M3 Operation Number**	**M4 Operation Number**	**M5 Operation Number**	**M6 Operation Number**	**M7 Operation Number**	**M8 Operation Number**	**M9 Operation Number**	**M10 Operation Number**
J1	7	8	9	10	1	3	4	2	6	5
J2	7	1	8	3	4	9	2	10	6	5
J3	5	6	8	9	10	1	7	4	3	2
J4	1	3	5	4	6	7	8	2	9	10
J5	3	5	6	7	8	4	2	9	10	1
J6	1	10	4	6	3	5	2	7	8	9
J7	1	4	9	2	3	8	6	7	5	10
J8	3	5	2	6	4	9	10	7	8	1
J9	8	9	10	6	3	1	5	2	7	4
J10	2	1	3	4	5	7	6	8	9	10

Table 3. Duration of operations from tasks assigned to individual production facilities.

Products	Available Production Equipment									
	M1 Duration of Operations	**M2 Duration of Operations**	**M3 Duration of Operations**	**M4 Duration of Operations**	**M5 Duration of Operations**	**M6 Duration of Operations**	**M7 Duration of Operations**	**M8 Duration of Operations**	**M9 Duration of Operations**	**M10 Duration of Operations**
J1	97	23	17	29	73	82	43	54	6	48
J2	57	23	23	54	54	69	82	43	7	6
J3	98	37	48	32	78	79	9	24	47	30
J4	25	87	75	58	61	81	97	95	78	86
J5	40	92	74	32	52	10	67	15	82	97
J6	93	30	83	75	24	98	89	7	16	84
J7	77	18	84	62	31	74	33	35	12	23
J8	17	98	42	64	26	96	1	49	21	33
J9	44	54	95	42	25	13	16	38	36	27
J10	57	9	79	33	62	90	66	11	74	62

Based on these data, a simulation model of a fictitious production system was compiled and then the individual acquired solutions to the sequential scheduling problem were compared. The created simulation model of a fictitious production system was created by an automatic mode, which is part of the proposed DPSS system. The automatic mode of creating the simulation model creates communication channels between the sources used to perform the experiment and the input data on which the experimental verification is based.

4.1.1. Application of Priority Rules in Solving Production Scheduling

Based on the input data for the selected experimental verification, it is necessary to insert the initial variant of the experiment into the DPSS system, based on which it is identified whether the proposed DPSS system meets the functional requirements for solving the problem of sequential production scheduling. Table 4 shows the precisely defined steps of processing the individual operations from the tasks, which are precisely given for experimental verification. Each production plant has individual sequences of processing operations from individual tasks.

Table 4. Initial solution of the sequential problem of production scheduling.

	Available Production Equipment									
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**
	Product	**Product**	**Product**	**Product**	**Product**	**Product**	**Product**	**Product**	**Product**	**Product**
Initial sequence of product processing	J6	J2	J8	J2	J1	J3	J2	J1	J3	J5
	J7	J10	J10	J7	J2	J9	J6	J9	J2	J8
	J10	J7	J6	J10	J9	J1	J5	J3	J7	J3
	J2	J3	J2	J9	J7	J7	J1	J7	J1	J2
	J3	J1	J7	J6	J6	J6	J7	J4	J9	J9
	J10	J9	J3	J3	J10	J10	J9	J10	J10	J1
	J9	J8	J9	J1	J8	J2	J10	J6	J6	J7
	J5	J5	J1	J8	J3	J5	J3	J2	J8	J10
	J4	J4	J5	J5	J5	J8	J8	J8	J5	J6
	J8	J6	J4	J4	J4	J4	J4	J5	J4	J4

4.1.2. Validation and Verification of the Innovative DPSS System

Validation and verification are the most important parts of the experimental verification set up in this way. The verification itself identifies the functionality and accuracy of the results obtained after the application of the DPSS system to solve the problem of sequential production scheduling.

By inserting a precisely defined sequence of processing operations from individual tasks, individual indicators were obtained, which show how accurate the output data was achieved by the proposed DPSS system. Indicators used for evaluation were as follows:

- Total processing time for all tasks from the experiment;
- Capacity utilization of production resources; and
- The total duration for which the applied system reached the solution.

4.1.3. Application of the DPSS System to a Solution without an Initial Schedule

The DPSS system was designed so that it is possible to obtain a positively feasible solution to the sequential production scheduling problem. Based on a precisely defined sequence of processing individual beds, the correctness of the decisions made with the optimization methods of the proposed system was identified. Subsequently, the experiment was performed without setting the initial sequence. In the experimental verification without an initially defined sequence of processing operations of individual products on available production facilities, the possibility of the substitutability of production facilities was not applied as the given experiment does not mention any possibility of the interchangeability of production facilities. The experiment was defined in this way with a whole set of decision rules, which the innovative DPSS system contains. Figure 5 shows the processing sequence of all operations of individual products from the experiment. When evaluating the acquired solutions, the same indicators as in the initial variant of the set-up experiment are used.

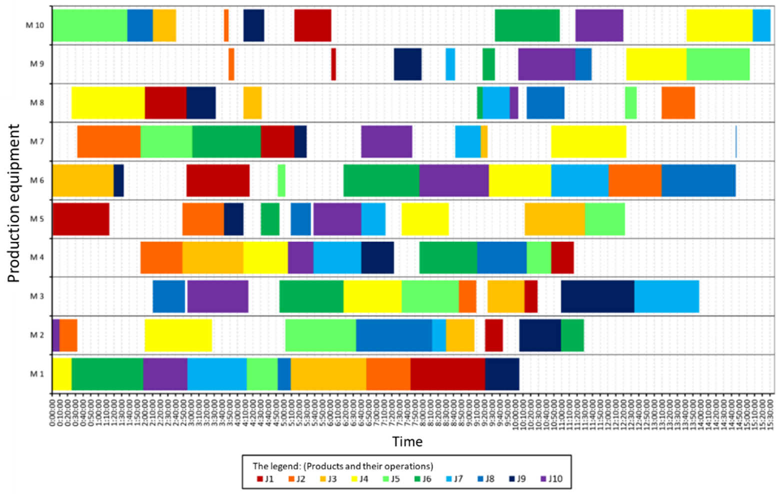

Figure 5. Sequence of processing operations of individual products.

From the sequence of processing operations of individual products by the DPSS system, the total processing time of all products from the experiment was 931 minutes. Compared to the starting sequence, the total processing time of all products was reduced by 243 min, which represents 20.69%. Subsequently, the capacity utilizations of individual production facilities were acquired (Figure 6).

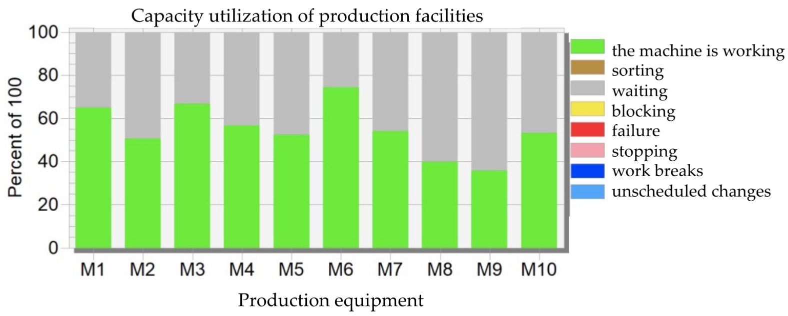

Figure 6. Capacity utilization of production facilities.

Subsequently, after performing all the experiments in the DPSS system, a comparison was made with the rules of various systems used to solve the problem of sequential production scheduling (Figure 7).

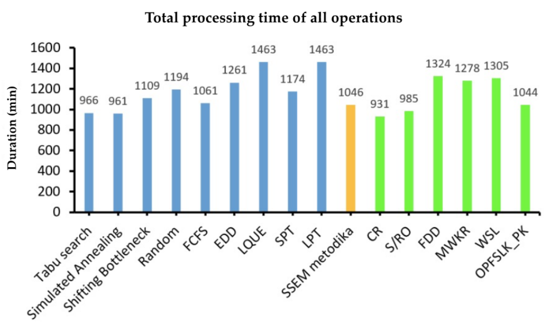

Figure 7. Capacity utilization of production facilities.

Figure 7 illustrates the application of various methods to the solved problem of the range of 10 × 10 assembled experiment of samples of the production system. The DPSS system uses six methods in the acquisition of various variants of the solution of the sequential problem of scheduling, the results of which are shown in Figure 7. After the application of the sanction function, the most suitable solution was an experiment in which the solution was applied with a critical ratio. The results of the solution are given, whether the sequence of processing operations from individual beds or the capacity utilization of production equipment was based on the used method of critical ratio, in which the substitutability of equipment was not considered. The total running time of all DPSS solutions was 1.68 minutes.

The proposed DPSS system does not contain all the available optimization algorithms, methods, and tools that are designed to solve the sequential problem of production scheduling. The DPSS system is modular, and represents an opportunity to add various other optimization methods, algorithms, and tools. Optimization methods were chosen for the proposed system, which allow for experiments with both robust and smaller problems of sequential production scheduling. The applied methods are heuristics, namely:

CR—Critical ratio $Z_j = \frac{(d_j-\tau)}{\sum_{t=q}^{O_j} \check{p}_{tj}}$;

S/RO—Release of residual operations from the task until the due date;

$$Z_j = \frac{r_j}{\sum_{t=q}^{O_j} \check{p}_{tj}}$$

FDD—Flow of residual operations from the task to the due date;

$$Z_j = r_j + \sum_{t=1}^{q} \check{p}_{tj}$$

MWKR—Select a larger remaining operation time for the task;

$$Z_j = \sum_{t=q}^{O_{(j)}} \check{p}_{tj}$$

WSL—Relieve job waiting;

$$Z_j = d_j - \left(\tau + P_{q+1} + \sum_{t=q}^{O_{(j)}} \check{p}_{tj}\right)$$

OPFLSK/PK—Reducing the operational flow of operations to the remaining processing time;

$$Z_j = d_j - \left(\tau + P_{q+1} + \sum_{t=q}^{O_{(j)}} \check{p}_{tj}\right)$$

Z_j—index of the priority of the job j;
j—index of the job;
q—index of the operation;
O_j—number of operations in the job j;
τ—the current time when the decision is to be made;
d_j—due date of the job j;
r_j—release date;
p_{tj}—the remaining time of operations from the task; and
P_{q+1}—processing time of the next operation of the job j.

4.2. Testing of the Innovative DPSS System on a Real Production System

The real production system to which the innovative DPSS system was applied deals with the production of positive railway cars. In a company with such a production system, positive railway wagons and bogies are manufactured, the components of which are manufactured directly in the production system. The components for the production of wagons and bogies will be the area where the DPSS system has been verified. The company decided to relocate the available production facilities to one production hall as the production facilities were scattered across several production halls. Subsequently, there was a requirement to check the capacity of available production facilities in order to identify the critically exploited production facilities according to the data provided.

Based on data on the future state of the production system, future estimates of requirements from customers, and the available capacities of production facilities, it was necessary to verify the proposed solution, which was to identify capacities and ability to meet future requirements from customers. To identify the above-mentioned indicators, the proposed DPSS system was applied to the solution, which was to point out the emerging limitations in the newly created solution of the company. The achieved results verified the functionality and the possibility of the DPSS system to create variants of robust solutions to the scheduling problem, which contributed to the verification of the proposed DPSS system in the conditions of practice.

4.2.1. Data Provided by the Company

The company provided data on the incoming requirements of customers, data on the final products and the associated components, the number of pallets found in the production system, and premises for their storage. In the individual analysis, an increase in the emerging customer requirements was also considered as well as a detailed analysis of the flow of individual materials through the production system. From these data and the generated estimates, a simulation model of the company's production system was compiled. The individual data were loaded into the designed DPSS system.

4.2.2. Creating a Simulation Model of a Physical Production System

The innovative production system contains a library of objects, between which a communication channel is created that is necessary for work with input data as well as the actual management of material flow in the entire production system, which represents the management physical production system with its internal processes. The simulation model in the DPSS system was solved in automatic mode.

4.2.3. Setting Up a Parametric Simulation Model for Experimentation

When performing the experiments, the automatic mode of creating variants of the sequential scheduling problem was used. The automatic mode verifies all the possibilities of the decision rules and can also use the substitutability of production facilities. In a real production system with production equipment, it is possible to use the option to select a candidate from replaceable production equipment.

After setting up the experiments, the period was defined for which we wanted to obtain a solution for the capacity utilization of available production equipment, fulfillment of emerging requirements from customers, the number of components produced for individual changes, and the acquisition of such a sequence of processing operations of individual components that could be directly applied to the workshop level.

An algorithm was compiled for experimentation, which represents the customer requirements for the final products that must be met by the required deadline to create sufficient space for the assembly of the final product.

4.2.4. Results of Performed Experiments

When creating various experiments, it was conducted not starting from any starting schedule, according to which it would be possible to identify whether there were any improvements in the application of different decision rules. In this case, it was proceeded by applying a sanction function to each acquired solution, which identified the differences between the individual solutions of production schedules and facilitated the selection when choosing a feasible production schedule.

Each of the acquired production schedules consisted of various incoming orders, while the indicators were monitored during the evaluation, which decided how the individual indicators in the sanction function changed by the set control rule.

When setting up the individual experiments, the possibility to apply the substitutability of production equipment to the solutions was chosen because when verifying the proposed system in the example, one of these options was not available.

By verifying the created model of the physical production system with a whole set of optimization methods, individual indicators for the physical production system were identified based on the provided input data.

Subsequently, a set of optimization methods was applied for the solution. It is listed below the capacity utilization of individual production facilities available to the production system when verifying the proposed changes in the production system (Figure 8).

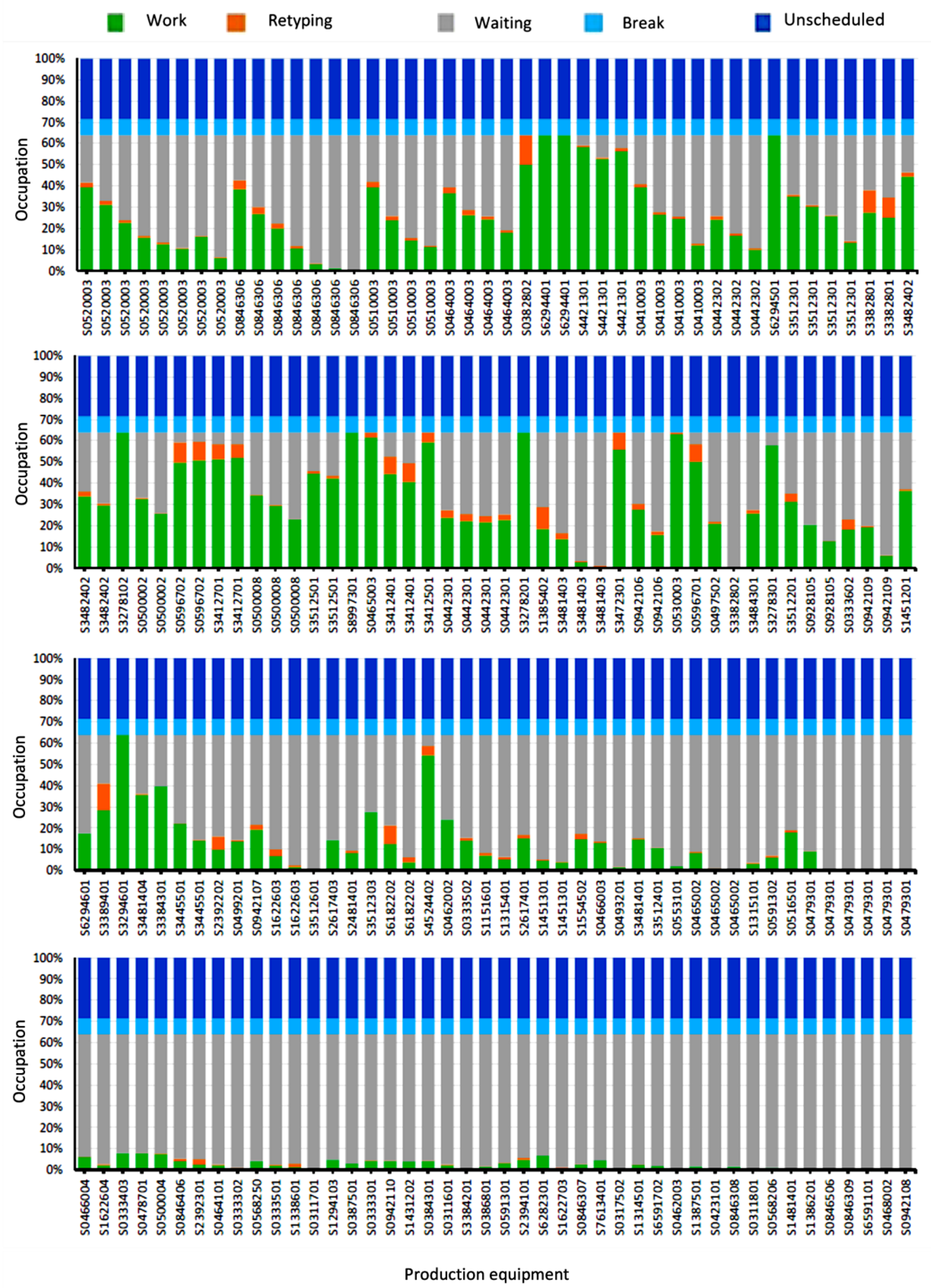

Figure 8. Capacity utilization of production facilities.

5. Conclusions

The following facts were identified by individual experimental verifications:

The proposed DPSS system can be applied to both small and robust solutions of the sequential production scheduling problem.

The use of decision rules in the DPSS system has been shown in comparison with other applied rules to be appropriately chosen to solve not only practical problems but also research assets, which approximates the first example of experimental verification.

It makes it possible to experiment with production systems and provide data for the short-term as well as long-term implementation of production systems to identify emerging risks or uncertainties resulting from an insufficient capacity of production facilities.

The possibility of applying the DPSS system to production systems producing products that do not easily and do not figure in any assembly in a verified production system or with products that enter the assembly units and create the final product.

The possibility of using the DPSS system for solutions in the law of a newly created solutions company, which creates new respect in the restructuring of the original production systems to obtain such data that correspond to the emerging questions of uncertain or risky decisions and thus verify pollution of production systems that may mean spending additional investments or their waste in performing insufficient analyses in the legal stages of the solution.

Based on the individual parts of the proposed system for production scheduling, we define further development as follows:

Incorporation into the proposed system of other existing resources, which may limit the production system such as workers, accessories, equipment.

Incorporation of information obtained from input warehouses of production systems. These data will make it possible to calculate whether the amount of the given material will be processed at the end of the observed period and whether the materials will not be sufficient in terms of quantity and at what time they will be fully consumed in the physical production system.

Development of algorithms for sequential production scheduling problems and the possibility of their application to the proposed system.

Developments in the field of knowledge systems represent an opportunity to create smarter feasible solutions for production schedules. This makes it possible to combine knowledge based on which they can set up an experiment in such a way that the user can obtain a feasible production schedule without performing several experiments and then selecting a solution that will achieve the required indicators of a physical production system.

Creation of a module for statistical processing of input data for the creation of solutions with a long-term horizon with the application of statistical methods to create more accurate estimates.

According to our research and findings for piece and small series production, the most suitable method is one that can respond quickly to any changes, so the most suitable solution is to combine classical methods and dispatching rules for scheduling production with dynamic simulation. The simulation model can precisely imitate a real production system and apply optimization algorithms in real time. The simulation can make multiple schedule variants at one time and evaluate the best result for each specific case. Priority rules or a combination of them was the most effective for simulation scheduling. The duration of the simulation depends on the complexity of the system and usually lasts from a few seconds to a few minutes.

Author Contributions: Conceptualization, B.M. and V.B.; Methodology, M.K. (Matej Kovalsky) and I.A.; Software, M.K. (Matej Kovalsky); Validation, J.S. and M.K. (Martin Krajcovic); Formal analysis, J.S.; Investigation, M.K. (Martin Krajcovic); Resources, M.K. (Matej Kovalsky); Data curation, M.K. (Matej Kovalsky); Writing—original draft preparation, V.B.; Writing—review and editing, V.B.; Visualization, I.A.; Supervision, B.M.; Project administration, V.B and L.P.; Funding acquisition, B.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Slovak research and development agency, grant number APVV-19-0305.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in the case study are available from the corresponding author.

Acknowledgments: This work was supported by the Slovak Research and Development Agency under contract no. APVV-19-0305.

Conflicts of Interest: The authors declare no conflict of interest.

List of Abbreviations and Symbols

ACO	Ant Colony Optimization
APS	Advanced Planning and Scheduling
CR	Critical Ratio
DPSS	Dynamic Production Scheduling System
ECT	Earliest Creation Time
EDD	Earliest Due Date
ERP	Enterprise Resource Planning
FDD	Flow Due Date
FIFO	First In First Out (FCFS—First Come, First Served)
GRASP	Greedy Random Adaptive Search Procedure
HC	Hill Climbing
ILS	Iterated Local Search
JSSP	Job Shop Scheduling Problem
LCT	Longest Creation Time
LIFO	Last In First Out
LPS	Longest Process Sequence
LPT	Longest Processing Time
LTPT	Longest Total Processing Time
LTWR	Least Total Work Remaining
LWT	Longest Waiting Time
MES	Manufacturing Execution System
MTWR	Most Total Work Remaining
MWKR	Most Work Remaining
NN	Neural Networks
OPFSLK/PK	Operational Flow Slack per Processing Time
S/RO	Slack/Remaining operations
SA	Simulated Annealing
SCADA	Supervisory Control of Data Acquisition
SPS	Shortest Process Sequence
SPT	Shorted Processing Time
SSEM	Scheduling using Simulation and Evolutionary Methods
STPT	Shortest Total Processing Time
SWT	Shortest Waiting Time
VNS	Variable Neighborhood Search
WSL	Waiting Slack

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