

Article

A Hybrid Linear Programming and Heuristic Approach for Production Scheduling—A Case Study in Automotive Part Manufacturing

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Abstract

Background: Reducing production time while making efficient use of resources is a key challenge in modern manufacturing, particularly in environments with high variability in specific components for the automotive industry. **Methods:** This paper presents a hybrid approach to production scheduling that combines linear programming (LP) principles with heuristic decision-making. A structured literature review is conducted to compare exact methods, heuristics, and metaheuristics in terms of their applicability and limitations. Based on this analysis, a hybrid scheduling method is proposed, where LP defines the objective function and constraints, while heuristic rules enable efficient assignment of operations to workstations under capacity limitations. The approach is validated through a case study involving over 900 product variants in an automotive part production system characterized by interchangeable workstations. The proposed heuristic algorithm was tested in terms of real company daily scheduling performance and compared with former scheduling performance. **Results:** The results show that the proposed approach achieves better solution quality with significantly lower computational effort, while also improving time utilization and production efficiency. **Conclusions:** The hybrid LP-heuristic approach provides a computationally efficient and practical tool for real-time production scheduling in high-variability manufacturing environments, effectively balancing solution quality and sub-minute execution speed under strict capacity constraints.

Keywords: production scheduling; linear programming; heuristics; manufacturing logistics; capacity optimization

1. Introduction

In today's manufacturing settings, reducing production time is very important for boosting efficiency and staying competitive. The need for an APS (Advanced Planning System) in manufacturing and OP (Operations Planning) processes is essential for streamlining processes. OP processes with ambitious aims, operating within a complex planning environment, are difficult if not impossible to implement without the support of APS systems [1]. This focus on shortening production time is vital not just for cutting costs but also for enhancing product quality and customer satisfaction, which are increasingly seen as measures of success in manufacturing. With the rise of Industry 4.0, indicating major changes in industrial automation, the shift towards Industry 5.0 shows the necessity of tailoring manufacturing processes to be more human-centered while incorporating advanced technologies like artificial intelligence and the Internet of Things [2]. This change is



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marked by the rising need for customized solutions that meet the particular needs of consumers in a quickly changing market. The combination of these technologies also reveals the complexity of modern manufacturing logistics, where linear programming acts as an essential tool for finding the shortest production time across different workstations and stages of operation [3]. This advanced use of mathematical methods enables manufacturers to better use their resources and improve their processes significantly. The main objective of this paper is to clarify the various methods used in this context, ultimately providing insights into how production time can be reduced efficiently while upholding high output standards. By looking at the complex relationship between technological progress and production methods, this study aims to add to the existing knowledge and offer practical benefits to industry stakeholders, thus promoting a culture of ongoing improvement and innovation in manufacturing practices.

Production time, i.e., how long it takes to make products, is an important part of the production cycle, covering everything from getting materials to putting things together at the end. It matters because it affects how well a company works, how much it produces, and in the end, how much profit it makes. By knowing and improving production time, companies can make more products while wasting less, which is good for sustainability and the environment. Production time is not just a way to measure how well a factory runs but is also very helpful in managing resources and controlling stock. Moreover, using new technologies like artificial intelligence and data analysis helps to make production better, as shown in [4]. These methods support fixing machines before they break and making operations smoother, leading to better use of resources and shorter waiting times. This fits well with the idea of a circular economy, which supports eco-friendly production methods [4,5]. Also, by tracking data in real time, factories can spot problems and inefficiencies in their workflows, allowing for quick changes that help improve overall results. Because of this, careful checking of production time is key to creating smart plans that improve how operations run and aid in making important choices in manufacturing logistics. Moreover, a detailed look at production time can greatly help in making investment choices and setting achievable production goals, which are crucial for keeping customers happy and staying competitive in a fast-changing market [6].

Effective optimization of production time presents several formidable challenges, particularly in contemporary manufacturing environments that are increasingly influenced by globalization and technological advancements. The complexity of planning and scheduling processes has grown, necessitating innovative approaches that can accommodate varied operational contexts and fluctuating market demands [7]. For instance, in brownfield settings, layout planning poses unique difficulties since every facility possesses distinct characteristics that impact efficiency [8]. Furthermore, the integration of automated systems and improved workflows can complicate optimization efforts, as such modifications often require comprehensive redesign and collaboration among various stakeholders. By implementing a Zone Model Predictive Control (ZMPC) method based on a Fast Adaptive Harmony Search (FAHS) algorithm, these systems can be fine-tuned to enhance performance in real-time scenarios, directly addressing the challenges of accuracy and efficiency in production settings [9]. Addressing these challenges demands not only accurate data and resource allocation but also the development of flexible strategies that can adapt to changing conditions. Ultimately, understanding and mitigating these obstacles are crucial for enhancing productivity and ensuring sustainable operations within manufacturing frameworks.

In contemporary manufacturing environments, reducing production time is essential for maintaining competitiveness and ensuring efficient resource utilization. Production scheduling plays a key role in achieving these objectives, particularly in systems character-

ized by high product variability and flexible resource allocation. Linear programming (LP) provides a structured mathematical framework for optimization. However, exact methods often become computationally infeasible in complex environments. Heuristic approaches provide faster, near-optimal solutions. This paper combines both perspectives. The following sections of this article present a Literature Review, divided into four subsections; Materials and Methods, which consists of two main parts—methodology and the case study; and Discussion and Conclusion.

The contribution of this paper is twofold: there is a structured and comparative review of scheduling approaches, and a hybrid LP–heuristic method validated in an industrial setting. Unlike existing approaches, the proposed method emphasizes practical applicability by combining a formally defined optimization structure with lightweight heuristic rules suitable for real-time decision-making.

2. Literature Review

Production scheduling has long been recognized as one of the most important decision-making problems in manufacturing systems, as it directly affects production lead times, resource utilization, delivery reliability, and overall operational efficiency. The increasing complexity of modern manufacturing environments, characterized by product customization, fluctuating demand, shared resources, and alternative routing possibilities, has stimulated the development of a wide range of scheduling and optimization approaches.

Over the past decades, researchers have proposed various methods to address production scheduling problems, ranging from mathematically rigorous optimization models to more flexible heuristic and metaheuristic techniques. Each methodological stream offers distinct advantages and limitations with respect to solution quality, computational effort, scalability, and adaptability to dynamic production conditions. Exact optimization methods, such as linear programming (LP) and mixed-integer linear programming (MILP), are capable of producing optimal solutions under well-defined constraints but often encounter computational difficulties when applied to large-scale industrial problems. In contrast, heuristic approaches provide fast and practical decision support, while metaheuristic algorithms offer improved solution quality through intelligent search strategies at the expense of increased computational complexity. Given these trade-offs, recent research has increasingly focused on hybrid approaches that seek to combine the strengths of different optimization paradigms. Such approaches are particularly relevant in manufacturing environments with high product variability, interchangeable workstations, and strict capacity constraints, where both solution quality and computational efficiency are critical.

To provide a structured overview of the current state of research, the literature is categorized into four methodological groups:

1. Exact optimization methods.
2. Heuristic scheduling approaches.
3. Metaheuristic algorithms.
4. Hybrid optimization frameworks.

The following sections review representative studies within each category and discuss their applicability to production scheduling in complex manufacturing systems.

2.1. Exact Optimization Methods (LP, MILP)

Linear programming (LP) is a mathematical optimization technique used to determine the best outcome in a model with linear relationships, subject to constraints. In production scheduling, LP is often applied to allocate resources and minimize production time. Heuristic methods, on the other hand, provide approximate solutions to complex optimization problems within a reasonable computational time. They are particularly useful in large-

scale or dynamic environments where exact methods become computationally infeasible. Efficient production time in manufacturing not only influences overall product quality but also has significant ramifications for supply chain management and logistics costs. The ability to minimize production time directly impacts the competitiveness of manufacturing entities, as shorter cycle times facilitate quicker responses to market demands. This need for efficiency is underscored by the strategic imperative of optimally structuring warehouse networks, which has been shown to minimize total logistics costs through effective supply chain management [10]. Moreover, innovative methodologies such as agent-based modeling (ABM) have emerged, enabling manufacturers to simulate and optimize processes in real-time, thus alleviating delays and boosting productivity [11]. The importance of production time is further highlighted in recent research, which indicates that the layout and organization of facilities play a crucial role in driving productivity and efficiency. An integrated approach to layout planning, which allows for simultaneous determination of both machine arrangements and transportation paths, is essential for creating an effective production environment [12]. The relationship between production time and the layout of manufacturing facilities cannot be overlooked, as evidenced by findings that suggest strategic planning of plant layout significantly influences operational performance over the long term [12]. By considering the various features and characteristics of manufacturing systems during layout design, companies can ensure that material flows are optimized and distances minimized, contributing to reduced production times and higher productivity levels in manufacturing settings. As industries navigate the complexities of global supply chains, understanding the intricate relationship between production time and logistical outcomes becomes paramount, emphasizing the necessity for continuous optimization efforts within manufacturing processes [13].

The effect of production time on how well operations run is very important in today's manufacturing settings, where cutting down on delays can save costs and boost output. Long production times can slow down the whole supply chain, causing a chain reaction that harms overall performance and increases waste [14]. Using methods like lean manufacturing and just-in-time production can help improve workflows, allowing companies to quickly adapt to market needs while keeping quality high [14]. In addition, new technology, such as digital twins, helps with real-time monitoring and predictive analysis, enabling businesses to adjust production processes in real-time [15]. As companies depend more on statistical techniques and linear programming to improve their production schedules, knowing the links between production time and operational efficiency is crucial for staying competitive in the global market. Therefore, a solid understanding of this connection is vital for ongoing operational improvements.

Furthermore, a general framework for modeling production processes has been introduced, which guides the formulation of deterministic models to accurately represent the components of production lead time. This approach enables a more precise accounting of factors such as unequal-length planning periods and non-integer lead times, allowing for a more comprehensive analysis of manufacturing systems [16]. Other studies have demonstrated the potential of mixed-integer linear programming to optimize production plans in hybrid manufacturing environments [16–18]. By considering the trade-offs among different operational costs, including the quality of returns, quality-based segregation, and capacity readjustment, these models offer a holistic perspective on the complexities inherent in modern manufacturing. The study by Hans et al. builds upon these foundational works, proposing a linear programming-based approach to determine the optimal production plan that yields the shortest manufacturing timeline [18–20]. This methodology is applied to the operational data of an office equipment manufacturer, providing a case study to

evaluate the efficacy of the proposed model and the implications for broader manufacturing logistics [21].

The close link between production time and lowering costs has attracted much focus in manufacturing logistics, especially as companies work to boost efficiency. Cutting production time can reduce unit costs through economies of scale, which can then enhance competitive edge. Advanced methods like mixed-integer linear programming (MILP) have been key to improving production processes by effectively using resources and cutting down waste, leading to significant cost savings in areas like inventory and transport [20]. Additionally, as shown in recent conferences about vehicle routing and logistics, the use of new routing techniques has had positive effects on improving logistics operations, further aiding production time efficiencies [21]. Therefore, the connection between managing production time effectively and reducing costs highlights the need for manufacturers to use advanced analytical tools to succeed in a competitive market. Using advanced methods like Additive Manufacturing (AM) shows this link, as it reveals how production and transport processes can be made more efficient, leading to much shorter delivery times. For example, the Simultaneous Production and Transportation Problem (SPTP) focuses on improving routing while following set delivery schedules, which helps ensure that customer orders are fulfilled on time [22]. Additionally, the need for flexible supply chains has shown the benefits of mobile facilities, which help solve production and distribution issues while also allowing adaptation to different customer preferences [23]. By using mixed-integer linear programming models, companies can reduce both production and distribution costs at the same time as cutting lead times, improving their overall ability to respond to market needs.

Exact optimization methods provide mathematically optimal solutions and rigorous treatment of capacity constraints. However, their computational requirements increase rapidly with problem size and system variability. For manufacturing environments characterized by hundreds of product variants and alternative routings, solving large-scale MILP models in real time becomes difficult.

2.2. Heuristic Scheduling Approaches

In the field of manufacturing logistics, traditional methods for improving time have focused on simple rule-based job dispatching and numerical programming techniques. Each of these methods has its own pros and cons. Simple dispatching uses basic rules to decide which jobs to prioritize, like processing the job with the shortest remaining time or the earliest due date, which can help make operations more efficient in changing environments. However, this method often struggles to find the best scheduling solutions in complex factory setups, leading to possible underperformance in some cases [24]. On the flip side, numerical programming offers accurate models that can find the best solutions for scheduling issues. Yet these methods often face challenges due to the huge number of possible combinations and are very computationally demanding, making it hard to adapt to the changes in flexible manufacturing settings [25]. Therefore, while traditional methods do provide useful insights, their ability to deal with the complexities of modern production challenges is an important area that needs more investigation.

The integration of modern technologies into manufacturing processes has fundamentally transformed the paradigms of production efficiency and logistics management. As industries grapple with increasing global competition, the adoption of sophisticated decision support systems and advanced mathematical models becomes paramount for optimizing operational workflows [26]. Notably, the role of technologies such as linear programming is crucial in optimizing production time by facilitating the identification of the shortest manufacturing cycles across diverse workplaces. This aligns with the development of an information model that leverages PHP, JavaScript, and MySQL to solve complex opti-

mization problems, enhancing operational efficiency through predictive analytics and data integration [27]. Such a technological emphasis promotes seamless integration and cooperation throughout the supply chain, underscoring the necessity of information sharing among stakeholders [28]. Furthermore, innovations in automated routing and freight optimization systems enhance logistical frameworks, contributing to more effective transportation of goods while adhering to supply constraints [29]. Collectively, these advancements not only streamline production but also foster a more agile and responsive manufacturing environment, which is essential for contemporary market demands.

Case studies demonstrate that good optimization methods in manufacturing show how much technology helps production efficiency. For example, some companies have used artificial intelligence (AI) and linear programming techniques to improve supply chain management, leading to lower lead times and inventory costs. Importantly, the use of AI-driven predictive analytics with enterprise resource planning (ERP) systems has helped manufacturers make operations smoother through better forecasting and logistics, which helps lessen supply chain issues and increases responsiveness to market needs. These methods back up the theories discussed in the literature and point out best practices that aid in decision-making in manufacturing. This evidence stresses the need for manufacturers to adopt new technologies to keep their competitive edge in complicated and changing industrial environments [30,31].

The integration of innovative methodologies, such as those presented in the conceptual information model tailored for complex optimization problems, exemplified by the cutting-edge approaches utilized in technologies like PHP and MYSQL, demonstrates a promising trajectory towards achieving substantial improvements in operational efficiency and productivity levels within manufacturing environments [32]. Moreover, advancements in constraint answer set programming not only highlight significant breakthroughs in automated scheduling and problem-solving but also indicate that hybrid techniques may offer superior performance when compared to traditional linear programming methods, thereby providing manufacturers with more robust tools to streamline their operations [33]. Ultimately, this synthesis of contemporary research underscores the necessity for ongoing exploration, rigorous testing, and the adoption of advanced optimization strategies, which are vital to facilitating more streamlined and effective manufacturing processes [34]. Such efforts will be essential to maintain competitiveness and responsiveness within an ever-evolving industrial landscape, where adaptability and innovation are paramount to success. By embracing these advanced methodologies, organizations stand poised to enhance their operational capabilities and thrive amidst the challenges posed by global market demands. The need for immediate solutions in an industrial environment where thousands of orders are processed can be met by using specialized heuristic methods that significantly outperform manual planning. This links theoretical models with the practical needs of the manufacturing plant, thereby increasing production flexibility and efficiency while meeting strict delivery deadlines [35].

Heuristic methods are widely used in industrial environments because they generate feasible schedules within seconds and can easily react to changes in demand or machine availability. Their main limitation is the lack of guaranteed optimality.

2.3. Metaheuristics

Metaheuristic algorithms extend heuristic search through systematic exploration of the solution space. Studies have shown that simulated annealing, genetic algorithms and tabu search can achieve near-optimal schedules for complex manufacturing systems. Nevertheless, these methods often require extensive parameter tuning and substantially higher computation times than simple dispatching heuristics.

The use of mixed-integer linear programming and simulated annealing metaheuristics has shown great promise in changing facility layouts, resulting in at least a 32% reduction in travel time in manufacturing settings while also reducing congestion risks, as mentioned in [34]. Moreover, the impact of digital culture on company performance and knowledge management highlights the need to combine digital transformation strategies with traditional manufacturing methods. The research explains positive links between adopting digital technology and increased productivity, suggesting that a focus on developing digital environments can significantly boost manufacturing efficiency, as outlined in [36]. All in all, these findings stress the vital connection between advanced methods and digital technologies as key elements for reducing manufacturing times and improving logistics processes.

2.4. Hybrid Optimization Approaches

This methodology is applied to the operational data of an office equipment manufacturer, providing a case study to evaluate the efficacy of the proposed model and the implications for broader manufacturing logistics [37,38]. Several authors have attempted to combine exact optimization and heuristic search in order to balance solution quality and computational efficiency. In such approaches, mathematical programming is typically used to define constraints and optimization objectives, while heuristic procedures perform operational decision-making. Hybrid approaches have demonstrated promising results in production planning and logistics applications, particularly where exact optimization alone becomes computationally prohibitive.

The authors Kim and Shin present an innovative hybrid heuristic algorithm called GRHS (Greedy Rolling Horizon Search), which is designed to solve complex production planning problems in distributed supply chain networks. The authors focus on optimizing batch sizes while accounting for capacity constraints, multiple product levels, and back-order possibilities, which is mathematically defined as an NP-hard mixed-integer linear programming problem. The proposed method combines local search with a sliding time window and an exact mathematical solver, thereby effectively balancing solution quality and computational time. Experimental results confirm that this approach achieves lower total costs and higher speed compared to traditional metaheuristics [39].

Similarly, Li and Zhang have introduced an innovative method for solving linear semivectorial two-level programming, a complex mathematical model of hierarchical decision-making with multiple lower-level objectives. They proposed a hybrid heuristic approach that transforms the original problem into a more solvable form of mixed-integer linear programming using adaptive scalarization and duality theory. To efficiently search for the optimal solution, they developed a special mixed-encoding differential evolution algorithm that works in conjunction with a classical linear programming solver. A key contribution is the variable grouping strategy, which significantly reduces computational complexity by dividing the problem into discrete and continuous parts. The practical applicability of this model is demonstrated by the successful solution of a customer-oriented production and distribution planning problem [40].

Optimization problems can also arise from another area of logistics, specifically urban logistics, where unused luggage space on long-distance buses is utilized for the efficient transport of small goods. The authors define a new mathematical model based on multicommodity network flow, incorporating real-world constraints such as time windows, fleet diversity, and multiple transport routes into the calculations. The main objective of the research is to optimize two conflicting criteria: minimizing operating costs and reducing total transit time. Since this is a computationally intensive NP-hard problem, the study proposes and tests three heuristic algorithms designed to reduce the problem size and

find near-optimal solutions within a reasonable time. The results show that while the LP-and-Fix method excels at reducing costs, the combined hybrid algorithm appears to be the most effective tool for accelerating the delivery of goods within the transportation network [41].

Minimizing total production costs in the specific context of the cable industry is another optimization problem addressed by Daneshdoost et al. A complex single-machine job scheduling problem is analyzed, with the mathematical model incorporating not only processing costs but also expenses associated with machine setup and inventory storage. To solve this challenging optimization problem, they propose two hybrid metaheuristic algorithms that combine the tabu search (TS) method with simulated annealing (SA) and variable neighborhood search (NS) algorithms. The research utilizes unique theoretical rules to generate optimal initial solutions, which significantly increase the efficiency of the entire process. Experimental results on real industrial data confirm that the proposed TS-SA approach outperforms existing methods as well as exact solvers, thereby offering a practical tool for more efficient management of manufacturing operations [42].

An innovative hybrid approach utilizing Ant Colony Optimization (ACO) to solve the complex problem of integrated planning in flexible manufacturing systems was used to design a method that simultaneously optimizes machine assignment and operation sequencing, while managing transportation via automated guided vehicles (known also as AGVs) is controlled via a specialized heuristic algorithm. The main contributions are the vector structure of decision nodes and the vehicle rescheduling mechanism, which together increase the efficiency of logistics and production with the aim of minimizing total lead time. Numerical tests confirm that this model outperforms existing metaheuristic approaches and demonstrates high stability and solution quality even for large-scale and complex industrial tasks [43].

The study of improving production time has important effects for future research and practice, especially in using new methods like artificial intelligence and automated stock management systems. Researchers need to look more into how AI can work with traditional optimization methods such as linear programming, as these combined methods can greatly improve efficiency in manufacturing logistics [30]. Moreover, there is an urgent need for real-world studies that evaluate how well Internet of Things (IoT)-enabled inventory management systems perform, since they have shown significant improvements in performance measures [44]. By examining how AI, linear programming, and IoT work together, future research could lead to new ways of reducing production time while tackling difficult supply chain problems. In the end, it will be crucial to encourage teamwork between academia and industry to put these findings into action, which will help advance optimizing manufacturing logistics.

To sum up, improving production time in manufacturing is an important issue that greatly affects both efficiency and competition. By using methods like linear programming and planning factory layouts, manufacturers can cut down on waste and boost productivity. A key part of this effort is moving towards sustainable practices that not only focus on making money but also involve local communities and stakeholders. The use of technologies like 3D laser scanning and virtual reality, as mentioned in recent studies, helps to create a clearer and more engaging way to plan factory layouts, leading to better decisions and quicker project rollouts [8]. Additionally, as ongoing research shows, aligning production processes with modern technology is crucial for managing the challenges of today's manufacturing logistics [45]. Therefore, focusing on improving production time is crucial for encouraging innovation and securing long-term success in the manufacturing industry.

Although hybrid approaches represent a modern trend, a detailed analysis shows that most authors focus on integrating mathematical programming with computationally

intensive metaheuristics (e.g., genetic algorithms (GAs), SA or ACO) [39,42,43]. These models are optimized for static planning. However, in operational management conditions (like the case study below with 900+ products), the response speed is critical. The use of metaheuristics here encounters a computational barrier. The research gap lies in the absence of frameworks that exploit the structured power of LP to identify bottlenecks and directly couple it with deterministic real-time dispatching rules. Our approach differs in that it does not directly solve the iterative state-space search but sequentially applies capacitive filters to the technological matrix, which is immediately applicable in practice.

To address the lack of analytical comparison, the literature is structured into five groups: exact methods, pure heuristics, metaheuristics, Traditional Hybrids (LP + Metaheuristics) and the proposed approach (LP + lightweight heuristic). A structured comparison of these approaches is summarized in Table 1.

Table 1. Comparison of method applications.

Method Type	Representative Examples	Computational Complexity	Real-Time Suitability (<1 min)	High-Variability Capability (900+ Products)	Main Practical Limitation
Exact Methods (LP/MILP)	CPLEX and Gurobi models ¹	High (Exponential growth)	Unsuitable (Hours to days for large tasks)	Low (Combinatorial demandingness)	Computationally infeasible with hundreds of alternative routings
Pure Heuristics	FIFO ² , SPT ³ , EDD ⁴ dispatching rules	Very Low (Linear)	Excellent (Milliseconds)	High (Fast processing)	Often generates suboptimal solutions and ignores global bottleneck capacities
Metaheuristics	GA, TS, SA	Medium to High	Limited (Depends on parameter tuning)	Medium (Requires state space reduction)	Requires complex parameter tuning for every production line change
Traditional Hybrids (LP + Metaheuristics)	GRHS ⁵ approaches, DE ⁶ + LP solvers	Medium	Low to Medium (Iterative search loops remain)	Medium	Primarily designed for supply chain networks, not real-time shopfloor rescheduling
Proposed Approach (LP + Lightweight Heuristic)	This case study (LP structure + capacity dispatching rule)	Low (Sequential processing with LP filter)	Excellent (Seconds)	High (proposed to 900+ variants)	Solution is pseudo-optimal and depends on fixed priority sorting

¹ CPLEX and Gurobi models—commercial mathematical optimization tools designed to solve challenging mixed-integer programming (MIP) tasks; ² FIFO—First In, First Out; ³ SPT—Shortest Processing Time; ⁴ EDD—Earliest Due Date; ⁵ GRHS—Genetic-Random Heuristic Search; ⁶ DE—Differential Evolution.

As illustrated in Table 1, the proposed approach explicitly bridges the gap between computationally heavy optimization and over-simplified dispatching rules, offering a unique combination of capacity awareness and sub-minute execution time.

LP methods provide optimality but scale poorly. Heuristics are efficient but less accurate. Metaheuristics improve solution quality but require more computation. Good choices are Traditional Hybrids (LP + metaheuristics); they operate as ready-made applications and are commercially available but still time-demanding for making a solution. Therefore, the proposed approach (LP + lightweight heuristic) seems to be a very suitable choice for this case study.

Research gap: Few studies integrate LP structure with lightweight heuristics for real-time scheduling in high-variability systems. This study addresses this gap by proposing a

hybrid approach that combines the strengths of linear programming and heuristic decision rules to achieve efficient and feasible production schedules under capacity constraints.

3. Materials and Methods

3.1. Case Study Description

The case study is based on a real manufacturing company operating in the automotive supply chain, specializing in the production of electronic components for emission control systems. The research focused on the finishing part of the manufacturing process, where these components are finalized in a plant designated as VTM (Varnish Tube Marking), which receives NO_x (Nitric Oxides) electronic sensors. The sensor consists of an electronic component mounted on a printed circuit board that is assembled in a closed case, hermetically sealed, and fitted with an attached cable.

The finalization consists of customizing the sensors according to the requirements of individual customers, i.e., adapting the length of the cable, marking with identification tapes of different colors (approximately 43 types), terminating the conductive parts of the cables with clip terminals, fitting with plastic clips, etc. The planning complexity of the VTM production department is due to the very high customization of the products, which causes an increase in product variations up to more than 900 different types, which constitutes the output of VTM (see Figure 1).

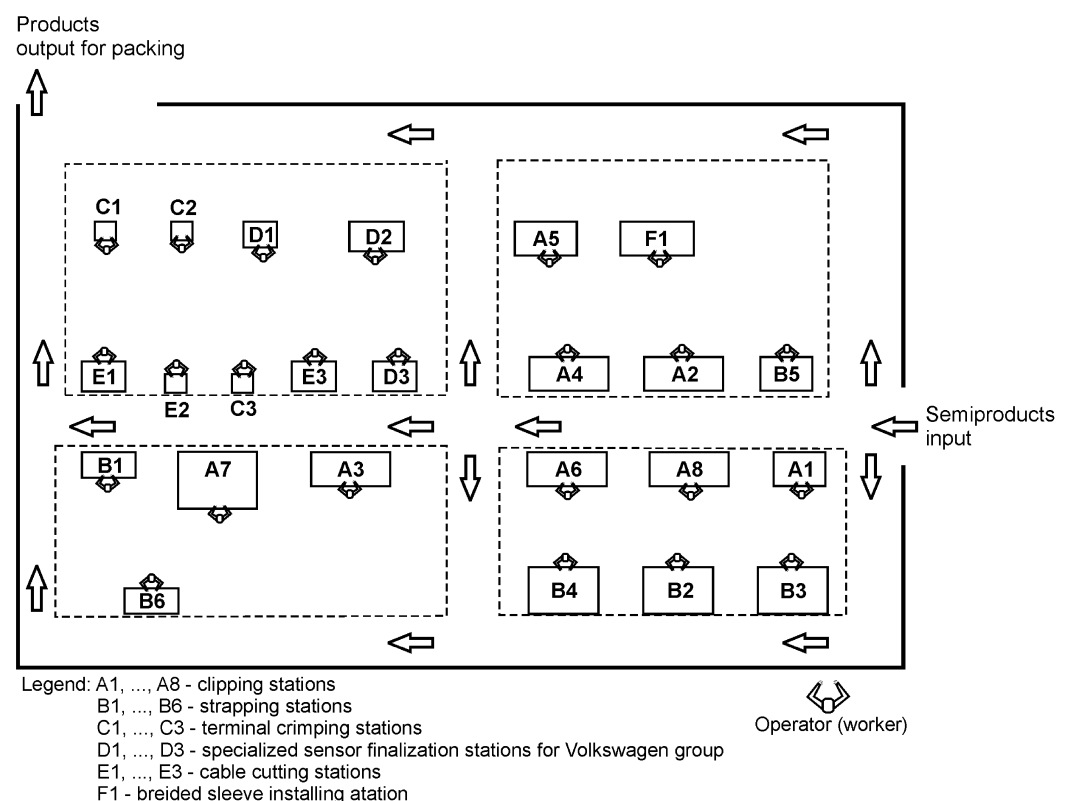


Figure 1. VTM manufacturing process layout.

Many of the products can be produced in multiple ways; i.e., multiple workstations can be used for one operation, and the workstations are partially interchangeable. Each workstation is operated by a universal worker; i.e., everyone should be able to operate each station. This means that even if the capacity of an operation needs to be increased, a worker from another station can be assigned or vice versa. Generally, it is planned that all machines are to some extent utilized and have an operator.

In summary, the VTM department involves

- Over 900 product variants.
- Interchangeable workstations (workplaces), i.e., workplaces of one group, e.g., A, where this operation can be performed for all products.
- A shared workforce.

3.2. Mathematical Model

3.2.1. Optimization Objectives

The primary objective of the proposed scheduling model is to minimize the total processing time required to manufacture the scheduled products. For each operation, the model searches for the workstation alternative that achieves the shortest processing time. The resulting routing therefore represents the fastest feasible manufacturing operation for a given product.

However, minimizing processing time alone does not guarantee that a production plan can be executed in practice. Therefore, the second objective of the model is to ensure the feasibility of all scheduled orders by respecting workstation capacity constraints. Whenever the workstation associated with the minimum processing time does not have sufficient remaining capacity, the model selects the next best feasible workstation alternative.

Consequently, the proposed approach combines two decision levels:

- (1) Minimization of total processing time.
- (2) Generation of a feasible production schedule under capacity limitations. The model thus seeks the fastest possible schedule while ensuring that all assigned operations can be executed using the available production resources.

3.2.2. Model Assumptions

Product variability is represented through differences in processing times and available routings. Although products share a common manufacturing structure, customer-specific modifications (cable length, terminal type, tape marking, and clips) generate different operation times and alternative workstation assignments. The proposed scheduling model is based on the following assumptions:

- (1) Products do not necessarily require the same manufacturing sequence. Depending on customer specifications, each product may consist of a different subset of manufacturing operations. In the studied VTM department, the number of required operations varies from 2 to 20 per product.
- (2) Product variability is represented by differences in the required operations and their corresponding processing times. Consequently, the total manufacturing time differs among product variants according to their technological requirements.
- (3) Several workstations are capable of performing the same operation; however, workstation interchangeability is limited to workstations designed for the same type of operation. For example, alternative workstations may exist for cable cutting, cable strapping, terminal crimping, tape marking, or clip assembly, but workstations dedicated to different operation types are not interchangeable.
- (4) Processing times for the same operation may differ among alternative workstations due to differences in equipment configuration, tooling, workstation layout, and operational efficiency.
- (5) Each workstation has a finite available capacity within the planning horizon. The cumulative processing time assigned to a workstation must not exceed its available capacity.

Transportation times between workstations, machine failures, and other stochastic disturbances are not considered. The scheduling problem is therefore treated as deterministic.

3.2.3. Mathematical Formulation

It follows from the above that, first of all, such technology (a workstation that can provide the required operation) is sought, such that the total time to produce a given quantity of the desired products is minimal. So the following objective function (1) is expressed:

$$Z_{k,o} = \min \{ Q_k \times t_{k,o,p} \} \text{ for all } p = 1, 2, \dots, m; \forall t_{k,o,p} \neq 0 \quad (1)$$

where

$Z_{k,o}$ —the shortest operation time t for a product k at operation o ;

$t_{k,o,p}$ —operation time for product k , operation o , and at workstation p ;

Q_k —number of products k ;

p —workstation;

m —total number of workstations.

The optimal manufacturing time for product k is obtained when one of the operations o achieves the lowest possible total production time (2). However, if one of the minimum operations is unavailable due to capacity exhaustion of a workplace p , then another possible operation with a minimum time is sought. The total number of all possible operations (routings) for many products can reach a high number, which greatly complicates optimal scheduling without the use of a computational algorithm.

$$Z_k^{opt} = \sum_{o=1}^n Z_{k,o} \quad (2)$$

where

Z_k^{opt} —the optimal manufacturing time of product k ;

n —total number of operations for each particular workstation p .

The matrix of production times of the product “ k ” for workstation “ p ” and operation “ o ” is the most important input parameter for optimal manufacturing time calculation, as described in Figure 2.

For the product 1 (1st), $k = 1$:

o/p	p_1	p_2	p_3	...	p_m
o_1	$t_{1,1,1}$	$t_{1,1,2}$	$t_{1,1,3}$	...	$t_{1,1,m}$
o_2	$t_{1,2,1}$	$t_{1,2,2}$	$t_{1,2,3}$	...	$t_{1,2,m}$
o_3	$t_{1,3,1}$	$t_{1,3,2}$	$t_{1,3,3}$	...	$t_{1,3,m}$
⋮	⋮	⋮	⋮	⋮	⋮
o_n	$t_{1,n,1}$	$t_{1,n,2}$	$t_{1,n,3}$	...	$t_{1,n,m}$

For the last product (M), ($k = M$):

o/p	p_1	p_2	p_3	...	p_m
o_1	$t_{M,1,1}$	$t_{M,1,2}$	$t_{M,1,3}$	...	$t_{M,1,m}$
o_2	$t_{M,2,1}$	$t_{M,2,2}$	$t_{M,2,3}$	...	$t_{M,2,m}$
o_3	$t_{M,3,1}$	$t_{M,3,2}$	$t_{M,3,3}$	...	$t_{M,3,m}$
⋮	⋮	⋮	⋮	⋮	⋮
o_n	$t_{M,n,1}$	$t_{M,n,2}$	$t_{M,n,3}$	...	$t_{M,n,m}$

Figure 2. Matrix of production times of the product “ k ” for workstation “ p ” and operation “ o ”.

The available technology for the production of product k may not always be optimal, as a workplace may already be out of capacity. In such a case, a second or nearest technology achieving the minimum time Z_k is sought and chosen so that the following conditions are applied not to exceed available capacity. Each workstation p has a limited available capacity (KMP_p), which constrains the total assigned processing time (3).

$$\begin{aligned}
Q_1 \sum_{o=1}^n t_{1,o,1} + Q_2 \sum_{o=1}^n t_{2,o,1} + \dots + Q_M \sum_{o=1}^n t_{M,o,1} &\leq KMP_1 \\
Q_1 \sum_{o=1}^n t_{1,o,2} + Q_2 \sum_{o=1}^n t_{2,o,2} + \dots + Q_M \sum_{o=1}^n t_{M,o,2} &\leq KMP_2 \\
&\vdots \\
Q_1 \sum_{o=1}^n t_{1,o,m} + Q_2 \sum_{o=1}^n t_{2,o,m} + \dots + Q_M \sum_{o=1}^n t_{M,o,m} &\leq KMP_m
\end{aligned} \tag{3}$$

where

KMP_p —capacity possibilities of workstation p [time units];

$t_{k,o,p}$ —production time of product k at operation o , at workstation p ;

Q_k —required quantity of product k , $k = 1, 2, \dots, M$.

3.2.4. LP-Based Heuristic Framework

The LP model first estimates workstation loading and identifies bottleneck resources. The heuristic subsequently performs detailed operation assignment. The production scheduling problem is formulated as a linear optimization problem in this stage. The LP model defines the objective function and the set of capacity constraints governing workstation utilization. The objective of the LP model is to minimize the total processing time required to manufacture all scheduled products while respecting workstation capacity limitations. For each product k , operation o , and workstation p , the processing times $t_{k,o,p}$ are known and constitute the primary input data set.

The proposed approach does not use the LP formulation as a standalone optimization solver. Instead, the LP model serves as a decision-support layer that evaluates the feasibility of workstation assignments before the heuristic scheduling stage begins (Figure 3).

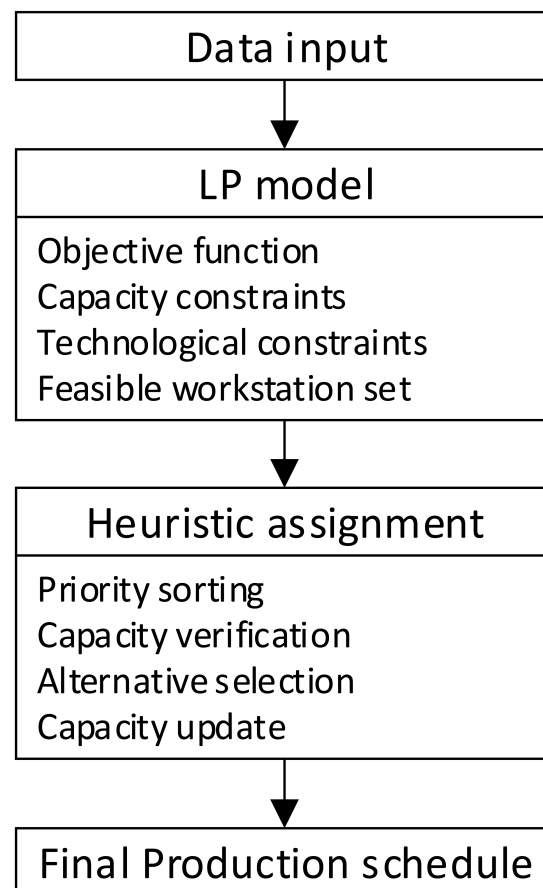


Figure 3. Framework process flow.

To clarify the hybrid nature, the optimization is strictly decoupled into two phases: Phase 1 (LP formulation) solves the global feasibility problem by acting as a mathematical capacity filter; it defines where a product can be made without breaking system constraints. Phase 2 (heuristic procedure) solves the operational scheduling problem; it decides when and on which specific workstation the order is processed based on due-date priorities. Without the LP filter, the heuristic would scale poorly and risk computational failure due to the 900+ variants; without the heuristic, the LP alone cannot sequence orders in real-time.

In the first phase, the LP formulation evaluates all feasible workstation alternatives for every product operation by simultaneously considering

- Technological feasibility;
- Processing times;
- Workstation capacity limits.

Rather than directly generating a complete production schedule, the LP model defines the feasible solution space and identifies the set of workstation alternatives satisfying the mathematical constraints.

The heuristic algorithm then operates exclusively within this LP-defined feasible solution space. For each operation, workstation alternatives are ranked according to increasing processing time while maintaining LP feasibility. Capacity consumption is updated after every assignment, and feasibility is repeatedly verified using the LP capacity constraints. Consequently, the heuristic never evaluates infeasible workstation assignments because all candidate solutions satisfy the LP model. The LP component therefore reduces the search space, guarantees feasibility of candidate assignments, and guides the heuristic toward low-processing-time solutions without solving the complete large-scale optimization problem. Another limitation of LP is based on the fact that not every product can be produced at every workplace.

It should be emphasized that the proposed hybrid approach differs from a purely dispatching heuristic because workstation selection is not performed over the complete set of available resources. Instead, the heuristic receives a mathematically filtered candidate set generated by the LP formulation. Therefore, the optimization process is divided into two complementary phases: an LP-based feasibility evaluation and a heuristic scheduling procedure. This decomposition significantly reduces computational complexity while preserving compliance with technological and capacity constraints.

3.2.5. Heuristic Scheduling Procedure

The proposed scheduling procedure combines processing-time minimization with capacity verification. The algorithm operates sequentially and assigns operations to workstations according to the priority of customer orders.

First, all products are sorted according to their priority, which is determined by the required completion date. Products with the earliest due dates are scheduled first. For each product, the algorithm evaluates all required operations and identifies the workstation that provides the shortest processing time for a given operation. This workstation is considered the preferred alternative because it minimizes the contribution of the operation to the total manufacturing time.

After selecting the preferred workstation, the algorithm verifies whether sufficient capacity is available within the current planning period. If the required capacity is available, the operation is assigned to the workstation, and the remaining workstation capacity is updated accordingly. If the preferred workstation does not have sufficient available capacity, the algorithm searches for an alternative workstation capable of performing the same operation. Alternative workstations are evaluated according to their processing times, and the feasible workstation with the shortest processing time is selected.

Following each successful assignment, the available capacity of the selected workstation is reduced by the processing time required for the scheduled production quantity. The procedure then continues with the next operation of the product. If no feasible workstation can be found for one or more required operations because all eligible workstations have exhausted their available capacity, the product is marked as unschedulable within the current planning period. Such products are transferred to the next planning period and assigned the highest scheduling priority.

The procedure is repeated until all products have been evaluated. The resulting schedule represents a feasible allocation of operations to workstations while minimizing processing times and respecting workstation capacity constraints.

Consider an example in which all possible operations o and possible executions on workstations p are given for product k as follows. For a product k (let us have $k = 1$), the production time matrix is structured as follows (Table 2).

Table 2. Production time matrix of product 1 and operations o_i at workstations p_j .

o/p	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}
o_1	34	0	31	0	28	0	18	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_2	29	32	0	0	20	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_3	0	0	0	21	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_4	21	34	21	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_5	22	0	0	0	28	23	24	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_6	0	28	0	0	0	16	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
o_7	0	0	35	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The gray matrix entries indicate feasible technologies (workstations that can provide the required operation). Green matrix entries indicate the optimal technology performed on workstations where minimum operation times are achieved. This means that if operation 1 is performed on workstation 7, operation 2 on workstation 5, etc., then the optimal technology is used for production, provided that these workstations have sufficient capacity. At workstations where the operation time $t_{1,o,p} = 0$, the operation cannot be performed. Before the actual selection of the technology, the given time is multiplied by the quantity of product k (Q_k) required to check the available capacity of the workstation (3). Once selected, the capacity option is reduced by the capacity load required by that product, and the algorithm proceeds to the next operation. When finished, it moves on to the next scheduled product (see the program algorithm, Figure 4). Compared with the former scheduling procedure, the proposed method achieves better scheduling performance and production efficiency while requiring significantly lower computational effort.

Figure 4 illustrates the heuristic scheduling procedure consisting of priority-based product selection, processing-time minimization, capacity verification, alternative workstation assignment, and capacity updating.

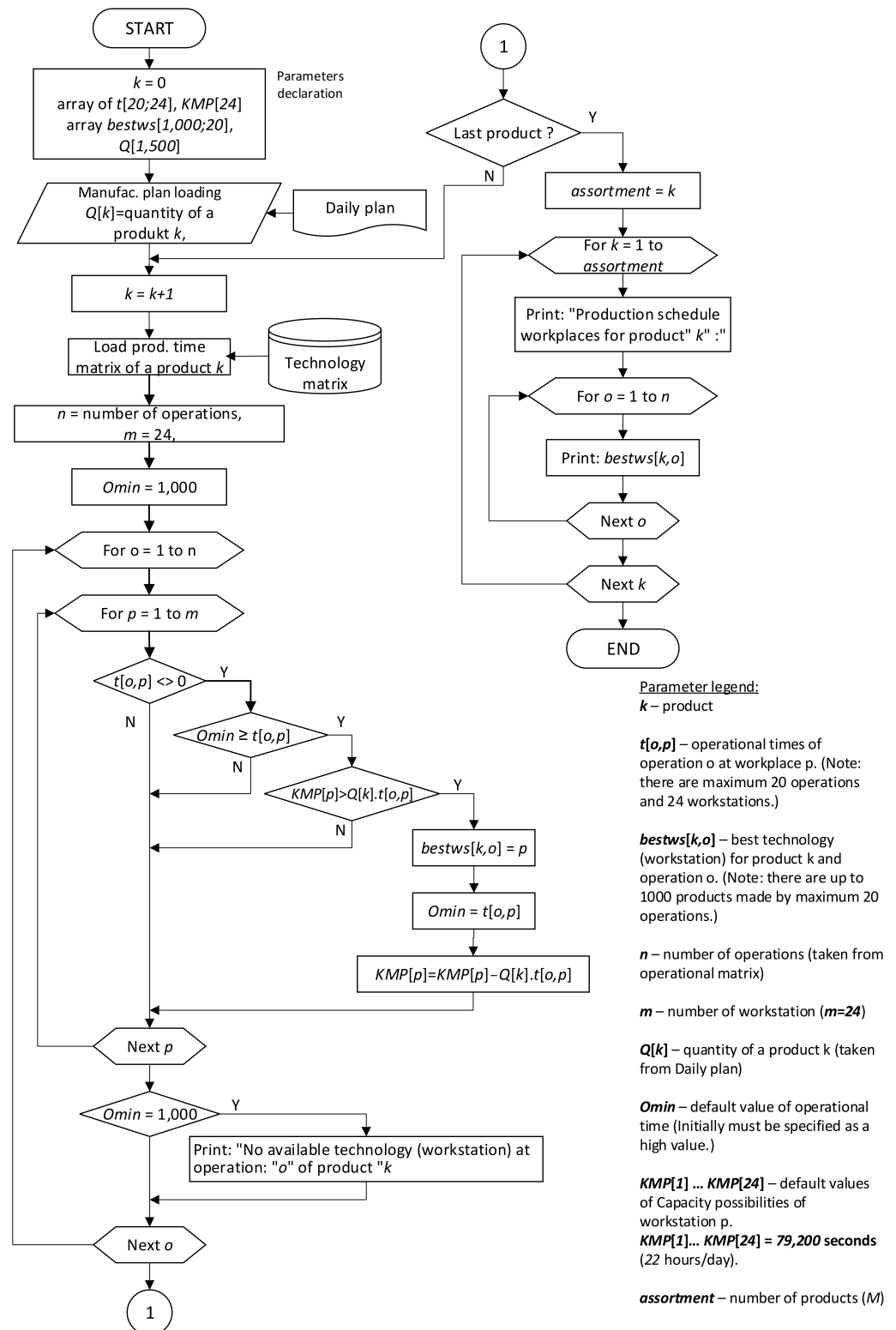


Figure 4. Scheduling process algorithm.

4. Results

Increasing production efficiency through improved workstation planning is one of the key factors for competitiveness and cost optimization in industrial enterprises. Good workplace planning enables better use of available resources, minimizing downtime and increasing employee productivity.

4.1. Illustrative Example

For our case of finding the optimal production time of product 1 ($k = 1$), a matrix of times is used (as shown in Table 2). A customer has ordered 300 units of product 1 ($Q_1 = 300$). It is necessary to find the optimal solution for assigning operations to workstations. The heuristic approach shown in the algorithm (Figure 4) is used to calculate the minimization of the total time, with the following conditions:

- Each operation o_i can only be executed at one workstation p_j , where the time value is non-zero ($t_{k,o,p} \neq 0$).
- Many workstations have different execution times for the same operation.
- Each workstation has 81,000 s available per day ($KMP_p = 81,000$ s), which is 22.5 h of a working day because the operation runs in three shifts, and the extra time (1.5 h) is a capacity reserve.

The most efficient workstation (the workstation with the shortest operating time, $t_{1,o,p} \rightarrow \min$) is selected provided sufficient capacity is available for each operation. The total time will be multiplied by the number of pieces, 300. The most advantageous allocation of workstations for the operations required for the production of product 1 will be as follows (see Table 3).

Table 3. Remaining available times at individual workstations (p_j) after the production of 300 pcs of product 1.

o_i	p_j	$t_{1,o,p}$ [s]	$Q_1 \cdot t_{1,o,p}$ [s]	KMP_j [s]
o_1	p_7	18	5400	75,600
o_2	p_5	20	6000	75,000
o_3	p_4	21	6300	74,700
o_4	p_1/p_3	21	6300	74,700
o_5	p_1	22	6600	74,400
o_6	p_6	16	4800	76,200
o_7	p_5	21	6300	74,700

From the above, it can be seen that a total of 41,700 s is required to produce 300 pcs of product 1. After consuming 5400 s of time on workstation 7, 75,600 s is still available, and this workstation is freed up for the next product, one of whose operations is processed on workstation 7. This is applicable for other workstations. If all operations have workstations assigned, the algorithm proceeds to assign workstations to operations on the next product. In this way, a schedule is prepared for all the scheduled products for that working day. If the available capacity of a workstation is exhausted and the product does not have an alternative technology (another workstation), the system will indicate that the product cannot be produced for that day. However, the individual products are ordered by priority, from highest to lowest, according to the date or time at which the product needs to be ready. Therefore, the highest priority products for which there is sufficient capacity are prioritized for production.

This example illustrates how operations are assigned to workstations for the production of the first product; i.e., the first cycle of the production algorithm for product 1 ($k = 1$) is done. Operations are assigned to subsequent products in a similar manner until the available capacity of needed workstations for the required products is exhausted. In the VTM case, products are prioritized based on due dates, and the algorithm iteratively assigns operations while respecting capacity constraints. Therefore, the priority of orders is based on due dates, which are incorporated as a sorting rule before the scheduling process begins.

4.2. Evaluation Methodology

To rigorously validate the performance of the proposed scheduling approach, a comprehensive data collection framework was established. The evaluation compared the operational indicators of the VTM department before and after the system implementation over a 6-month pilot testing phase. The data were gathered using a combination of automated enterprise systems and direct shopfloor measurements:

- **Downtime and productivity:** Data regarding workstation availability, setup times, micro-stops, and total output volume were extracted directly from the company's ERP system database. This ensured an objective baseline for comparing historical schedule execution against the new heuristic performance.
- **Operator movement:** To quantify changes in worker movement, standard industrial time studies (timekeeping using stopwatches) and spaghetti diagrams were conducted. The physical distance traveled by universal workers per shift was measured based on repetitive tasks (such as picking components, moving between interchangeable stations, and transporting finished sensors to the packing zone).
- **Delivery performance:** Delivery reliability was evaluated through the On-Time Delivery (OTD) metric tracked within the ERP system. Since the algorithm explicitly prioritizes orders based on their customer due dates before scheduling, delivery performance was measured as the percentage of orders completed strictly within their allocated planning horizon without being transferred to the next period as unschedulable.

The current planning procedure (baseline case) relied on manual scheduling based on expert knowledge and static spreadsheets, which lacked real-time capacity verification. The proposed approach was benchmarked directly against this historical baseline under identical production conditions.

4.3. Operational and Delivery Performance Results

To systematically evaluate the performance measures, a direct comparison was executed between the current planning procedure (manual/Excel-based) and the proposed hybrid approach. Tables 4 and 5 quantify these differences across the selected performance KPIs.

Table 4. Time comparison before and after the implementation of a heuristic production scheduling solution.

Scenarios	Product No.	Product Quantity	Oper.	Processing Time per Unit (s)	Total Processing Time (s)	Total Processing Time (s) Before	Time Savings (%)
Scenario 1	1	300	7	139	41,700	52,520	20.60
Scenario 2	5	400	2	42	16,800	20,400	17.65
Scenario 3	12	600	20	488	292,800	383,420	23.63
Scenario 4	50	500	12	274	137,000	171,400	20.07

Table 5. Operator movement comparison before and after the implementation of a heuristic production scheduling solution.

Scenario	Product No.	Operations	Operator Movement [m/day]	Operator Movement [m/day] Before	Improvement
Scenario 1	1	7	530	680	22.06
Scenario 2	5	2	120	145	17.24
Scenario 3	12	20	1250	1780	29.78
Scenario 4	50	12	750	990	24.24

As demonstrated, the current planning procedure suffered from higher downtime due to suboptimal sequence changes. In contrast, the proposed approach reduced setup-related downtime by 20% by dynamically grouping products with similar configurations. Furthermore, while the current manual procedure often failed to balance operator utilization—leading to excessive movement (the baseline tracking)—the new approach minimized total travel distance by 30% through optimized operator-to-workstation allocation.

Other factors, which were identified by the initial extensive analysis, also had an impact on increasing the efficiency of the production process. These will be the subject of a subsequent paper to be prepared by the authors. These include measures such as

- Optimizing the supply of parts so that only the components that are needed are on site.
- Reducing the need for warehouse space directly next to the assembly working stations, improving the movement of operators and materials.
- Implementation of information aids such as manuals of correct design, photographs of finished products, and lists of previous and subsequent operations.
- Introduction of partial automation of workstations to assist with repetitive tasks such as taping, crimping, or assembly of additional elements.

After six months of testing the implemented system, the following facts were found:

- Only minimal interventions in production scheduling by a planner, as the production expert, were necessary.
- Reduced downtime by approx. 20% (see Table 4).
- Increased productivity by approx. 20%.
- Reduced unnecessary employee movements by approx. 30% (see Table 5).

In addition to the metrics shown in Tables 4 and 5, a significant improvement was recorded in delivery performance. Prior to the implementation, manual planning often led to delayed orders due to capacity bottlenecks. By utilizing the capacity verification and automated alternative workstation routing, the system achieved a near-zero delay rate for high-priority orders, drastically stabilizing the automotive supply chain requirements.

Heuristic approaches can increase the efficiency of manufacturing processes by finding good solutions faster than exact optimization methods. They do not always guarantee an absolute optimal solution, but they provide sufficiently good results in a short time (the so-called pseudo-optimal solution), which is often advantageous in practice.

5. Conclusions

The main contribution of this paper lies in the development and practical validation of a hybrid scheduling approach that incorporates linear programming principles within a heuristic decision-making framework, enabling efficient real-time allocation of operations to alternative workstations. Improving workplace planning is an ongoing process that requires regular analysis and innovation. The use of modern production planning software like enterprise resource planning (ERP) or Manufacturing Execution Systems (MESs) to effectively manage capacity, materials and human resources is often not sufficient due to the specifications of the production process. The workstation scheduling of the VTM department lacked an automated system for assigning orders (and the operations themselves) to VTM workstations. The implementation of the above heuristic solution, which applied technological procedures, defined criteria and “Cycle Time”, i.e., the operating times of the individual operations in the orders, resulted in an increase in the efficiency of the VTM department’s production in the form of faster execution, which also meant a reduction in costs. The demanding job of the production scheduler for the VTM department thus shifted to the role of checking the accuracy and approving the created plans.

Despite the promising results, the proposed approach has several limitations that should be acknowledged. First, the model assumes a deterministic environment and does not consider stochastic factors such as variability in processing times, machine failures, or unexpected disruptions, which are common in real manufacturing systems. Second, transportation times between workstations are not included in the model, which may affect the accuracy of the estimated production time, especially in larger or spatially distributed production layouts. Third, the empirical validation is limited in scale, as the approach has been tested on a relatively small number of products and scenarios, which may restrict the generalizability of the findings to more complex production environments.

In the highly synchronized context of automotive supply chains, where Just-in-Time and Just-in-Sequence principles dominate, even minor stochastic disruptions can trigger severe effects across the logistics network. By omitting transportation times and machine breakdown variables, the current model serves as a deterministic baseline rather than a fully dynamic execution tool. In spatial shopfloor layouts characterized by complex material flows, this simplification might cause minor deviations from actual cycle times. Acknowledging these limitations, however, underscores the primary contribution of this work: providing a computationally lightweight, robust operational outline that guarantees structural feasibility under strict daily capacity constraints before stochastic tuning is applied.

Future research should therefore focus on extending the proposed model to address these limitations. In particular, further validation on large-scale production systems with a higher number of products and operations would provide a more comprehensive assessment of the method's robustness and scalability. To address these limitations, future methodological iterations should focus on transitioning from a deterministic model to a stochastic or fuzzy linear programming framework. This would allow the algorithm to absorb operational noise, such as rolling variations in operator cycle times ($t_{k,o,p}$) or unexpected machine downtime. Furthermore, another promising research path lies in multi-stage hybridization. While the current lightweight heuristic effectively tackles immediate local capacity bottlenecks, integrating it with a metaheuristic layer (such as TS or GA) could prevent the system from getting trapped in local optima as the product variants scale beyond the 900 types. This structural combination would elevate the framework's mathematical rigor while preserving its rapid execution speed. Additionally, integrating the approach with real-time data and decision-support systems, such as Manufacturing Execution Systems (MESs), could enhance its applicability in dynamic and continuously changing production environments.

Overall, the proposed hybrid approach provides a practical and computationally efficient solution for production scheduling, offering a suitable balance between solution quality and computational complexity in real-world manufacturing settings.

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Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-Based Modeling
ACO	Ant Colony Optimization
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
APS	Advanced Planning Systems
DE	Differential Evolution
GA	Genetic Algorithms
ERP	Enterprise Resource Planning
EDD	Earliest Due Date
FAHS	Fast Adaptive Harmony Search
FIFO	First-In, First-Out
GRHS	Genetic-Random Heuristic Search
IoT	Internet of Things
LP	Linear Programming
MES	Manufacturing Execution Systems
MILP	Mixed-Integer Linear Programming
NS	Neighborhood Search
OP	Operation Planning
PHP	Hypertext Preprocessor
SA	Simulated Annealing
SPT	Shortest Processing Time
SPTP	Simultaneous Production and Transportation Problem
TS	Tabu Search
VTM	Varnish Tube Marking
ZMPC	Zone Model Predictive Control

References

1. Hernández, J.E.; Mula, J.; Ferriols, F.J. A reference model for conceptual modelling of production planning processes. *Prod. Plan. Control* **2007**, *19*, 725–734. [\[CrossRef\]](#)
2. Ghobakhloo, M.; Iranmanesh, M.; Ming-Tseng, L.; Grybauskas, A.; Stefanini, A.; Amran, A. Behind the definition of Industry 5.0: A systematic review of technologies, principles, components, and values. *J. Ind. Prod. Eng.* **2023**, *40*, 432–447. [\[CrossRef\]](#)
3. Akundi, A.; Euressti, D.; Luna, S.; Ankobiah, W.; Lopes, A.; Edinbarough, I. State of Industry 5.0—Analysis and Identification of Current Research Trends. *Appl. Syst. Innov.* **2022**, *5*, 27. [\[CrossRef\]](#)
4. Klieštík, T.; Nica, E.; Ďurana, P.; Popescu, G.H. Artificial intelligence-based predictive maintenance, time-sensitive networking, and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things. *Acon. Copernic.* **2023**, *14*, 1097–1138. [\[CrossRef\]](#)
5. Sánchez-García, E.; Jínez-Falcó, M.; Marco-Lajara, B.; Manresa-Marhuenda, E. Revolutionizing the circular economy through new technologies: A new era of sustainable progress. *Environ. Technol. Innov.* **2023**, *33*, 103509. [\[CrossRef\]](#)
6. Martínez-Jurado, P.J.; Moyano-Fuentes, J.; Jerez-Gómez, P. Human resource management in Lean Production adoption and implementation processes: Success factors in the aeronautics industry. *BRQ Bus. Res. Q.* **2014**, *17*, 47–68. [\[CrossRef\]](#)
7. Li, S.J.; Li, Y.; Liu, Y. Effects of process planning upon production scheduling under concurrent environment. In Proceedings of the 6th World Congress on Intelligent Control and Automation (WCICA), Dalian, China, 21–23 June 2006; Volume 1, pp. 7282–7286.
8. Nåfors, D. Brownfield Factory Layout Planning Using Realistic Virtual Models. Dissertation Thesis, Chalmers University of Technology, Gothenburg, Sweden, 2021.

9. Peng, H.; Wu, J.; Zhang, Y.; Dong, M.; Wang, Z. Zone Model Predictive Control for Upper-Limb Exoskeleton Based on Improved Harmony Search Algorithm. In Proceedings of the 5th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), Nanjing, China, 29–31 March 2024; pp. 2163–2168. [\[CrossRef\]](#)
10. Sysoiev, V.V. Optimizing the number and location of warehouses in logistics networks considering the optimal delivery routes and set level of reserve stock. *Club Econ. Miskolc* **2013**, *9*, 85–93.
11. Rouzafzoon, J. Development of Transportation and Supply Chain Problems with the Combination of Agent-Based Simulation and Network Optimization. Ph.D. Thesis, University of Vaasa, Vaasa, Finland, 2023. Available online: <https://osuva.uwasa.fi/server/api/core/bitstreams/e29897ce-5bd6-4cb8-8be6-bbb117bd818f/content> (accessed on 24 May 2024).
12. Watanapa, A. Plant Layout Design: A Review Survey. *Int. J. Bus. Manag.* **2013**, *1*, 2. [\[CrossRef\]](#)
13. Jaber, H.; Marle, F.; Vidal, L.A.; Didiez, L. Criticality and propagation analysis of impacts between project deliverables. *Res. Eng. Des.* **2018**, *29*, 87–106. [\[CrossRef\]](#)
14. Dolgui, A.; Ivanov, D.; Sokolov, B. Ripple effect in the supply chain: An analysis and recent literature. *Int. J. Prod. Res.* **2017**, *56*, 414–430. [\[CrossRef\]](#)
15. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: Values, Challenges and Enablers From a Modeling Perspective. *IEEE Access* **2020**, *8*, 21980–22012. [\[CrossRef\]](#)
16. Hackman, S.T.; Leachman, R.C. A General Framework for Modeling Production. *Manag. Sci.* **1989**, *35*, 478–495. [\[CrossRef\]](#)
17. Dorsey, R.C.; Hodgson, T.J.; Ratliff, H.D. Technical Note –A Production-Scheduling Problem with Batch Processing. *Oper. Res.* **1974**, *22*, 1271–1275. [\[CrossRef\]](#)
18. Polotski, V.; Kenné, J.; Gharbi, A. Optimal production scheduling for hybrid manufacturing–remanufacturing systems with setups. *J. Manuf. Syst.* **2015**, *37*, 703–714. [\[CrossRef\]](#)
19. Han, S.J.; Dong, M.; Lu, S.; Leung, S.C.H. Production planning for hybrid remanufacturing and manufacturing system with component recovery. *J. Oper. Res. Soc.* **2012**, *64*, 1447–1460. [\[CrossRef\]](#)
20. Myrelid, A.; Olhager, J. Hybrid manufacturing accounting in mixed process environments: A methodology and a case study. *Int. J. Prod. Econ.* **2019**, *210*, 137–144. [\[CrossRef\]](#)
21. López-Sánchez, A.D.; Sánchez-Oro, J.; Vigo, D. Preface to the special issue on optimization in vehicle routing and logistics. *Networks* **2020**, *76*, 125–127. [\[CrossRef\]](#)
22. Dwivedi, G.; Chakraborty, S.; Agarwal, Y.K.; Srivastava, R.K. Simultaneous Production and Transportation Problem: A Case of Additive Manufacturing. *Transp. Sci.* **2023**, *57*, 741–755. [\[CrossRef\]](#)
23. Mahdavi, M.; Ramezani, R. Integrated Production and Distribution Scheduling in Mobile Facilities. *Adv. Ind. Eng.* **2021**, *55*, 115–132. [\[CrossRef\]](#)
24. Kasper, T.A.A.; Land, M.J.; Thürer, M. Unique control priorities for parallel machines in high-variety manufacturing. *Prod. Plan. Control* **2023**, *35*, 1189–1198. [\[CrossRef\]](#)
25. Liu, S.; Li, L.; Zhang, L.; Shen, W. Game Theory Based Dynamic Event-Driven Service Scheduling in Cloud Manufacturing. *IEEE Trans. Autom. Sci. Eng.* **2024**, *21*, 618–629. [\[CrossRef\]](#)
26. Rokonzaman, M. The Integration of Extended Supply Chain with Sales and Operation Planning: A Conceptual Framework. *Logistics* **2018**, *2*, 8. [\[CrossRef\]](#)
27. Tynykulova, A.; Mukhanova, A.; Mukhomedyarova, A.; Khamzina, A.; Bagisov, Z. Development and application of an integrated information model for optimizing land use and forecasting yields in agricultural production. *KazUTB* **2024**, *23*, 135.
28. Lourenço, H.R. Supply Chain Management: An Opportunity for Metaheuristics. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=273425 (accessed on 24 May 2024).
29. Dekhtyaruk, M. Automated System for Freight Transportation Optimization on the Transport Network. *Period. Polytech. Transp. Eng.* **2023**, *51*, 386–393. [\[CrossRef\]](#)
30. Grover, N. AI-Enabled Supply Chain Optimization. *Int. J. Adv. Res. Sci. Commun. Technol.* **2025**, *5*, 28–44. [\[CrossRef\]](#)
31. Adenekan, O.A.; Solomon, N.O.; Simpa, P.; Obasi, S.C. Enhancing manufacturing productivity: A review of AI-Driven supply chain management optimization and ERP systems integration. *Int. J. Manag. Entrep. Res.* **2024**, *6*, 1607–2624. [\[CrossRef\]](#)
32. García-Mata, C.L.; Burtseva, L.; Werner, F. Scheduling of Automated Wet-Etch Stations with One Robot in Semiconductor Manufacturing via Constraint Answer Set Programming. *Processes* **2024**, *12*, 1315. [\[CrossRef\]](#)
33. Faust, R.C.; Minetto, R.; Volpato, N. Parallel tool-path generation for Additive Manufacturing: A GPU-based zigzag filling. *Adv. Ind. Manuf. Eng.* **2023**, *6*, 100107. [\[CrossRef\]](#)
34. Aslan, A.; Vasantha, G.; Raoui, H.E.; Quigley, J.; Hanson, J.; Corney, J.; Sherlock, A. Smarter facility layout design: Leveraging worker localisation data to minimise travel time and alleviate congestion. *Int. J. Prod. Res.* **2024**, *63*, 1326–1353. [\[CrossRef\]](#)
35. Oujana, S.; Amodeo, L.; Yalaoui, F.; Brodard, D. Mixed-Integer Linear Programming, Constraint Programming and a Novel Dedicated Heuristic for Production Scheduling in a Packaging Plant. *Appl. Sci.* **2023**, *13*, 6003. [\[CrossRef\]](#)
36. Cardoso, A.; Pereira, M.S.; Sá, J.C.; Powell, D.J.; Faria, S.; Magalhães, M. Digital Culture, Knowledge, and Commitment to Digital Transformation and Its Impact on the Competitiveness of Portuguese Organizations. *Adm. Sci.* **2023**, *14*, 8. [\[CrossRef\]](#)

37. Mahapatra, S.; Pal, R.; Narasimhan, R. Hybrid (re)manufacturing: Manufacturing and operational implications. *Int. J. Prod. Res.* **2011**, *50*, 3786–3808. [[CrossRef](#)]
38. Li, X.; Ji, X.; Zeng, X. Optimizing supply chain networks using mixed integer linear programming (MILP). *Theor. Nat. Sci.* **2024**, *41*, 20240642. [[CrossRef](#)]
39. Kim, D.; Shin, H.J. A hybrid heuristic approach for production planning in supply chain networks. *Int. J. Adv. Manuf. Technol.* **2015**, *78*, 395–406. [[CrossRef](#)]
40. Li, H.; Zhang, L. A hybrid heuristic approach with adaptive scalarization for linear semivectorial bilevel programming and its application. *Memetic Comp.* **2022**, *14*, 433–449. [[CrossRef](#)]
41. Guimarães, L.R.; de Sousa, J.P.; Prata, B.d.A. Variable fixing heuristics for the capacitated multicommodity network flow problem with multiple transport lines, a heterogeneous fleet and time windows. *Transp. Lett.* **2022**, *14*, 84–93. [[CrossRef](#)]
42. Daneshdoost, F.; Hajiaghaei-keshteli, M.; Sahin, R.; Niroomand, S. Tabu Search Based Hybrid Meta-Heuristic Approaches for Schedule-Based Production Cost Minimization Problem for the Case of Cable Manufacturing Systems. *Informatica* **2022**, *33*, 499–522. [[CrossRef](#)]
43. He, N.; Sahnoun, M.; Zhang, D.; Bettayeb, B. A hybrid approach using ant colony optimisation for integrated scheduling of production and transportation tasks within flexible manufacturing systems. *Comput. Oper. Res.* **2025**, *1820*, 107058. [[CrossRef](#)]
44. Ugbebor, F.; Adeteye, M.; Ugbebor, J.O. Automated Inventory Management Systems with IoT Integration to Optimize Stock Levels and Reduce Carrying Costs for SMEs: A Comprehensive Review. *J. Artif. Intell. Gen. Sci.* **2024**, *6*, 306–340. [[CrossRef](#)]
45. Weinand, J.M.; Sörensen, K.; Segundo, P.S.; Kleinebrahm, M.; McKenna, R. Research trends in combinatorial optimization. *Int. Trans. Oper. Res.* **2021**, *29*, 667–705. [[CrossRef](#)]

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