A Digital Twin-Based Decision Support System for Dynamic Labor Planning

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Abstract. The digital twin technology coordinates digital and physical spaces in order to improve the current and future actions in the system based on the real-time data. It allows organizations to follow and optimize their systems in a virtual environment before performing actions in reality. Digital twin can play a role in labor planning within an organization as well as in smart manufacturing environments such as performing the simulation of different scenarios, helping to determine the most efficient use of multi-skilled workers. In case of unexpected absences or changes in labor resource during a shift, organizations need to reconsider labor assignments to reduce downtime and inefficiencies. Traditionally, these actions are performed by the shift supervisor. In industry 4.0 concept, we design a digital twin-based decision support system with simulation capabilities for dynamic labor planning. The proposed system allows the unit to adapt to new conditions and also provides performance measures for the future state of the system. Additionally, the operator can simulate different scenarios and evaluate their performances. We present the results and performance of the proposed system on a case example.

Keywords: Digital twin · workforce planning · cross trained workers · absenteeism · job shop

1 Introduction

Manufacturing systems are often faced with unexpected absences or fluctuations in labor resources during a shift, which can have a significant impact on productivity, efficiency, and profitability. On average, unplanned absences consume 2.0–2.3% of all scheduled work hours in the U.S. service sector and up to 5% in certain industries [9]. To address this issue, planners can consider applying an automatic labor allocation system that can adapt quickly and easily to changes in labor resource levels. Dynamic labor planning involves assigning cross trained operators to different jobs in real-time [1]. Cross-trained workers help reduce the impact of absenteeism on production output and overtime cost [8]. The key issue here is for organizations to have multi-skilled workforce that are ready to accomplish the new mission. Easton [9] examined the performance of full and partial cross-training policies with that of dedicated specialists and found that the cross-trained

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workforce often, but not always, dominated the performance of a specialized workforce. In recent years, cross-training has attracted the interest of researchers and practitioners due to its potential to increase productivity and improve workers' socioeconomic welfare [2–4].

While long-run labor scheduling has been a widely studied problem in the operations management literature (see e.g., review articles [5, 6]), short-run dynamic labor planning has received relatively less attention. There is considerable research on staffing and scheduling decisions, while a few articles address real time labor allocation, where cross-trained workers are redeployed in real time to adjust the labor supply and demand [1]. Simulation is a widely used technique for making staffing and operational decisions. Feng and Fan [10] studied the dynamic multi-skilled workforce planning problem by exploring the effect of worker pool size and cross-training level on the performance of the production line through simulation. Mou and Robb [1] designed a simulator for typical grocery store operations such as in-store shopping, checkouts, shelf inventory management, and evaluate effects of reallocation decisions. Annear et al. [11] applied approximate dynamic programming to schedule multi-skilled technicians throughout the job shop. Easton [9] used two-stage stochastic model to schedule cross-trained workers and then simulate the system under uncertain demand and employee attendance to reallocate available cross-trained workers.

A manufacturing cell is an arrangement of machines in a job shop environment to produce families of parts with similar processing steps [7]. A *seru* production system is a novel variant of the cellular manufacturing system (CMS). It merges the flexibility of job shops and conveyor assembly lines [3]. One of the critical elements of the *seru* production is multi-skilled workforce. Ertay and Da Ruan [7] presented a decision-making approach for multi-skilled labor assignment problem in a CMS. Ferjani et al. [12] studied the dynamic assignment problem of multi-skilled workers and presented an online heuristic approach.

According to the above, the current methods in the literature do not adequately reflect the flexibility of labor planning problem. Smart technologies such as digital-twin can help collect and analyze the necessary data in real-time, contributing to the dynamic nature of the problem. In this study, we present a decision-making framework based on digital twin technology. The inputs of the decision-making approach and the abstraction level of the digital twin technology can be adapted according to the technological advancement of the organization. To show the implementation and performance of the system, we performed an example case from a cellular manufacturing system in job shop environment.

2 Digital Twin Technology-Enabled Decision Making

The digital twin is a critical technology for industrial digital transformation in the era of Industry 4.0 [17]. The shop floor has always been an important application object for the digital twin [18–20]. The digital twin can be described by three main components [16]: (1) A physical reality, (2) a virtual representation, and (3) a process of decision making and interpretation between physical reality and virtual representation as represented in Fig. 1.

Physical systems, physical processes and the physical environment are the building blocks of physical reality [16]. In our study, physical system refers to the labor working

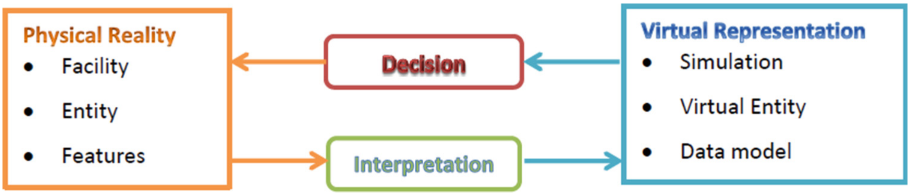


Fig. 1. Description of digital twin components

place, which can range from a single unit to the entire working place. In the physical system, the tasks are performed by human laborers or automated operators like robots and cobots, which are called the entities. The performance of the physical system is measured based on the inputs and outputs, including the use of resources and production results.

The physical processes in this study include factors which affect the state of entities. The states of the entities could be absenteeism or availability at some level while the factors, which cause state changes over time, could be training, rotating, resignation, maintenance, and fluctuations in demand etc.

The physical environment covers the management information systems as well as the processes where the data is collected. The physical system is surrounded by a management environment using (primitive or advanced) information systems. The databases, resource tracking systems, and resource planning software help to manage the physical environment. In our system, amount of resources, their abilities, resource requirements of units, constraints, restrictions, capacities are collected from the environment for a given time horizon.

The virtual representation of physical reality depends on the level of abstraction. Abstraction is the process of simplifying a complex system by focusing on its essential features and ignoring irrelevant details. A virtual representation with a shallow level of abstraction will have a more general and simplified view of the physical system, while a deeper level of abstraction will result in a more complex and detailed representation. This tradeoff between accuracy and complexity is important to consider when creating a digital twin or other virtual representations, as the level of detail required for an accurate model may not be feasible or cost-effective. Ultimately, the level of abstraction used will depend on the specific needs and requirements of the application.

The main components of the virtual representation are the construction of the model, the characterization of the entity and the simulation of the system as shown in Fig. 1.

Construction of the model refers to the process of formulating the system behavior using mathematical equations, models, algorithms or other computational methods. Here we design a decision support system which process the data from physical environment and returns the resource allocation plan. Digital twin technology enabled these decisions to move from the tactical level to the operational level. In this way, it is possible to obtain the best possible resource allocation plan in real-time, depending on the current state of the system. The main inputs of the decision support system are related to resources and their characteristics, as well as resource requirements of production cells and specifications. These inputs are usually available either digitally or on a simple worksheet in any physical environment. The most critical part of the proposed methodology is the determination of which inputs are necessary and at what level of detail. Depending on these answers, the level of abstraction of the virtual representation will be formed. Unnecessary input data increases the cost of data collection and storage, and reduces the computational performance of the system. On the other hand, missing a required input can result in loss of information and reduced accuracy.

The interpretation element pre-processes data to provide input to the model in an appropriate format, and also provides warnings about features when necessary. It also helps to get quick responses in case of abnormal situations.

Once the model and attributes of the entity are established, the system can be simulated. Simulation allows users to observe how the system responds to the resource allocations provided by the model and to evaluate alternative scenarios, either user-specified or system-generated. With the help of virtual representation of the labor planning system, it is possible to take reasonable actions in emergency situations, evaluate proposals, and predict future performance without executing the solution in real-life.

Based on this general outline, we next present the details of a digital twin technology-enabled decision support system (TW-DSS) for dynamic labor planning. Although we show the implementation on a cellular manufacturing system, it is possible to adapt it to flow shops and production lines.

2.1 The TW-DSS Framework

In a cellular manufacturing system, the machines, equipment and labor are grouped into a cell to produce families of similar products [13]. The labor force and their cross-training abilities are essential inputs to a cellular manufacturing system. We propose a digital-twin framework integrated with a decision support system (DSS), which is capable of evaluating labor planning strategies at the shop level. Figure 2 illustrates the main components of the framework.

A cell can consist of machines, assembly tables, equipment, etc. This content is allowed to change, but we assume that we know the final configuration. Other assumptions regarding the cell are as follows.

- The production plan for a given cell is ready before the start of the shift.
- Preventive maintenance interruptions are also known and considered in the production plan.
- Some jobs may have urgency.

There are several means of disturbances, either external or internal, in a manufacturing system. External ones are the variations in demand and supply, while the internal disruptions are variations in processing times, worker absenteeism, machine failures and defects. The responding mechanism against these disruptions is either using buffering strategies such as safety stock, excess capacity, rescheduling, or flexibility strategies such as labor and machine [14]. Buffering strategies are often used to address variations in demand and supply, but these strategies may not be as effective for dynamic labor planning for a short period of time. The unexpected changes in labor resource generally occur within a short period of time, such as hours or a shift, and may limit the ability to adjust schedules. Therefore, labor and machine flexibility provide efficient solutions compared to costly buffering strategies.

The labor flexibility corresponds to the number of machines or stations that a worker has qualification. Operators have varied skill sets and levels depending on their experience at different stations. The machine flexibility refers to the number of multi-purpose machines performing different operations [15]. In this study, we only consider the labor flexibility and the allocation of available operators in order to maximize the utility of the unit, which is measured as the expected number of jobs completed and the operator utilization. The assumptions regarding the resource level are as follows.

- Operator skills and levels are known, and unused skills do not expire.
- The working hour capacity of each operator is known.
- There are several positions in each cell, and each position requires single qualified operator.
- Operators may not be available on a given shift due to health problems, training exercises, breaks etc.

There can be some constraints such as the number of qualified workers necessary for each cell, or the set of partner cells that are able to support a cell. All of the above are inputs for the proposed DSS. There are daily work hour limits for each operator. These limits are determined by the characteristics of the job assigned to the operator. For example, if the job requires the operator to work while standing, this may be detrimental to his/her health. Therefore, we have included daily limits depending on the characteristics of the jobs.

The assignment of operators to cells and positions based on their skills is performed using the DSS. The DSS module first determines the *capacity* of each cell in terms of available machining hours. This information is usually available in advance and is not expected to change in the short term, but it is reduced by (un)scheduled maintenance. The *lack_of_labor* procedure calculates the difference between the required labor level and the available labor level for each cell and a given shift, depending on the capacity and the production schedule. However, this is not enough to determine the *performance* of a worker. The experiences a worker has, called history, and his/her displeasure from these practices are used to determine his/her performance for a given position. The *limit* of an operator refers to the restriction of working hours according to the characteristics of the jobs.

The assignment procedure determines the allocation plan of operators in a shift. The aim of this procedure is to assign operators to positions in order to maximize the expected number of completed jobs and sum of operator utilization. For this purpose, we suggest two strategies as *fastest-operator-first* or minimum *deviation* from average workload (workload balance of operators). The procedure evaluates the availability, production plan, limit and performance of operators, and additional constraints.

The workforce simulator module is used to evaluate the labor-job allocation plan returned from the DSS module and also to make real-time reallocations of workers and observe its effect on the system. The digital twin gets the real time availability of workforce and can monitor their assignment plan. The user can change the positions of operators using the menu. When the workers are overloaded or underskilled, the alerts warn the user. After running the simulator, performance graphs and tables are produced.

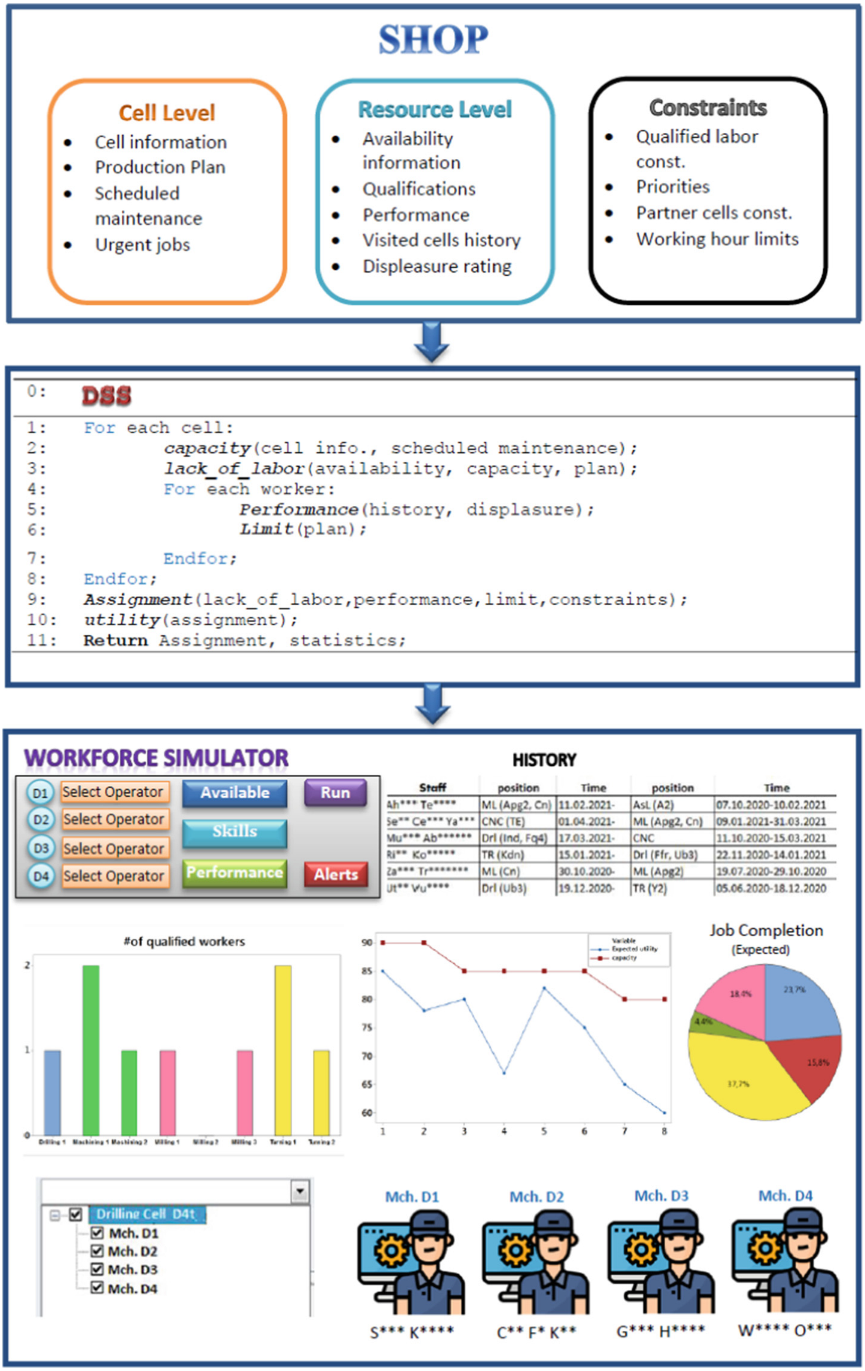


Fig. 2. Illustration of the TW-DSS Framework

3 Computational Results

In the case example considered in this section, we simulate a manufacturing cell and worker reallocation scenarios under fluctuations on worker resource and machine breakdowns. There are 5 operators and each operator is assigned to a single machine in the cell. There are 6 different jobs in a weekly production plan with different sizes such as j1:25, j2:30, j3:38, j4:13, j5:45, j6:30 units. The expertise and skill level of each operator to process these jobs is different and is shown in Table 1. There are 4 skills coded as A, B, C, and D. The skill level 1.0 refers to the expertise on this skill, while a skill level less than 0.4 is considered unskilled. The skill requirement of jobs and standard time are as follows: j1(A)[80min], j2(B,D)[40min.], j3(B)[100min.], j4(A,C)[60min.], j5(C,D)[120min.], and j6(D)[20min.]. The daily capacity of an operator is 480min. - machine breakdown duration. The processing time p_{ij} of a job j by operator i depends on the standard time s_j and the skill level requirement of the job j, i.e., $p_{ij} = \max_k \left\{ \frac{s_j}{l_{ik}} \right\}$ where l_{ik} is the skill level of operator i for skill k.

Table 1. Skill levels of operators

Operator i	Skill A	Skill B	Skill C	Skill D
1	1.0	0.8	0.8	0.7
2	0.8	0.9	0.8	0.7
3	0.7	0.6	0.9	0.8
4	0.9	0.7	0.8	0.7
5	0.8	0.9	0.3	0.9

The probability that a worker is unavailable in a day is assumed to be uniformly distributed and less than 0.05. The probability of a machine breakdown is also less than 0.05. The breakdown duration t (min.) is from U[0, 48].

The DSS explained above determine the worker assignments according to two strategies. The *fastest-operator-first* strategy is called the *Strategy*1, the balancing strategy is called the *Strategy*2, and the current assignment determined by the cell supervisor is called the *current*.

3.1 Results and Discussion

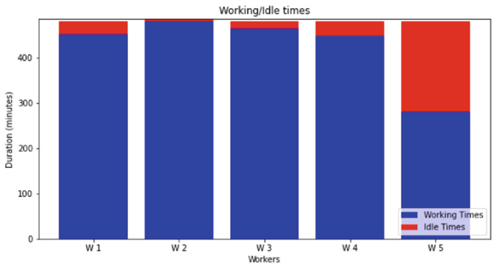
All algorithms were coded in Python 3.8, and experiments were conducted on a personal computer with Intel(R) Core (TM) i5-11400H 2.7 GHz 16GB RAM.

Table 2 shows the average processing time (min.) of jobs in each strategy. In the simulation, Operator 5 was absent on one day of the week. In addition, the machine that Operator 3 operates breaks down for 30 min. According to this table, Strategy 1 helps to complete jobs faster since it assigns an incoming job to the fastest available worker. The processing times in Strategy 2 are not better than Strategy 1, even close to the current situation; however, it presents a balanced workload, as can be seen in Fig. 3.

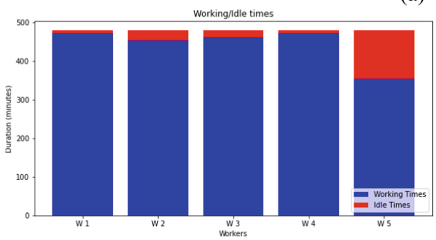
Table 2. Average processing time (min.) of jobs in each strategy

Job	*Current*	*Strategy*1	*Strategy*2
J1	98.2	90.1	96.7
J2	53.9	47.8	54.0
J3	129.5	116.1	127.3
J4	78.3	75.0	75.8
J5	164.3	151.4	161.7
J6	25.4	22.4	25.3

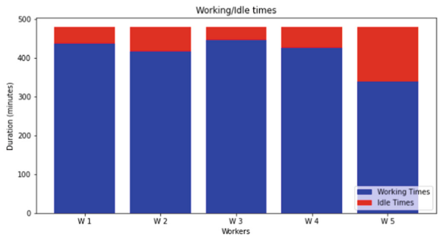
Figure 3 shows the average (daily) working and idle times for each operator. As shown in the figure, Operator 5 worked less on average because he was absent one day. However, Strategy 2 loads more jobs to Operator 5 in the remaining days to balance the workload of operators. On the other hand, the current system and Strategy 1 do not perform reallocations by taking into account absenteeism and downtime, i.e., they are memoryless.



(a) Current



(b) Strategy 1



(c) Strategy 2

Fig. 3. Average working and idle times of each operator

Figure 4 illustrates the percentage of completed and incomplete jobs for a weekly schedule. According to this figure, a higher percentage of jobs are completed when strategy 1 is applied. Strategy 2 is close to the current situation.

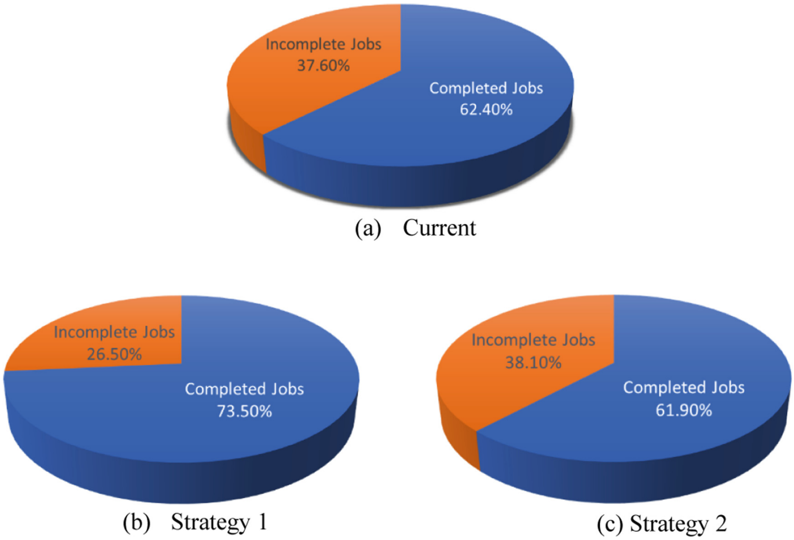


Fig. 4. Ratio of completed/uncomplete jobs (weekly) for each strategy

4 Conclusion

This study presents a digital twin-based decision support system for reallocation of operators in real-time under absenteeism and downtimes. The DSS reallocates jobs based on one of two strategies. According to our simulation results, in the fastest-worker-first strategy, more jobs are completed as expected. The TW-DSS framework has the ability to simulate the system in real-time, and also allows the user to make real-time changes in the positions of operators and observe the performance measures. Since the framework takes into account the real-world dynamics, such as alerts for overload or unskilled worker assignments, worker availability, limits and performance, etc., it is applicable.

The further research direction could be to integrate green strategies into the DSS of this framework. For example, prioritizing energy-efficient machines, while performing jobs, can contribute to the sustainability of the system.

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