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SIMULATION-OPTIMIZATION OF DIGITAL TWIN

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ABSTRACT

With rapid advancements in Cyber-Physical manufacturing, the Internet of Things, Simulation software, and Machine Learning algorithms, the applicability of Industry 4.0 is gaining momentum. The demand for real-time decision-making in the manufacturing industry has given significant attention to the field of Digital Twin (DT). The whole idea revolves around creating a digital counterpart of the physical system based on enterprise data to exploit the effects of numerous parameters and make informed decisions. Based on that, this paper proposes a simulation-optimization framework for the DT model of a Beverage Manufacturing Plant. A data-driven simulation model developed in Simio is integrated with Python to perform Multi-Objective optimization. The framework explores optimal solutions by simulating multiple scenarios by altering the availability of operators and dispatching/scheduling rules. The results show that simulation optimization can be integrated into the Digital-Twin models as part of real-time production planning and scheduling.

1 INTRODUCTION

In the recent wave of Industry 4.0, Smart Factories and Intelligent Manufacturing have received significant attention from both researchers and industries. Smart Factories aim at achieving high adaptability, enhanced efficiency, increased productivity, and clearer visibility of operations. This requires generating, processing, and learning a tremendous amount of data-driven knowledge from different parts of the manufacturing system. There exists a growing body of literature focusing on integrating multiple technologies like IoT, simulation, optimization, and Machine Learning to create a Cyber-Physical manufacturing system. A complete real-time presentation of the state of the intelligent manufacturing system is a challenge; however, the emergence of Digital Twin (DT) has made it possible to solve this problem (He and Bai 2020). The whole idea revolves around creating a virtual and digital counterpart of the physical system based on enterprise data to exploit the effects of numerous parameters and make informed decisions.

The concept of Digital Twin was put forward by Michael Grieves in 2002, which focused on product life-cycle management (Kritzinger et al. 2018). In the manufacturing setting, DT is perceived as a virtual simulation model of a physical system, which is applied to optimize the operational processes to achieve precise control over the whole assembly (He and Bai 2020). However, DT in the manufacturing industry is more than just a simulation model. It is an integration of smart digital machines, a simulation model, a network of widespread data, and the adoption of information/communication technologies by manufacturing systems. In order to fully exploit this potential, it is vital to realize this collaboration between humans, machines, environment in the simulation model, and the manufacturing process (Zheng et al. 2019).

Apart from the proven benefits, implementing a fully efficient DT can be inherently a complex process. This calls for the need for experimentation with several configuration settings, parameter testing, and an

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optimization framework to achieve the desired performance. This need is conventionally facilitated with the support of Discrete Event Simulation (DES) software applications. A central aspect of the DES model is its capability to utilize data to simulate a real-life process and provide insights into various possible scenarios. This process can be real-time where the simulation model is integrated with an Enterprise Resource Planning (ERP) system. This need is conventionally facilitated with the support of Discrete Event Simulation (DES) software applications. An ERP system facilitates the flow of information, a variety of reports, and data analytics of an organization. The feature of providing access to real-time manufacturing data like orders, schedules, human and material availability and much more can be exploited to build a simulation model. A central aspect of the DES model is its capability to utilize data to simulate a real-life process and provide insights into various possible scenarios. For the DT to replicate the true behavior of the physical process, it must incorporate detailed constraint model of the process. That includes all the equipment, labor, tooling, transportation and material along with the equipment and material characteristics driving the operational decisions. It is essential to factor in the business rules that regulate the operations such as inventory policies, labor policies, operating procedures, and transportation restrictions, for example. And finally, it must be able to capture the detailed day- to- day decision logic as applied by the planners, operators, and supervisors managing the process. A DES software is uniquely positioned to be able to model at this level of detail while also capturing the inherent variability present through the system. A DT can be fully generated and driven by Enterprise data. For example, an Enterprise Resource Planning (ERP) system can provide master data that defines all the resources in the system, along with material requirements and costing information. A Manufacturing Execution System (MES) can provide a definition of the resources on the factory floor, along with the current status of machine up-time, downtime, and work in process. Connecting the DT to such systems, will allow it to automatically adapt to changes in the environment such as additional equipment, new labor and skill requirements, new parts/SKUs, etc. The DT when connected to real- time data, would allow it to make predictive and perspective decisions based on the current status of the system.

In addition, DES provides an environment to deploy manual or systemic experimentations to analyze multiple what-if scenarios. This enables decision-makers to test various process plans and scheduling techniques to obtain an optimized responsive planning, management, and decision making. This paper aims to propose a simulation-optimization (SO) framework to demonstrate its applicability for DT implementation. This framework takes advantage of data-driven modeling where a simulation model is directly linked with an ERP system to imitate the manufacturing facility. Therefore, the contributions of this paper as follows:

- Design a simulation-optimization Digital Twin (SODT) framework
- Implement SODT by integrating a DES package with an optimization algorithm
- Demonstrate the applicability of the proposed SODT in a manufacturing setting and provide insights for future developments

This project is completed by integrating Simio with Python. Simio is a powerful DES package and is written in C# on a .NET platform. The Simio API allows for flexible integration with other systems, which is important for the ability to not only connect to Enterprise systems but also allow for the ability to integrate optimization and artificial intelligence with the DT. The model can be connected to an external system in several ways, but most popular for a DT, is either with a direct database connection or with the WebAPI. For integrating optimization with the DT, the .NET platform and robust API makes Simio flexible enough to couple it with a high-level programming language like Python. Python makes use of Python Package Index (PyPI) containing third-party modules making it possible to interact with other platforms. It's ability to handle multiple data types, editing, writing, and manipulating other software proves a key feature to execute combined operations. The extent of libraries available to perform statistical, mathematical and optimization calculations makes Python a great tool for simulation-optimization framework. These features of used software packages facilitate integration and provide a unique platform to optimize a simulated DT.

The rest of this paper is organized as follows: The literature review in Section 2 represents an overview of applications and use-cases pertaining to simulation and digital twin models in the manufacturing industry. Section 3 explains in detail the methodology used to integrate SODT with a Beverage Production Plant. Section 4 puts forward results obtained by simulating multiple scenarios with a continually optimized solutions through an optimization algorithm. Conclusions and future works are addressed in section 5.

2 LITERATURE REVIEW

The multifaced definitions of DT prevailing in the manufacturing domain as well, motivated (Zhang et al. 2021) to work on two specific research questions, 'What is the definition of Digital Twin in the scientific literature?' and 'What is its role within Industry 4.0?'. The authors put forward a comprehensive study with a focus on providing a solution to the problem from the point of view of model engineering and simulation. This indicates that DT is at the stage of rapid development where researchers start to explore real practices and technologies in the industry (Liu et al. 2020). According to Zheng et al. (2019), the ongoing extensive research on Cyber-Physical systems and Digital Twins has gradually become one of the key research directions of intelligent manufacturing. An extensive review published by He and Bai (2020), identified Production line and process simulation as one of the key development areas for DT for intelligent manufacturing. Al-Ali et al. (2020) asserts that the application of DT in manufacturing could help in higher flexibility, higher production, and better maintenance of the manufacturing and automation process, thus improving the overall operational efficiency. Santos et al. (2019), proposed the usage of DT for Manufacturing Executing System (MES) to obtain an optimum production schedule. The system consisted of an IoT platform, simulators, and user applications to provide changing inputs. Similarly, a decision support system for improving the order management process was proposed by Kunath and Winkler (2018). The proposed system is capable of generating a simulation model automatically using information from the Digital Twin of the manufacturing system. Another Digital Twin-based Cyber-Physical Production System was proposed by Ding et al. (2019) to optimize real-time monitoring, simulation, and prediction of manufacturing operations. Developing a combined simulation-optimization method with DT is another upcoming research topic popular in the manufacturing domain. Balderas et al. (2021) developed a Digital-Twin framework that integrates a metaheuristic optimization and a direct Simulink model for printed circuit boards (PCB) design and processing. The promising results obtained from the experiment show the benefits of integrating metaheuristic optimization into the Digital-Twin concept. Similarly, Liu et al. (2021) proposed a simulation-optimization scheduling platform for an aeroengine gear production workshop. The model was found efficient in optimizing scheduling by shortening both transit and waiting times within the production process.

Dynamic scheduling by continuous decision-making, predicting machine availability, bottleneck detection, and performance evaluation are common focus parameters among the reviewed studies. Zhang et al. (2021), demonstrates the use of optimization in DT to reduce the makespan and total tardiness by 14.5% and 87.1%, respectively, and increase the average utility rate by 14.9% of a hydraulic valve machining job-shop. Park et al. (2021) puts forward a novel production control model that applies DT and horizontal coordination with RL-based production control to a re-entrant job shop problem. Zhang et al. (2020) argues that it is difficult to find an effective simulation-based optimization method to solve the large-scale discrete optimization problems in digital twin shop floors. And to overcome these challenges, the authors propose an improved multi-fidelity simulation-based optimization method based on multi-fidelity optimization. The novel method makes use of heuristics algorithms to accelerate the solution space search integrated with a DES-based simulation optimization system. A joint simulation optimization and DT model to optimize stacked packing and storage assignment of the warehouse was proposed by Leng et al. (2019). The proposed model was able to maximize the utilization and efficiency of the large-scale automated high-rise warehouse product-service system. Park et al. (2021), puts forward a DES and Digital Twin framework for dispatching assistance in port logistics. Gyulai et al. (2020) makes use of DES model for the detailed representation of a complex shop-floor logistics system, employing automated robotic vehicles (AGV).

While some researchers believe that the concept of DT is in the initial stage, the growing interest is evident by the various use-cases published in recent years. Upon meticulously analyzing the selected studies it can be concluded that the use of simulation-optimization techniques combined with DT is a promising research topic. This can be achieved by merging three things:

- A simulation model – visually replicating a physically happening process
- Real-time data processing, monitoring, and controlling capabilities
- Estimating future state capabilities using optimizing and machine learning embedded models

A common note in all the reviewed papers is about tremendous research opportunities in the Digital Twin technology for Industry 4.0. To accelerate the process of implementation the researchers should address the limitations, develop a suitable framework, and parallelly, increase industrial use cases. In pursuit of the same, this paper demonstrates the implementation of integrating a Simulation-Optimization Framework for a Digital Twin model.

3 METHODOLOGY

3.1 The Proposed SODT Framework

The proposed SODT is an integrated simulation-optimization framework to enhance DT performance. As illustrated in Figure 1, this framework is a combination of three modules, i) data exchange, ii) optimization, and iii) simulation. Data exchange is the key element in the framework where connects all components together.

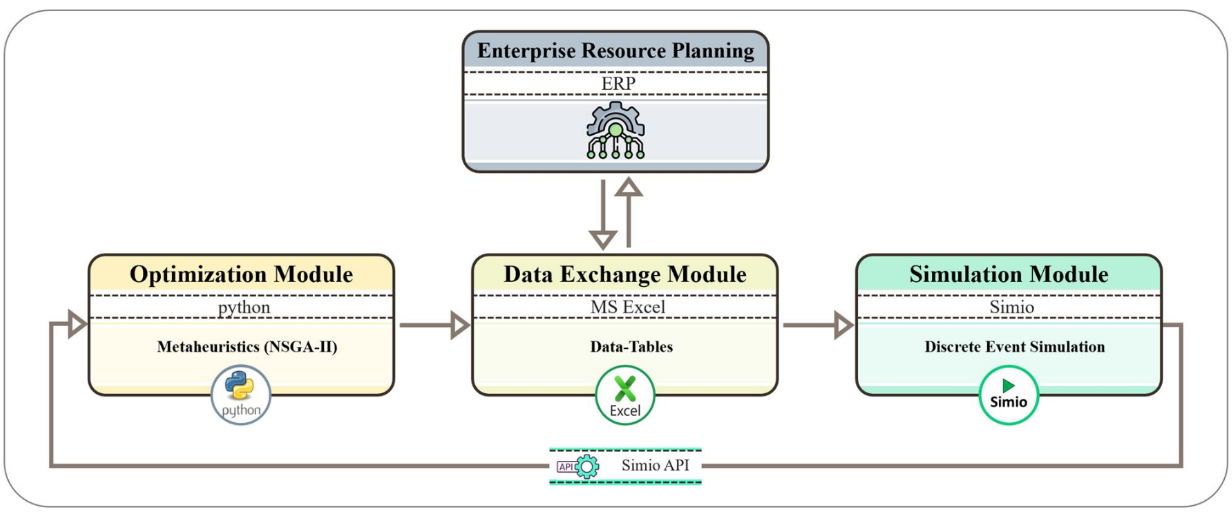

Figure 1: The proposed SODT framework structure.

The first function of data exchange is to connect the simulation model with the ERP system. This connection enables the simulation model to capture the real-life changes in real-time and reflect them in the simulation model. All of the ERP information can be stored in separate files (i.e., Excel or CSV) and linked to the simulation model. This Simio capability makes the simulation modeling process seamless, accurate, and efficient. The data tables can include a wide range of information for resources, materials, orders, dispatching rules, labor, schedules, entities, routings networks, etc.

The data-table module can also be used as a liaison between the simulation and optimization module. The optimization algorithm designed for this work takes data tables as an entry for the optimization model (decision variable) and tries to find the evolved table entries and provide the desired solution. Therefore, each of the ERP data tables can be subject to optimization depending on the user's needs. For instance, a user can optimize orders data-table to change order priorities to satisfy objectives. Another example would be optimizing the dispatching rule table to figure out the best set of rules to proceed with operation on the floor. As can be observed, the improvement opportunities with this unique framework are unbounded.

And finally, once the simulation optimization is completed, the optimal results are tabulated in data tables, and then the new results are populated back to the ERP system. At this point, the updated ERP info can be used in the actual system to perform optimally.

3.2 Implementation Of The SODT Framework

The proposed SODT framework was implemented and verified with a case study of the Beverage Production unit. The model was built using Simio Enterprise Edition to simulate a batch processing system that mixes and fills a beverage product. The model is capable of imitating the real-life scenarios as the inputs to the model can be dynamically changed by altering values in a table. To make these changes real-time the tables can be linked to the ERP database to continually update the input parameters of the model.However, this has not been tested in the current experimental design and lies on the future scope of the project. For the experimental purposes, the data tables representing output of ERP system can be altered manually. Furthermore, the model is capable of completely implementing all the real-life constraints of the resources to provide realistic operating scenarios. The validity of simulation model has not been tested with historical data since, the experimental analysis makes use of an in-built Simio example of batch scheduling with a minor change of measuring Tardiness Cost as well. The simulation model's entities and server are directly linked to the tables representing the manufacturing data from ERP system. The model configuration is made up of multiple tables like Manufacturing orders, Routing logic, Bill of material, Dispatching Rules for Mixing and Packing Operations, range of available workers, availability of raw material. The model properties can be easily changed by altering the excel files to accommodate changing real life scenarios manually or automatically. Figure 3 shows the Simio Facility layout of the model.

The Manufacturing Plat Orders consist of orders for both Intermediate Manufacturing Product and Finished Products. The three types of intermediate manufactured materials are – Green Bulk, Red Bulk, and Blue Bulk, which are mixed in available Mixing machines and later directed to the available Tanks. The order for finished good materials makes use of the stored manufactured material as described before. Finished products are first directed to the Filler machines and are later packed in the Packing Machines. The model also takes into consideration the requirements of Raw materials, such as bottles and labels, that are needed during the production process. It is imperative that the workers and manufacturing material are available at each step/machine to ensure smooth execution. The Processing time and Setup time for Manufacturing material and finished products on each machine is modeled as Triangular Distribution. This accounts for variation resulting due to machine downtime, errors in setup process, or other uncontrollable factors which cause variations in the manufacturing process. The model is enhanced by implementing Simio's custom dashboard features that display material, order details, and dispatch lists for use by operators. The model is simulated to generate a 30-day Operation Planning and Production Schedule based on the input orders, their attributes, resource constraints, and time availability. The following parameters were captured for the experimental analysis - Total Cost of operations, Tardiness Cost – corresponding to the late orders, Average Lateness, Number of late orders, and average time in the system. The Figure 2 show the block diagram of Process flow once the order is generated.

The efficiency of any production unit is highly dependent on the resource utilization and production schedule in execution. Following that, the model was tested for multiple scenarios by altering the availability of operators and dispatching rules for different processes. The production unit is designed to work in 3 shifts – with each shift requiring operators according to the production schedule. A set for four dispatching rules

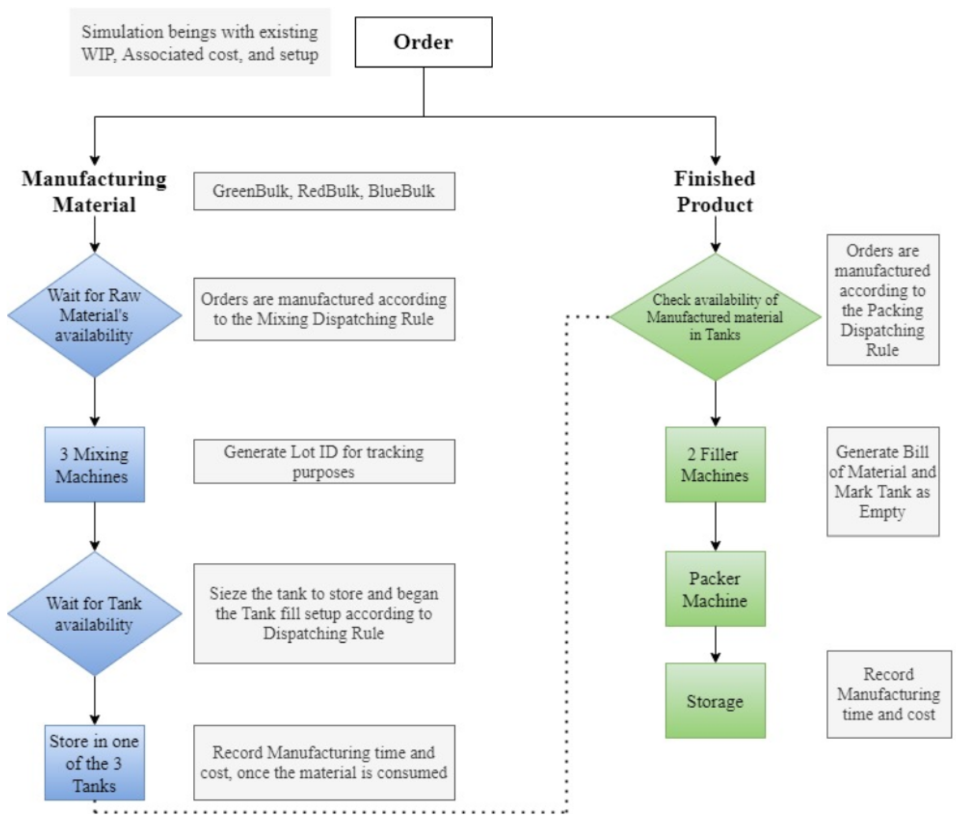

Figure 2: The process flow of simulation model.

- Least Setup Time (LST) - Setup time required to initiate an operation on a machine. Each type of intermediate manufacturing material and finished material has different setup time on different machines.
- Earliest Due Date (EDD) - Decided based on Due dates mentioned in the Manufacturing Order
- Largest Priority Value (LPV) - Priority as assigned in the Manufacturing Order table (range - 1,2 or 3)
- Largest Attribute Value (LAV) - Decided based on degree of Lateness.

can be applied in different permutations to the Mixing and Packing operations. If there exists a tie for sequence of Dispatching rule for an order then the one with least EDD is selected. The Mixing Dispatching Rule represents the sequence of dispatching rules for processing Mixing and Tank Fill operations required for intermediate manufacturing orders. Similarly, the Packing Dispatching Rule - represents the sequence of dispatching rules for Filling and Packing operations. Hence, the number of operators in the shift and sequence of dispatching rules were selected as Decision variables to analyze it's effect on Total manufacturing Cost and Tardiness Cost. The SODT framework used NSGA-II as a Multi-Objective Metaheuristic algorithm to evaluate the effect of change in the number of workers in each shift and sequence of dispatching rules on Total Manufacturing Cost and Tardiness Cost.

4 RESULTS

The NSGA-II initiates with a population that represents different number of operators in the shift and sequence of dispatching rules. The algorithm then investigates the trade-off between different objectives. When one objective cannot be improved without the worsening of another objective, we are on what is

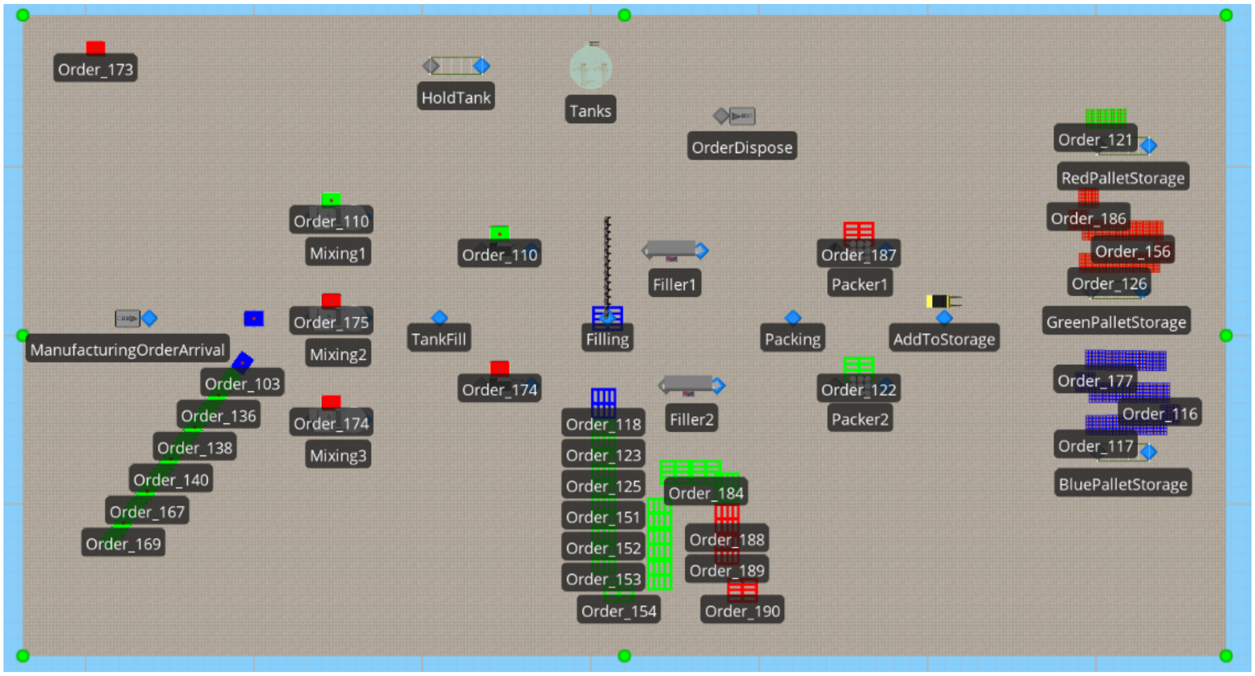

Figure 3: The simulation model.

known as the 'Pareto front'. Chromosome length represents the total number of decision variables. Which are- the sequence/order of the 4 mentioned dispatching rule for Mixing operation and Packing operation individually plus number of workers required in the three shifts. Making the chromosome length as 11. The initial parent population was set to 100 and from which 4 generations or children population were produced. The maximum and minimum number of children per generation were kept to 80 to 50 respectively. The crossover breeding was carried out using tournament selection method based on fitness scores with the crossover probability of 0.8. The mutation probability was kept being 0.09. And the algorithm terminated once the all the members selected for Pareto front were evaluated. Being ran on CPU and not GPUs the computation time for total execution of said model was forty minutes. This can be further optimized using GPUs and testing hyper-parameters of the model.

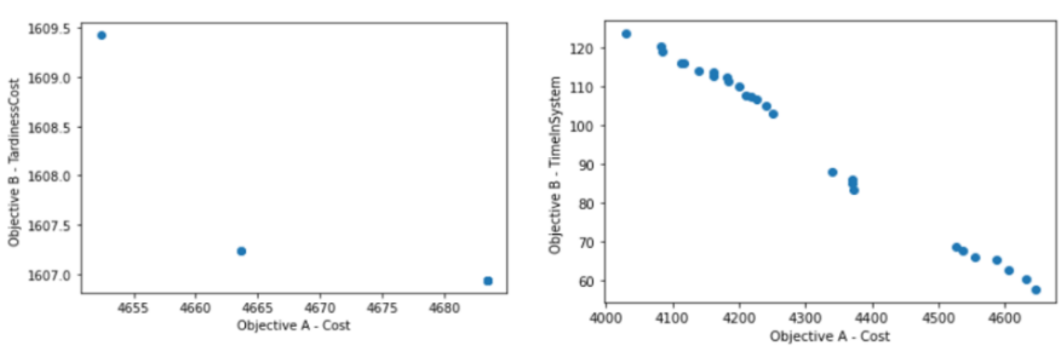

Figure 4: Pareto front graphs for the experiments performed. Objectives for experiment 1 were Total Cost and Tardiness Cost. Objectives for experiment 2 were Total Cost and Time in the system.

The Figure 4 shows the Pareto Front graphs that were obtained from two different experimental analyses. The objectives selected for the first experiment were Total Cost and Tardiness Cost. Upon analyzing, 3

Pareto front solutions were obtained. Upon looking Table 1, we can observe that there is a lesser deviation in Tardiness Cost among the Pareto Solutions but the Total cost has a considerable deviation. Achieving a small deviation in the tardiness cost can be attributed to the smart permutations of dispatching rules and balancing the number of operators in each shift. Given the due dates of the orders remain the same, these Pareto solutions could help the decision-makers to perform a trade-off between operator availability and Total Cost by merely altering the dispatching logic of the system.

Another experiment was run to test the relation between Total Cost and entity's Time in the system. Upon analyzing, 27 Pareto solutions were found as seen in the Figure 4. As seen in Table 2 the given model presents a considerable variation in near-optimum solution to perform a trade-off between the given objectives. Table 2 gives a glimpse of Pareto solutions obtained for this experiment. The values displayed in the table represent the extremes and center point of the Pareto graph. Following are the abbreviations used for the dispatching rules - Largest Attribute Value - LAV, Earliest Due Date - EDD, Least Setup Time - LST, Largest Priority Value - LPV

Table 1: Results for Experiment 1.

Solution	**Cost**	**Tardiness Cost**	**Number Operator at Shift-1, 2, 3**	**Sequence of Packing Dispatching Rule**	**Sequence of Mixing Dispatching Rule**
Solution 1	4652.34	1609.42	2, 4, 4	LAV, LST, EDD, LPV	LPV, LST, LAV, EDD
Solution 2	4663.60	1607.24	4, 3, 5	LST, EDD, LPV, LAV	LPV, LST, LAV, EDD
Solution 3	4683.40	1606.93	5, 5, 5	LAV, LST, EDD, LPV	LPV, LST, LAV, EDD

Table 2: Results for Experiment 2.

Solution	**Cost**	**Time in System**	**Number Operator at Shift-1, 2, 3**	**Sequence of Packing Dispatching Rule**	**Sequence of Mixing Dispatching Rule**
Solution 1	4084.81	119.12	1, 2, 3	LAV, EDD, LST, LPV	EDD, LST, LAV, LPV
Solution 2	4339.74	88.12	1, 2, 1	EDD, LAV, LST, LPV	LPV, LAV, LST, EDD
Solution 3	4646.05	57.61	3, 4, 3	LST, LPV, LAV, EDD	LST, LPV, LAV, EDD

5 CONCLUSION

This paper demonstrates successful implementation of the Simulation-optimization framework for the Digital Twin model of a Beverage Manufacturing Plant. The DT model is more than just a virtual representation as it integrates real-time data tables to build the simulation environment. The SODT framework is not only capable of harnessing the power of simulation engine but also capable of simultaneously optimizing the search space. The proposed approach can help maximize the utilization and efficiency of the plant by continually optimizing the DT model. With the help of Multi-Objective pareto front obtained from the SODT framework, decision makers can have a clearer picture of the production schedule in execution. The proposed SODT framework has the ability of rapidly adapt to the changes in orders, perform iterative optimization and analyze multiple scenarios to provide essential feedback.

The proposed SODT is a promising approach that can be extended to various future works. The experimentation example solely focused on the dispatching and labor tables. In fact, the used simulation model is developed using multiple input tables and each of these tables can subject to optimization. One interesting future extension could be to optimize order schedules and improve their release time to the manufacturing floor. Another example would be analyzing the impact of layout changes on the model. Since all resources are listed in a table, their coordinates can be easily changed to make new layouts. This experimentation can be done without manual intervention or sophisticated layout design software packages. The SODT model can develop multiple layouts based on the user expectation and evaluate them instantaneously. Another important advantage of this model is its capability to capture unexpected events on the real-world system and provide immediate responses. Other analyses could include studying the effect of machine failures, and new project/order arrivals using the SODT model. The proposed SODT is very promising and leads to numerous future works.

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