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Scheduling Analysis in Digitizing Factories: An Application

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Abstract: The manufacturing companies should be dynamic and flexible for the customers' demands nowadays. Thus, scheduling plays an important role in these dynamics and flexibility. The manufacturing companies should make digitizing the operations and processors for online scheduling. In this research, the fourth industrial revolution is explained, a literature search is done for scheduling in the smart manufacturing environment, and the tools that are used during the digitized factories are defined. A simulation-based model is proposed for the smart factory in Industry 4.0 environment. Then an application is done in an office furniture manufacturing company in the smart factory environment. The physical model is transformed to virtual model by the proposed simulation approach at the production line where the office chair for executive and operational produced. With the three dispatching rules such as first in first out, earliest due date, and scatter search approach, a scheduling optimization is done in the office furniture manufacturing company. The efficient solution method is proposed for furniture manufacturing companies in the digitizing factories.

Keywords: Online scheduling, Digitizing factories, Scatter search method, Furniture manufacturing

Introduction

Industrial revolutions have been developed to increase productivity of the manufacturing environment. There have been four industrial revolutions to date. Industry 1.0 began in the eighteenth century and lasted for nearly a century. The steam-powered machines were used for production instead of human and animal-powered machinery and higher productivity was utilized. Then, Industry 2.0 started around the second half of the nineteenth century. In Industry 2.0, introduction to mass production was done. In Industry 2.0, the production lines were developed by Henry Ford and used in production intensively. The electricity-powered machines were used instead of steam-powered machines at production and productivity was increased. After that, in the second quarter of the twentieth century, Industry 3.0 revolution started with the invention of the first computer, the Z3. In Industry 3.0, analogue and digital technologies were used during the production line and higher productivity was obtained.

In recent six decades, the manufacturing systems have been transformed from mass products to customized products, namely large batch to low batch and mixed production due to customers' demands. The demands for customized products are forcing the companies' dynamic and flexible manufacturing environment. For dynamic and flexible manufacturing, companies should adopt new technological methods and solutions. One of them is Industry 4.0. Nowadays, the Industry 4.0 term is very popular in academia and industrial environments. Technological development led to the emergence of Industry 4.0. The Industry 4.0 revolution was proposed by the German government in the first quarter of the twenty-first century. The aims of the Industry 4.0 revolution for the German manufacturing industry are increasing the global competition on product quality and decreasing production costs. Industry 4.0 has provided flexibility, high product or service quality, short lead times, just in time manufacturing, and as a result maximum customer satisfaction.

Industry 4.0 is called by the different terms in many countries such as "Industry 4.0" or "Smart Service World" in Germany, "industrial internet" or "smart manufacturing" in the USA, "smart factory" in South Korea, "Smart Industry" in the Netherlands, "Internet of Things and Industry 4.0" in Italy, "Made Different" or "Marshall 4.0" in Belgium, "Alliance Industry of the Future" in France and "Made in China 2025" in China (Yang et al., 2019; Alemão et al., 2021). In Industry 4.0, the data is collected and store then analyzed. With analyzed data, the companies better understand inputs of the manufacturing system such as equipment, materials, etc. and output such as products or services. With Industry 4.0, the introduction to the cyber-physical system based on smart machines, sensors, big data, robots, Internet of Things, simulation, vertical and horizontal system integration, cyber security, cloud computing, augmented reality, etc. are provided (Malik & Kim 2020; Kaya et al., 2020).

Also, connectivity between the physical world and the virtual world is done. Industry 4.0 provides horizontal and vertical integration. It connects the value chain along with the product or service lifecycle. Horizontal integration connects the process from suppliers to manufacturers. Vertical integration combines hierarchical levels in the production or service system (Alemão et al., 2021).

In digital factories, many of the manufacturing resources are converted into intelligent objects. The manufacturing, in the digital factories, is called smart/intelligent manufacture. Also, the factories are called smart factories or dark factories. The digitalization of the manufacturing process started after the 1970s (Malik & Kim 2020). The rapid increase in the sensor and automation technology has occurred in the information technology for the integration of the manufacturing objects. The digital revolution has created smart factories with Industry 4.0.

In this chapter, a detailed literature review on smart manufacturing for scheduling is made for the first time. Also, the digitizing tools of smart manufacturing are explained in detail. In the transition to smart manufacturing, an application was made for the first time in a furniture manufacturing company. The rest of the chapter is organized as follows. In Section 2, the literature has been searched about smart/intelligent manufacturing in the concept of the Industry 4.0 perspective for the scheduling approach. Tools digitizing for smart factories is explained in Section 3. Application for a furniture manufacturing company is given in Section 4. With the conclusion and future research in Section 5, the chapter is concluded.

Literature Analysis

Companies should improve their productivity, product, and service quality. They also need to lower their production costs to compete in the market. For these aims, the companies can adopt several improvement models from academia. One of them is Industry 4.0, which has developed in the last decade. Industry 4.0 has been extensively researched in academia in recent years. In Industry 4.0, to increase the efficiency of the production system, the technologies and agents are integrated. The implementation of Industry 4.0 in the manufacturing environment is defined as smart manufacturing (Ahuett-Garza & Kurfess 2018).A detailed literature analysis has been done about smart/intelligent manufacturing in the concept of the Industry 4.0 perspective for the scheduling approach. The studies are given below.

Ivanov et al. (2016) considered an algorithm that simultaneous consideration of both machine structure selection and job assignments in smart factories in Industry 4.0. They studied the multi-objective, multi-stage flexible flow-shop scheduling problem in a dynamic scheduling environment. Ortíz et al. (2018) considered flexible job shop scheduling problems in the smart factory environment. At first, they analyzed the problem, then, the problem is mathematically formulated, and finally, they proposed a model. To show the applicability of the model, they conducted an example in a textile company. Zhang et al. (2019) investigated transferring traditional scheduling into smart distributed scheduling. They reviewed literature about job shop scheduling and determined the traditional scheduling methods and techniques which can be combined and reused in smart distributed scheduling, then they defined the new techniques for smart distributed scheduling.

Finally, they developed a scheduling model for solving the job shop scheduling problem under Industry 4.0. Lin et al. (2019) investigated the job shop scheduling problem of based on edge computing framework in a smart manufacturing factory. To solve the job shop scheduling problem, they used the Q network (which combines deep learning and reinforcement learning) with the edge computing framework. To determine the performance of the proposed method, they made a simulation analysis. Malik and Kim (2020) proposed a task management mechanism based on resource-aware scheduling schemes. Their proposed mechanism uses two scheduling approaches. These are agent cooperation mechanisms and fair emergency first scheduling scheme. The agent cooperation mechanism goal is maximization per machine. Also, the goals of the fair emergency first scheduling scheme are minimizing the tasks starvation rate and maximizing machine utilization.

Moon and Jeong (2021) considered a deep Q-network for solving the job shop scheduling problem in a smart factory. They developed several cooperatively under the supervision of a cloud center for scheduling job processing. Zhou et al. (2021) proposed a reinforcement learning methodology for production scheduling in a smart factory. Their methodology is a composite reward function for data-driven scheduling of jobs under uncertainty in the smart factory environment. Their proposed model is first learned, second adapt, and then make scheduling decisions.

In a smart manufacturing environment, they tested their model with an experiment. In the other study, Zhou et al. (2021) proposed an artificial intelligence scheduler with novel neural networks to schedule dynamic operations. They designed reward functions to improve the performance of the proposed scheduler. They tested their proposed model in a smart factory through real-world case studies. Liaqait et al. (2021) considered the distributed job shop scheduling techniques in the industry 4.0 environments.

At first, they searched the studies about job-shop scheduling problems. Second, they classified the job shop scheduling problem. Third, they determined the solution algorithms for job shop scheduling, and finally, they integrated the job shop scheduling to industry 4.0 concepts. Ortíz-Barrios et al. (2021) proposed a multi-criteria approach for smart flexible job-shop systems. Their approach included the integration of the fuzzy AHP and TOPSIS. They used the fuzzy AHP to calculate the criteria weights under uncertainty. Also, they used TOPSIS for determining the rank of eligible operations. They employed their approach in the smart apparel industry. Alemão et al., (2021) searched the smart manufacturing scheduling approaches from the literature. They wanted to determine the constraints and targets of the manufacturing scheduling solutions in the literature studies. Also, they searched how the scheduling systems are designed and developed in the smart manufacturing environment.

Leng et al. (2022) investigated the dynamic scheduling problem within a "blockchain-networked" open manufacturing ecosystem. They proposed a decentralized iterative game theory approach to optimize resource sharing between smart factories. This study contributes to the Industry 4.0 vision of networked production by ensuring secure and transparent task allocation in distributed environments. Mourtzis et al. (2023) developed a "Digital Twin" (DT) based framework for real-time scheduling in smart manufacturing. Their approach utilizes real-time data from the physical production line via IoT sensors to dynamically update schedules. They specifically focused on increasing system resilience against unexpected machine breakdowns and sudden order changes, bridging the gap between virtual simulation and physical execution.

Zheng et al. (2024) addressed the assembly line scheduling problem under the emerging "human-robot collaboration" paradigm, reflecting the transition from Industry 4.0 to Industry 5.0. They utilized a multi-objective evolutionary algorithm to simultaneously optimize production efficiency (makespan) and worker ergonomics. The model was validated through an application in a smart electronics assembly factory. Sun et al. (2025) proposed a hybrid scheduling architecture for large-scale smart factories that combine Deep Reinforcement Learning (DRL) with Graph Neural Networks (GNN). By representing complex job workflows as graph structures, their model analyzes the relationships between tasks more effectively than traditional methods. Their results demonstrated superior performance and faster decision-making under high-frequency dynamic job arrivals.

Digitalization of the Factories

The main elements of the Industry 4.0 are the Internet of Things, Big Data, Cyber-Physical Systems, Additive Manufacturing, Robotics, and Machine Learning, Artificial Intelligence, and Digital Twin but not restricted only to these elements. For the digitalization of the factories, these elements should be integrated. The integration of these elements in the manufacturing environment is defined as a smart factory. In smart factories, the manufacturing resources such as materials and machines are integrated based on IoT and coordinated by scheduling algorithms (Zhou et al., 2021). The flow chart for the Industry 4.0 is given in Figure 1. The elements of the smart factory are explained as follows.

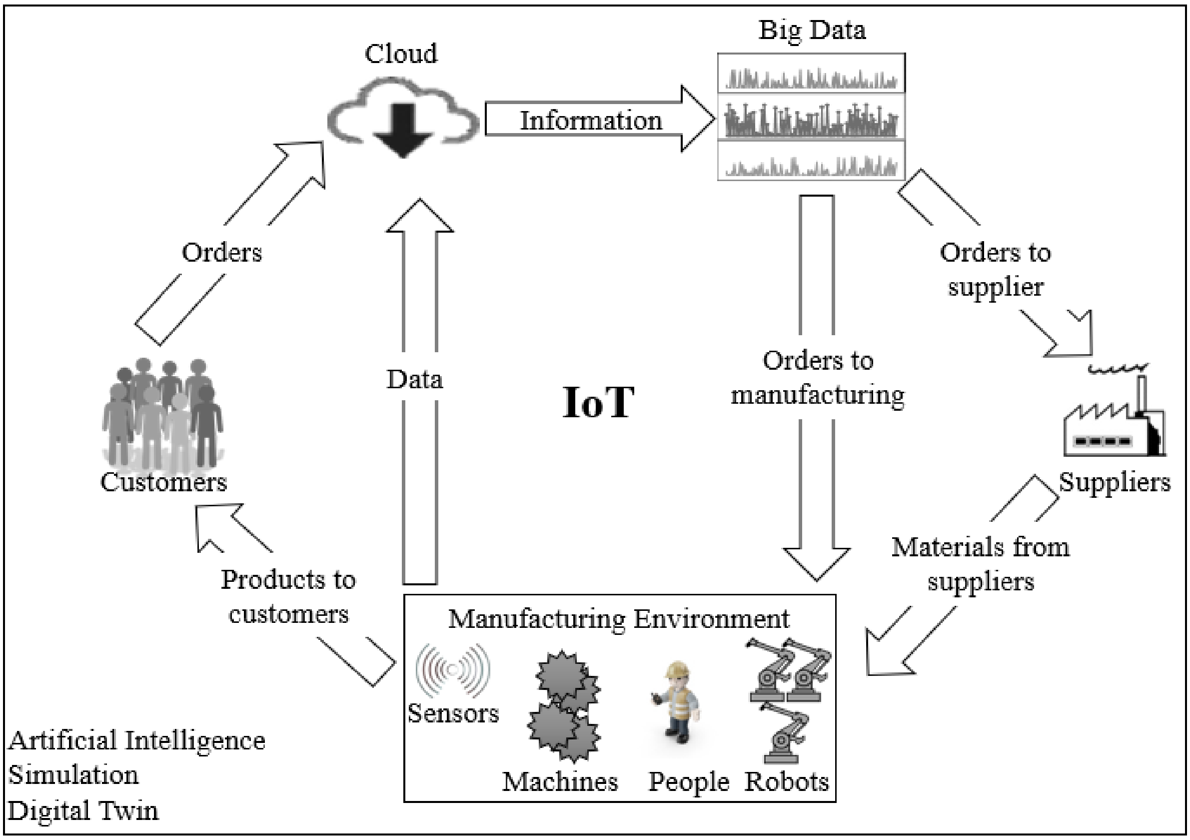

Figure 1. The flow chart of Industry 4.0 (Ahuett-Garza & Kurfess, 2018)

Internet of Things

The internet's access and connectivity are present in every stage of human life today. The internet evolution is given in Table 1. Here, the internet refers to internet-networking supported by wired and wireless technologies such as Ethernet, Wi-Fi, Bluetooth, ZigBee, radio frequency identification (RFID), or barcodes. Things refer to the physical and/or virtual objects which collect and/or exchange data. Vehicles, sensors, machines, robots, and humans, etc. are an example of things (Yang et al., 2019).

Table 1. The internet evolution (Yang et al. 2019)

Internet evolution area	Began and evolution dates
Telecommunication (Telephone, mobile phone, smartphone)	1844-2007-continue
Internet of Contents (emails, web browser, HTMLs)	1960-1989-continue
Internet of Services (E-commerce)	1995-1998-continue
Internet of People (LinkedIn, Facebook, Twitter, Google)	2003-2012-continue
Internet of Things (Sensors, actuators, etc.)	1999-continue

It can be seen in Figure 1; the Internet of Things (IoT) is one of the main elements of the Industry 4.0 revolution and smart factories. IoT is defined as the integration of objects. In the IoT, “Things” include sensors, actuators, materials, robots, machines, products, material handling equipment, and human operators, etc. (Yang et al. 2019). This integration is provided by embedded devices such as sensors, radio frequency identification, etc. which are connected by networks. IoT integrates things inside a manufacturing environment and with the outside environment. The control hierarchies of the IoT are Manufacturing Execution Systems and Enterprise Resource Planning. IoT has smart tags, smart sensing technologies, location tracking, etc. IoT connects smart machines to the network. The virtual twin of the physical world is created through the integration of IoT and cyber-physical systems. With IoT technology, each physical object in the manufacturing process has its virtual representation (Malik & Kim, 2020). Digital factories use the combination of Internet of Things technologies.

Cyber-Physical Systems (CPS)

The physical world relates to the virtual world through cyber-physical systems. The virtual objects are replicates of the physical objects in a virtual network. The integration of the IoT and cyber-physical systems creates a virtual twin (Malik & Kim, 2020). This integration is shown in Figure 2.

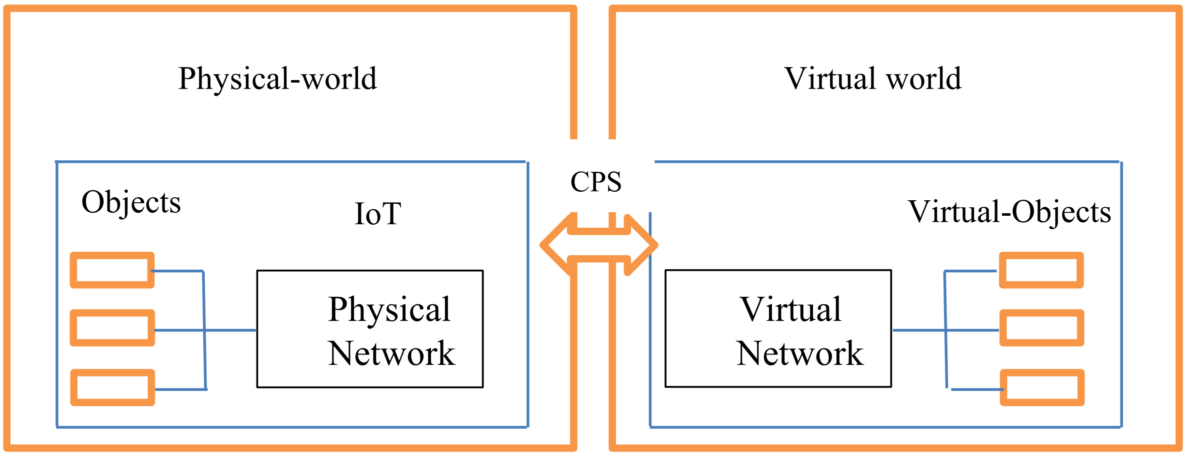

Figure 2. Integration of the IoT and CPS (Malik & Kim, 2020)

It can be seen in Figure 2; CPS connects the physical world to the virtual world. In the smart factory, cyber-physical system operates the operations.

Big Data

In the smart factory, with the sensors, radio frequency identification, etc. Huge volumes of data are collected from machines and other physical and virtual objects in the manufacturing environment. This data is known as big data. The big data updates dynamically the resources used for production and unexpected disturbances such as machine failures. To increase productivity and customers' satisfaction by minimizing products and service costs this big data should be collected and analyzed. During the analysis of this big data, artificial intelligence and machine learning approaches can be used for interpreting. The useful information can be extracted from the big data by the artificial intelligence and machine learning approaches and is used for smart manufacturing objectives such as maximizing the product quantity, customer satisfaction, and machine utilization and minimizing the production cost, and production time.

Additive Manufacturing

In Additive manufacturing, materials are joined by layer upon layer methodology to make objects from 3D model data (Bikas et al., 2016). By additive manufacturing, we can produce very intricate and complex geometries parts with near-zero material waste, including plastics and metals (Bikas et al., 2016).

Robotics

The use of robots in the manufacturing process is increasing flexibility, productivity, and quality. It also reduces manufacturing product costs and delay times for orders. It contributes to just-in-time production.

Machine Learning

The big data, which is collected in the manufacturing environment by sensors, radio frequency identification, etc., is analyzed by using a machine learning approach to extract the predictive maintenance, fault detection, and product's quality detection knowledge.

Artificial Intelligence

The artificial intelligence term first occurred in 1956 for machine simulating problems. Artificial intelligence is a field of computer science that replicates human intelligence (Zhang et al., 2019). Artificial intelligence learns from data and accumulated experience, and it proposes a dynamic solution for production problems.

Digital Twin

Also, digital twin can be used to build smart factories. The digital twin is a replica of a physical entity in the manufacturing environment. Before the actual production systems are built, with the construction of the digital twin systems, the problems which occur during the customized smart manufacturing can be identified before. These problems can be solved before optimal decisions can be made. Also, the digital twin can be used during the manufacturing process for optimization of operation, maintenance, and fault diagnosis. The digital twin increases the importance of modeling and simulation (Kim et al., 2019).

The digitalization of the factories has emerged the smart/intelligent factories. The performance of smart factories is dependent on the architectural design and scheduling optimization approach. In digital factories, real-time data is shared and devices, machines, and other objects are smart and interact with each other.

Application

Nowadays, to meet the market demands, companies should be more dynamic and flexible. Also, they can be adjusted and continue to improve their manufacturing process to the change in the global market. For this reason, scheduling is very important in the dynamic and flexible manufacturing process. The effectiveness of the manufacturing process, the satisfaction of the customers, the costs of the products and services, etc. are dependent on the scheduling methods' performance. There are a few methods for solving the scheduling problems from the literature. These are knowledge-based, simulation methods, exact methods, heuristic, and metaheuristic methods. In smart factories, during the scheduling process, usually the modeling and simulation methods are used to continuous improvement the production system. For production simulation, there are many commercial tools and environments such as layout design, scheduling, and fault diagnosis (Kim et al., 2019).

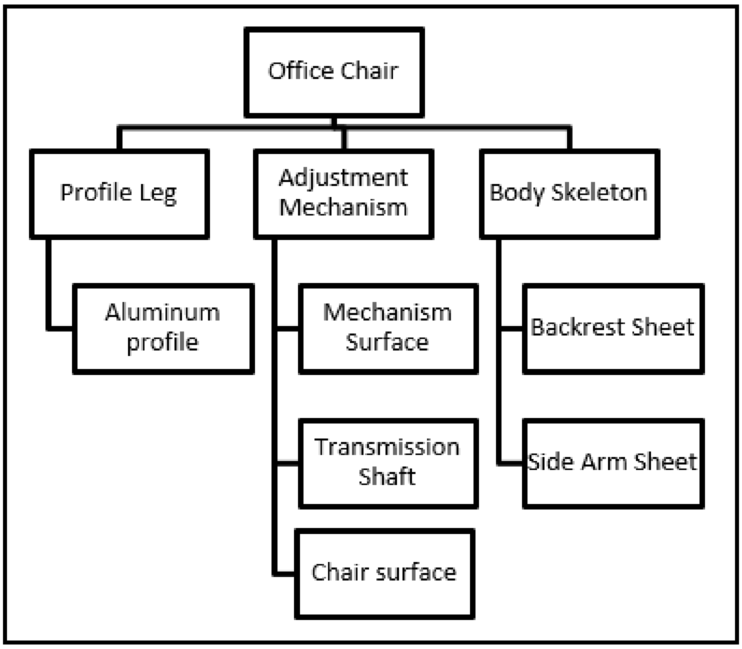

Figure 3. The product tree diagram of the office chair for executive and operational

In this study as a scheduling optimization approach, a simulation-based method is used for smart manufacturing in the Industry 4.0 environment. In the research, we focus on dynamic scheduling in a smart factory environment. Dynamic scheduling is a combinatorial optimization problem. We proposed a simulation model for dynamic scheduling problems at the office furniture manufacturing company in the smart factory environment. With the simulation model, we transformed the physical model to virtual model. The company is founded at Konya in Turkey. The company produces office furniture. The application is made on the production line where the office chair for executive and operational produced. The product tree diagram of the office chair for executive and operational is given in Figure 3.

Table 2. The tasks and definition architecture of the proposed model

Tasks	Type	Function	Definition of architecture
1-2	Information Technology	Assign numbers to the orders	The taken on-line orders by product reference number are transferred to production by giving an order number. The due date of the orders is determined.
3	Information Technology	Determine the material requirement	An intelligent decision system creates a work order for each part to be produced by calculating the sub-part needs according to the product types in each order.
4	Information Technology	Hold the orders until delivery	The architecture model keeps the order information until the order is produced and automatically sends information to the customer when the ordered products are ready, with the approval of an authorized person
5 – 16	Information Technology	Generate barcode number	A barcode number is generated for each sub-product of each order. With this barcode number, all information about the order can be tracked.
17-28	Barcode / Smart Jobs	Makes products smart	Barcode numbers produced in the architecture model are added to each piece. In this way, the product turns into a smart product (smart Jobs) that carries its own order information. These barcode numbers can also display machine route information, processing times information, etc.
29–36	Smart Machines (press, saw, laser cutting, weld)	Intelligently produces	Intelligent machines in the manufacturing processes can communicate with smart products and determine the set-up times that will occur between input and output parts.
37–46	Smart robot arms with smart inference systems	Load the parts to the systems based on rules	Through the sensors on the robot arms, a connection is made between the smart semi-finished products and the workstations. Semi-products are directed to the empty workstation for processing. When the workstation is full, the smart semi-finished products are kept in the buffer. When any workstation is emptied, according to the prioritization rule, semi-finished products are forwarded to that workstation for processing.
47–56	Sensor technology	Recognize smart jobs	The sensors detect the semi-finished products passing through the relevant point by reading the barcodes on the smart semi-finished products. Then, the setup times of the semi-finished products in the machines are determined.
57-69	Automated driving technology	Divert the products automatically	Intelligent conveyor systems, communicate with intelligent semi-finished products to be assembled and automatically direct these semi-finished products to the area where other sub-parts are located. Then, the sub-parts to be assembled are collected in a box. When all sub-parts are completed, these sub-parts are transported to the assembly station for assembly.
70, 71	Sensor technology	Recognize smart jobs	The sensor determines the completed orders by communicating with the smart products that have been assembled.
72-76	Information Technology	Arrange the delivery	Completed orders are sent to the loading department and shipment information is sent to customers via RFID.

As can be seen in Figure 3, the executive and operational office chair consists of a series of sub-assemblies, and each subassembly consists of a series of operations, and each operation is processed in order of priority on the suitable machines. The considered scheduling system, which executive and operational office chair production line in the smart factory environment is a hybrid flow shop scheduling with multi-layer assembly problem.

For the sensing tasks, the sensors are installed in the line of production. Machines and robots are controlled and directed with these sensors. The real-time data is collected from the machines and robots by these sensors such as jobs arriving at the machine and robot, operation time, machine and robot fault, machine and load balancing, machine and robot utilization, etc. This data is used for machine learning mechanisms. In other words, this data is used for building a knowledge-based mechanism by simulation model on application ex-ample. This knowledge has increased the efficiency of the proposed simulation model. The company has an e-catalog on the web page. The customers select the office chair for executive and operational from e-catalog and order by the product reference number to the company. The objective is to minimize the number of delayed customers' orders and makespan. Customer orders are processed as one piece on the production line. In other words, we adopted one-piece flow in the proposed model. The proposed simulation-based model architecture is explained as follows. First, the task and definition architecture is given in Table 2. The production line is given in Figure 4.

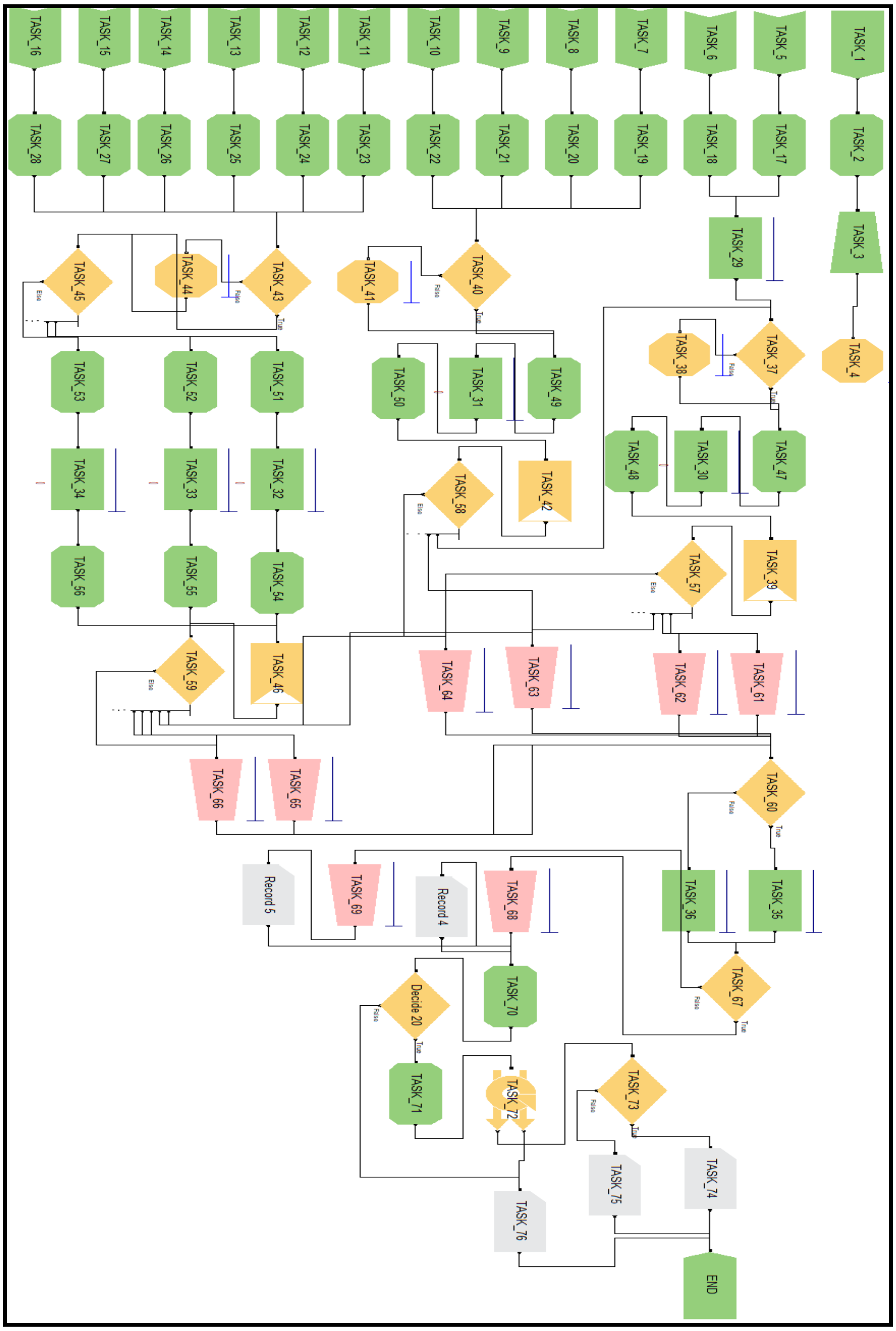

Figure 4. Production line of office chair for executive and operational

The simulation model is built using Rockwell Arena, ver-sion;16.10.00001. The proposed model is run on a Core i5-4210U 3.6 GHz CPU with the Windows 10 operating system (Shiue et al., 2018). The proposed simulation model uses three dispatching rules for optimization. These are the first in first out (FIFO), earliest due date (EDD), and scatter search approaches. The proposed scatter search approach is explained as follows.

Scatter Search Method

Scatter search is an evolutionary approach that developed in the 1970s (Engin et al., 2009; Engin et al. 2013). The proposed scatter search approach steps are given as follows (Külahlı et al., 2021; Başar et al., 2022; Oktay & Engin, 2006).

Step 1: Create an initial population by random,
Step 2: Generate a reference set from the population,
Step 3: Select a subset from the reference set,
Step 4: Apply a combination procedure to subset,
Step 5: Apply an improvement method to the combinations,
Step 6: Update the reference set,
Step 7: Repeat until the reference set is met,
Step 8: Repeat until the population size is met,
Step 9: Repeat until the stopping criterion is met,

During the application of the simulation-based model for executive and operational office chair production line in the smart factory environment, three dispatching rules are used for optimization. The performance of these three dispatching rules is given in Table 3.

Table 3. Performance of various dispatching rules in the Industry 4.0 simulation model

Dispatching Rules	Number of delayed customer orders
First in First Out (FIFO)	2
Earliest Due Date (EDD)	1
Scatter Search	1

It can be seen in Table 3 that in the digital factories, during the scheduling process for optimization several dispatching rules should be used in the simulation model. In this research three dispatching rules are used to sequence the customer's order. The statistics of the simulation model used are given in Table 4.

Table 4. The statistics of the simulation model

Time Statistics	Values (minutes)	
	FIFO	EDD
Order Delivery Cycle	21.21	11.66
Total Completion Time (C_{max})	81.03	73.22
Number of delayed customer orders	2	1

Conclusion and Future Research

In recent years, due to customizing the products and services demands, the manufacturing companies have had to increase productivity and customers satisfaction by minimizing products and service costs. For these new situations, new production improvement methods have occurred. These are lean production, agile manufacturing, and in Industry 4.0 environment smart manufacturing. In this study, the Industry 4.0 revolution is investigated. The scheduling studies in smart manufacturing are searched from the literature. The tools for digitizing factories are analyzed. A case study is done in an office furniture manufacturing company.

The physical production line where office chairs for executive and operational produced is transformed into a virtual model by the proposed simulation approach. The Rockwell Arena package is used for modeling digital factories. For scheduling optimization, three dispatching rules are proposed.

In future research, the proposed scatter search approach can be hybrid with the other methods to improve the performance of scheduling optimization. Also, the proposed simulation model can be used in the other production line in the company for other office furniture products.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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