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A CASE STUDY OF DIGITAL TWIN FOR A MANUFACTURING PROCESS INVOLVING HUMAN INTERACTIONS

Hasan Latif

Department of Industrial & Systems Engineering
The NC State University
Raleigh, NC 27606, USA

Guodong Shao

Engineering Laboratory
National Institute of Standards and Technology
Gaithersburg, MD 20899, USA

Binil Starly

Department of Industrial & Systems Engineering
The NC State University
Raleigh, NC 27606, USA

ABSTRACT

Current algorithms, computations, and solutions that predict how humans will engage in smart manufacturing are insufficient for real-time activities. In this paper, a digital-twin implementation of a manual, manufacturing process is presented. This work (1) combines simulation with data from the physical world and (2) uses reinforcement learning to improve decision making on the shop floor. An adaptive simulation-based, digital twin is developed for a real manufacturing case. The digital twin demonstrates the improvement in predicting overall production output and solutions to existing problems.

1 INTRODUCTION

Improving shop-floor performance is critical to the future success of manufacturing. In recent years, major manufacturing countries have made strategical responses that will help make those improvements. For example, there are “Smart Manufacturing” in the USA, “Industry 4.0” in Germany, “Made in China 2025” in China, and “Industrial Value Chain Initiative” in Japan. If successful, these collective responses will enable the transition from today’s automated shop floor to tomorrow’s “smart” shop floor. “Smart” is realized by information and communication technologies and the capability to use manufacturing data for a better decision making in an integrated system of a shop floor. Such a smart shop floor will require smart production systems, smart manufacturing resources, smart manufactured products, smart raw materials, and smart human operators. Smart production systems, for example, will include order planning, production planning, job scheduling, quality control, on-time delivery, and automated fabrication. All production-system functions have two major objectives: minimize energy and minimize cost.

In a smart shop-floor, the manufacturing resources should be easily reconfigured to respond to the changing market demands and changing shop conditions (Wang et al. 2017; Helu et al. 2020). The former includes customer orders and raw materials; the latter includes the real-time status of the operators, processes, equipment, and environment. That status is used as inputs to real-time, data-analytics tools whose goal is to make optimal decisions (Zhang et. al. 2019). Despite the significant progress, generating that status and making those decisions is still difficult given the typical challenges and problems on the shop-floor. The related technologies that help address these challenges include Digital Factory, Internet of Things (IoT), Cloud Computing, and Service-oriented Manufacturing System.

The aerospace, defense, and space industry are some of the top users of these technologies. Nevertheless, since their parts are normally very sophisticated and in low volume, humans are still an essential part of their production processes. There are usually about 5000 to 15 000 parts in production with different arrival times. The manufacturing process can get very complicated when it comes to a low-volume high-value product. This will add uncertainty and unpredictable breakdowns, which makes it difficult for production/factory managers to optimize or strategize the manufacturing operations. Most factory-floor inefficiencies are related to production plans. The use of digital twins will provide the production managers with timely meaningful insights to improve demand management, forecasting, schedule planning, production control, inventory management, and procurement.

There is a common misconception in the small and medium-sized enterprises (SMEs) that digitalization or digital twin modeling of their operations is too difficult or even impossible, especially in the manual process-based manufacturing industries. Therefore, the SMEs are concerned about making any significant changes in their manufacturing floor. In this paper, we demonstrate the argument made by Shao and Helu (2020) that digital twin implementations really depends on the context and viewpoint required for a specific use case, i.e., the digital twin is a fit-for-purpose digital representation by developing (1) A specific digital twin of a manufacturing process that has intensive human involvement and (2) a real case study to validate the adaptive simulation-based, digital twin.

The remainder of this paper is organized as follows: Section 2 provides some background information about digital manufacturing and digital twin. Section 3 introduces the general concept and the components of a digital twin for manufacturing processes. Section 4 discusses a case study of a manufacturing process to exemplify digital twins. Section 5 discusses the benefits and the limitation of the digital twin implementation. Section 6 concludes the paper and discuss the future work.

2 BACKGROUND

2.1 Digital Manufacturing

Digital manufacturing is an integrated approach to manufacturing that is supported by information technologies. The integration of products, processes, and resources helps manufacturers make better decisions. It not only enables data-driven, decision-support tools but also stimulates the development of new production forms such as smart manufacturing and Industry 4.0. Digital manufacturing will be essential to the creation of new solutions for manufacturing industries (Zhou et al. 2012).

Current literature in the digital manufacturing domain usually concentrate on building static models where digitalization is completely separated from the actual production floor. For increasingly complex production needs, the digitalized model lacks adaptability because of its stagnant model premise.

Digitalization provides manufacturers with more data for their products, production, and systems. Meanwhile, computing has emerged as the cheapest, most abundant resource that we can deploy to analyze that data. Stochastic simulation has been used to generate future "what if" scenarios; and, manufacturers use those scenarios to improve cost, quality, time-to-market, and throughput. In general, by combining the capabilities of data analytics, simulation, optimization, and real-time synchronization (Shao and Kibira 2018); a digital twin for manufacturing problems can be created. Of course, a specific digital twin implementation will totally depend on the scope, objective, and technologies selected for the manufacturing problem.

2.2 Digital Twin in Manufacturing

An on-going ISO standard effort defines a digital twin in the manufacturing context as "fit for purpose digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronization (ISO 2020; Shao and Helu 2020)." The concept of a digital twin was first adopted in spacecraft design by NASA (Boschert and Rosen 2016; Brenner and Hummel 2017; Ferguson, Bennett, and Ivashchenko 2017. Grieves 2014; Grieves and Vickers 2017), viewed a digital twin as a combination of modeling-based methods and optimization-based methods. (Alam and Saddik 2017; Soderberg et al. 2017), on the other hand, as a real-time simulation with the capability of transferring information from adjacent, product, lifecycle phases.

Schleich et al. (2017) introduced a conceptual framework for building digital twins for specific applications. That framework ensured certain model properties such as scalability, interoperability, expansibility, and fidelity. Latif et al. (2019) discussed an industrial, information-integration method using Open Platform Communications Unified Architecture (OPC UA) between the real process control and a simulation of that same process. Redelinghuys et al. (2019) propose a six-layer architecture that comprises physical twin as levels 1 and 2, local data repositories as level 3, IoT gateway as level 4, cloud-based repositories as level 5, and emulation and simulation as level 6. ISO is developing a standard "Digital Twin Framework for Manufacturing" to provide a generic guideline and a reference architecture for case-specific digital twin implementations (ISO 2020).

Currently, many case studies of digital twin implementations are within a laboratory environment. For example, an Automated Guided Vehicle (AGV) or Cyber Guided Vehicle (CGV) with self-adapting behavior was developed for solving a material handling problem (Bottani et al. 2017). There are also a few industrial cases of the digital twin implementation and evaluation. For instance, Liu et al. (2018) introduce a digital twin for an automated flow-shop, Zhang et al. (2019) show a digital twin driven cyber-physical production system, and Lin et al. (2019) describe a digital twin case study for the steel industry. However, the literature about digital twin in manufacturing does not cover the manual assembly-based situation yet. SMEs are still in the rudimentary level where workers are receiving raw materials, processing parts, assembling component parts, and inspecting the final product. The digitalization of this type of process will be challenging, but once implemented, it will help eliminate non-value-added production time and other inefficiencies. The digital twin of a human-involved operation will guide the operators interactively and provide production managers with actionable information that enables them to make their decisions more effectively. This paper provides a specific prototype of a digital twin implementation for a manufacturing process with intensive human involvement, where most of the operations and related data collection are manual or semi-automatic, to demonstrate the benefits and value of a digital twin.

3 DIGITAL TWINS OF A MANUFACTURING PROCESS

This Section introduces the general concept and the components of a digital twin for manufacturing processes. Creating a digital twin for a manufacturing process starts with establishing pipelines of manufacturing data. Some of the design and manufacturing data may be collected semi or fully automatically. There are normally two kinds of manufacturing operational data: real-time and historical. The real-time operational data may be collected using smart sensors and historical data may come from existing manufacturing applications. As shown in Figure 1, a digital twin must have the following basic components: a physical element, a digital element, and their integration.

Depending on the context of the manufacturing problem and technologies selected, a digital twin may contain a variety of computational or analytic models pertaining to its real-world counterpart. Those models could range from principles-driven (natural laws), data-driven (statistical, machine learning/artificial intelligence), and geometry-driven (3D CAD), and visually-driven (virtual and augmented reality). A digital twin does not have to have all these functionalities, it should be composed entirely based on specific use case requirements (Shao and Helu 2020). In general, a digital twin can simulate the state, predict the behavior, and optimally respond to the changing conditions of its physical element through the modeling and analytics of relevant data. A feedback loop from the digital twin to the physical element, may be controlled by a user, transfers the recommendations, which provide actionable decision guidance for the production managers. This decision aid should be intuitive and help tweak or adjust the manufacturing process parameters. The process may be repeated continuously until the best-case scenario or production target is achieved.

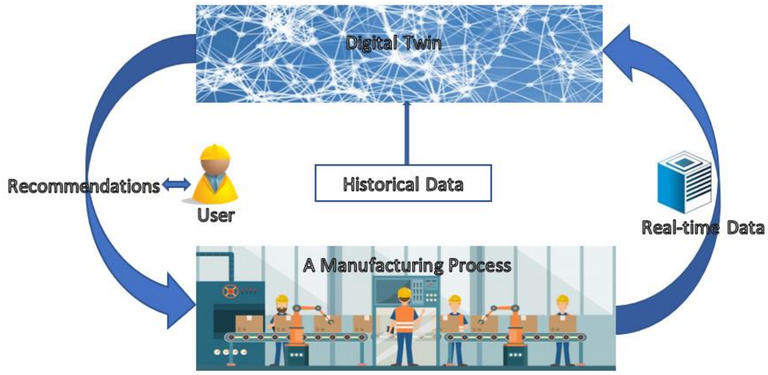

Figure 1: Concept of the Digital Twin of a Manufacturing Process

3.1 Physical Elements

In the manufacturing world, a physical element refers to the manufacturing equipment, systems, and processes on the production floor. A manual-intensive, manufacturing process may involve workers, workstations, assembly lines, and the products. The component parts arrive as raw materials. After going through all the different workstations, a final product is completed. For instance, a semiconductor process consists of raw material arrivals, fab test, die package, assembly, inspection, and delivery. Each of these elements can be the physical element of a digital twin.

3.2 Digital Elements

The digital element of a manufacturing process is the digital representation of its corresponding physical element. Depending on the use case requirements, it might include an optimization model that captures constraints and performance objectives. Or, it might include a simulation model where simulation logic and reasoning mechanisms are designed to mimic the physical operation. Or, then again, it might include a data analytics model to explore the insight of any collected data.

A database may be necessary for the digital twin to store real-time data, historical data, intermediate results, and recommendations (e.g., control commands). Data collected from the physical elements are crucial for the dynamic modeling of the manufacturing process. The data may include process parameters, product data, production-line-layout information, and information about production equipment and their operations, workpieces, material, tools, and fixtures. From a product lifecycle point of view, it may include as-designed data (product design specifications, process and engineering data), as-manufactured data (production equipment, material, method, quality, and operators), and as-maintained data (real-time and historical configuration and operation states, and maintenance records). The data may also include time and resources required to complete an operation. For a manual manufacturing processes, the data collection can also be a manual process.

3.3 Integration

A digital twin's feasibility and effectivity entirely depend on the integration between the digital element and the physical element, i.e., the two-way communication (Shao et al. 2019). The integration should be dynamic, bi-directional, and possibly real-time.

Other than the real-time data sent from the physical element to the digital element, a feedback loop (better if automated) is needed from the digital element to the physical element for a digital twin to be successfully integrated. In reality, a feedback loop often involves human interaction, e.g., production managers select a recommendation. Once the recommendations are applied, the quality, the efficiency, the time, and the cost for production will be effectively improved.

4 THE CASE STUDY OF A DEFENSE PRODUCT ASSEMBLY

In this study, we focus on a defense product that requires a manual, assembly process and a receiving, staging area. The objective of the study is to find the best sequence of assembly operations, given the uncertainties in part-arrival times, machine-breakdown times, data-communication times, integration, and part-obsolescence times. The physical system is approximated as a linear, discrete-event, time-invariant system. The users of the digital twin are the production managers. All data are collected monthly from the production floor.

A high-level instantiation of the digital twin concept (Figure 1) is shown in Figure 2. The top half depicts the digital elements and the bottom half represents the physical elements of the manufacturing process. From a database, historical data is fed into the digital twin, which is an adaptive simulation, as initial inputs. Initial data comes into two varieties: first pass yield (FPY) and hour per unit (HPU). The digital twin model provides process recommendations as the feedback loop. Then, the production managers can select and apply the recommendations to the manufacturing process. Real-time data is fed to the digital twin from the physical manufacturing process.

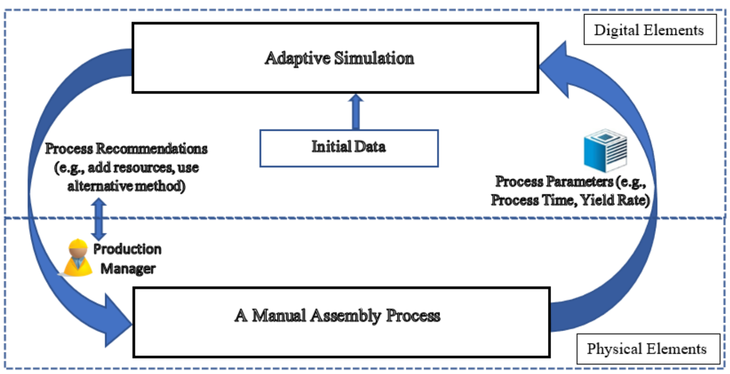

Figure 2: Data Flow of the Case Study

4.1 Physical Elements

The manufacturing process produces one product, called Z, which needs 44 raw materials - at different production stages - from various suppliers. Those stages involve 79 operational workstations including testing, assembling, soldering, torqueing, and inspecting. Each workstation is denoted as "opxx" where xx is the operation number. Operations along with FPY and HPU are collected for a two-year time frame starting from April 2017 to April 2019. Important assumptions about the process, for the purpose of data processing, are given below.

- Each day is 8 h and each month is 30 d.
- Only one operation can be processed at a time for an individual operation.
- There are no interruptions during the process of an individual operation, which means that the work on an operation cannot be paused in the middle and then continued later.
- All workstations are at their own location and the material is transported from one operation to another where the subsequent operation is performed. Due to missing information about transport, the time needed to transport material from one to another operation is set to zero.

- Breaks at work, failures, troubleshooting, etc. are included in the processing times.
- Maintenance work is not considered.
- The number of workers at the workstations is not considered.
- The work orders are dependent on each other. The operations are sequential based on their operation numbers.

4.2 Digital Elements

4.2.1 Physical Process Map

Creating a digital twin of a manufacturing process requires a good understanding of the process. First, a process map needs to be created with information about all the raw materials and operations. Since the core module of the digital twin is a simulation model, the process map provides the requirements for the development and execution of the model. The key requirements include (1) the definitions of the assembly scenario to be carried out, (2) the operational data captured and analyzed for identifying the key parameters, (3) the critical process parameters and operational constraints to determine the behavior of the physical elements, and (4) the simulation of the assembly scenarios and optimization according to a set of constraints.

An "input_final" text file is prepared to capture the process map. In Figure 3, the incoming operations are provided on the right-hand side of the vertical bar and the output operation is provided on the left. The incoming raw materials are listed based on alphabetical order such as AB, AC, and AD. Operation numbers are defined by 'opXX' and 'AssyX,' where X is the operation number. For instance, op50 consists of op40; material AB, AC, AD; and assembly operation 1.

```
op40|op30
Assy1|op40 AB AC AD
op50|op40 AB AC AD Assy1
op60|op50
op70|op60
op80|op70
op90|op80
op100|op90
op110|op100
op120|op110
op130|op120
Assy2|op130 AE AF AG AH AI AJ
op140|op130 AE AF AG AH AI AJ Assy2
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Figure 3: A section of the physical process map.

4.2.2 Data Processing

The initial dataset was taken from the first month of the data stored in an excel spreadsheet. This dataset includes operation numbers along with the time required to complete (FPY and HPU), incoming raw materials and their estimated numbers, and assembly operations. The data is pre-processed and converted into the CSV (Comma-Separated Values) format. The pre-process handles several data issues such as missing records of operations, missing operation-end timestamps, unintentional and deliberate errors, security issues related to privacy, and nondisclosure of business secrets. The clean CSV-formatted dataset is stored in a file for the simulation model to use as needed.

4.2.3 Simulation Logic

As indicated in Figure 2, the core of the digital twin is an adaptive simulation model. Traditionally, the off-line simulation has a minimal feedback loop, runs for the entire time period at once, and rarely provides assistance to the user for the next cycle. The adaptive simulation-based digital twin provides the decision-making assistance, allows real-time data input, and enables adjustment capability. The simulation runs for a specific time period (i.e., 1 month) with an initial/historical dataset (FPY and HPU for each operation). When a real-time dataset is collected, the simulation replaces that month's data with the real-time data. However, if it does not find the real-time dataset, the simulation continues with the existing dataset. The real-time dataset comes from the manufacturing process, and the data is collected, cleaned, processed, and stored in the CSV format. The simulation ends once the entire time period completes (i.e., 12 months). A recommendation list is generated by the digital twin; the list gets re-ranked constantly based on the score of each item on the list.

Figure 4 shows the simulation logic in a nutshell. When the adaptive simulation moves into the "wait" mode, it asks the users if they want to review the process for the worst performing operations. If the user wants to review the recommendation list, based on the latest information, the digital twin shows the five worst performing operations and the user selects one of them to review. Once the user selects and applies the recommendations from the list, the digital twin generates a dataset with improved parameters for that operation. Since the operations are picked from future time periods, the generated dataset waits for the actual operation to happen. Once the actual operation happens and the real-time data for that operation updates the dataset, the generated dataset is compared with the updated dataset. If the difference between the datasets stays below a pre-defined threshold value (30 % of the real-time dataset), it signifies that the recommendation has improved the process output. On the contrary, if the difference stays above the threshold value, it shows the selected recommendation has not worked better. Either way, the feedback goes to the recommendation list and re-ranks the list for the next cycle of usage.

4.2.4 Simulation Execution

The adaptive simulation model was developed using Python 3.6. When a specific operation (e.g., op560) is executed, assuming it is from the worst 5 operations, the user can compare the real-time dataset (FPY and HPU) with the generated dataset (10 % improved FPY and 10 % decreased time). After applying the recommendations, the real-time data should demonstrate significant improvement from the generated data. If the parameters (FPY and HPU) of the real-time dataset are more than 30 % of the parameters of the generated dataset, the applied recommendations will be regarded as a failure, will get a score of 0, and will get pushed down on the recommendation list. If the parameters are similar (real-time data is within 30 % of generated data), it indicates that the recommendations work well, it will get a score of 1, and will get push up in the recommendation list. In either cases, the recommendation list will be updated and stored in the database for use in the next cycle as the initial dataset. With this rule, the recommendation list for the operations always gets updated; this reflects the reinforcement learning (RL).

RL is a "trial-and-error" approach that the learning agents learn optimal decisions by interacting with the environment. The "trial-and-error" rule means RL agents make a trade-off between known decision exploitation and new decision exploration to achieve an optimal policy. Figrure 5a shows the RL model (Barto and Sutton 1997). A RL agent and its environment interact over a sequence of discrete time steps. At each time period t, the agent completes an iteration with the environment. The action a_t are the chocies made by the agent in state s_t. In the t^{th} iteration, the agent observes the current environment state s_t, and chooses an action a_t. After that, the environment transfers from the state s_t to s_{t+1} following the a state transition probability and returns a reward $r_t(s_t, a_t)$ according to the performance of a_t. So the rewards are the basis for evaluating agents' chocies. Figure 5b is an instantiaiton of the general RL concept for this case study. The environment is the recommendation list, the agent is the threshold value, the state is the simulation period, the reward is generated simulation data, and the action is to re-rank the recommendation list. In a different state, new data enters into the equation and the threshold value is compared with the generated input. A new recommendation list is created.

Eventually, all items in the recommendation list will truly represent the recommendations that have been tested and verified with a proven track record. In figure 6, the default initial recommendation list (Figure 6a) and the re-ranked recommendation list (Figure 6b) for Op560 in the next cycle are shown. The re-ranked recommendation list is showing “Find An Alternative Material” at number 1 because in the previous run, the user has selected and successfully found that the recommendation is helpful.

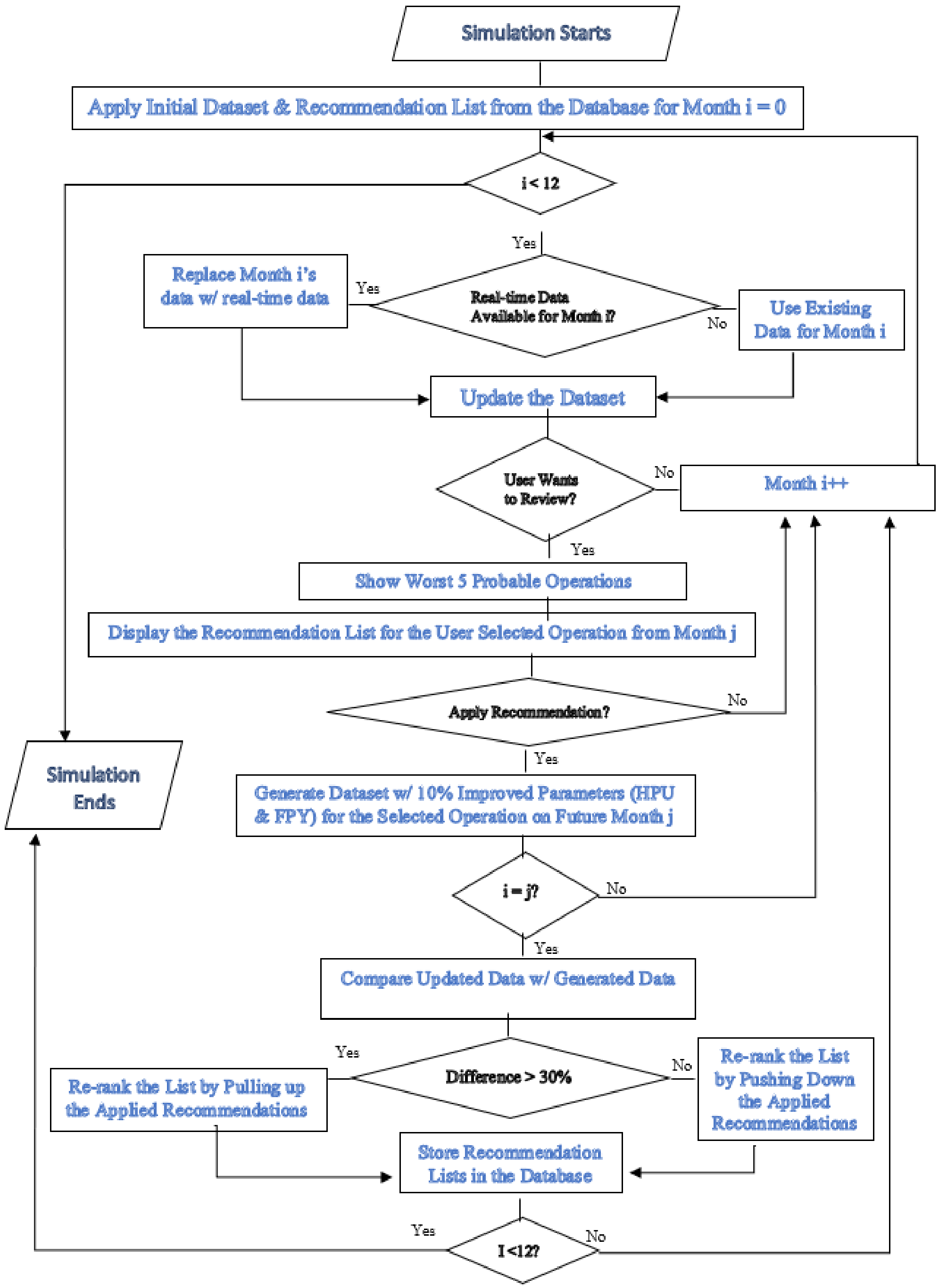
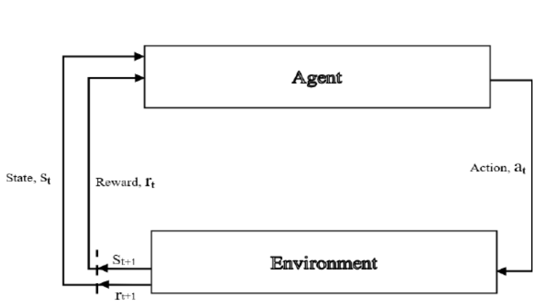


Figure 4: Simulation logic for the digital twin of the manufacturing process.



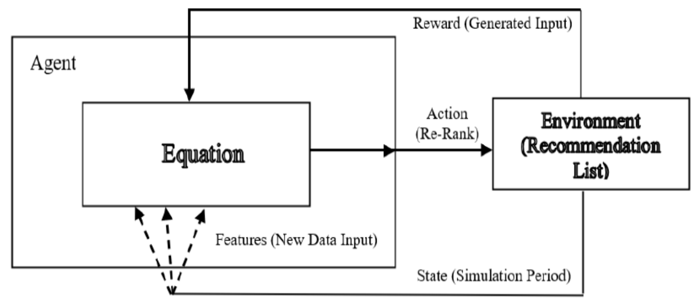
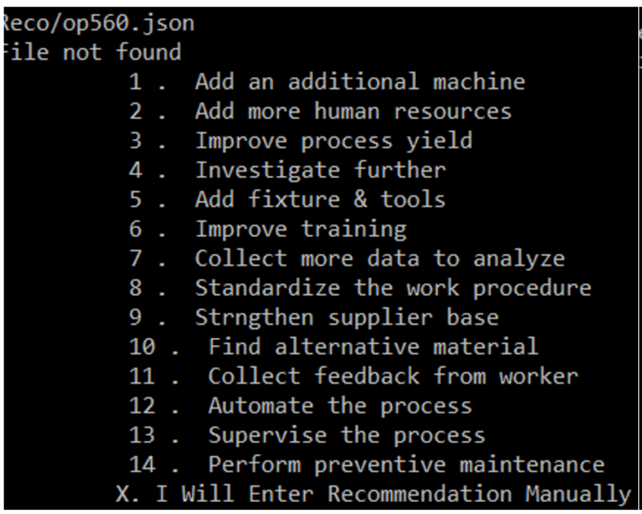


Figure 5a: The RL model.

Figure 5b: RL architecture for the case study.



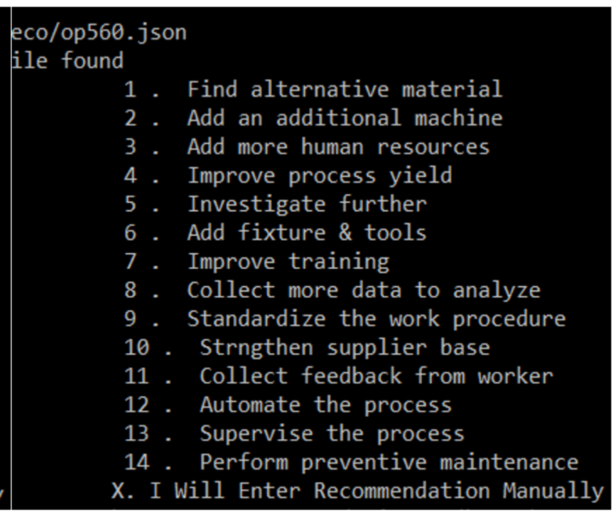


Figure 6a: Initial recommendation list.

Figure 6b: Re-ranked recommendation list.

4.2.5 Model Validation

To validate the model, 24 months of actual data is collected. The first 12 months data is used as initial data. The rest of the 12 months data is used to validate the model. In addition to that, a desk audit has been performed to validate the output of the adaptive simulation model. In future work, formal verification and validation techniques will be applied.

4.3 Integration

The digital twin includes two-way communications: (1) the real-time data is collected from the manufacturing process, processed, and updated in the digital twin and (2) the recommendation list is generated by the digital twin and applied to the manufacturing process. In this case study, most of the data are collected manually, processed in a separate application.

A Python-based parser was developed to interpret the CSV files, a text file provides the operation sequence. The recommendation list is saved in JSON. Each time the user manually enters a recommendation or updates the recommendation list, a new JSON file replaces the older one for that specific operation. For instance, if a user makes an update on OP560, the simulation first looks for a JSON file in the recommendation list. If it does not find the JSON file, it shows the default recommendation list. Based on user's selection, the recommendation list gets updated and saved in the OP560 JSON file. Next time, whenever the user wants to see the recommendation list for OP560, the OP560 JSON file is shown for the user. The Python parser does all the data transfer except the initial CSV file generation. The data is transferred once in every month, so the overall effort to run the digital twin is minimal. Even though the data transfers monthly, the data comes from the real-manufacturing floor, and therefore, it is considered as real-time data.

In this case study, the initial dataset comes from the historical database. It is the data from April 2017 to March 2018. The simulation will ask for the real-time data for each month, e.g., April 2018, May 2018, or June 2018, once the real-time data is available, simulation replaces the existing dataset with the real-time data, and recalculate the output at the end of the simulation. If the user wants to improve the efficiency or reduce the processing time of the operation, the simulation provides the worst, five, performing operations that have the highest potential to be improved and a recommendation list for the improvement of each operation. The equation used to find the worst five operations is given below.

$$x = HPU * FPY^2 \; . \tag{1}$$

For instance, OP560 has two parameters: FPY as 1.0 and HPU as 0.75. OP560's 'x' value calculates as 0.75. With a similar calculation, the top, five, worst operations are derived based on the lowest 'x' value. Therefore, operations with a lower yield rate and higher HPU will show up as a worse performing operation.

The collected data is fed into the digital twin to replace the previous dataset. Therefore, the digital twin can periodically adjust its prediction output and point out the areas to improve. The recommendation list brings useful insight to the worst operations. Based on the application and processed data feedback, the recommendation list constantly gets evolved. The successful recommendations come at the top of the list and the failed ones go to the bottom of the list. Therefore, every operation shows a unique list that has been tested and verified over the period of time. For instance, after multiple runs of the digital twin, a recommendation list can show the recommendations that have been successful for the similar situation multiple times. Therefore, the user can make a better decision.

5 DISCUSSION

The digital-twin concept is still new in the manufacturing domain. There are not many successful digital twin implementations available especially for those processes that have a lot of human interactions (Ma et al. 2019). In addition to the confusion of the digital twin concept, the advent of new information technologies also plays a role in this, because designing, implementing, and integrating digital twins with those technologies could get very complicated. The idea of a digital twin has to be a comprehensive virtual replication of all physical and functional activities within a shop floor makes it difficult for manufacturers to adopt, invest, and implement digital twins. Completing specific use cases of digital twins with a manageable scope will help them better understand the efforts they need to involve and benefit they will get. This case study provides a success story of digital twin implementation even for a manual, complicated, shop-floor problem with uncertainties associated with multiple materials, operation sequences, human interactions, and real-world data. The case also provides an implementation procedure.

Part of that procedure involves creating a process map. Other parts include data collection, data processing, and data integration. Users (i.e., production managers) need to understand the impact of these data-related issues on the digital twin output. In addition, since most of the operations involve manual assembly, managers need to understand how process variability contributes to the variability in the data. In our case, we simply used the average of the data to nullify that variability. However, an advanced level of mathematical technique could be deployed to tackle the variability problem.

Because of all these uncertainties, a dynamic simulation model is built. The simulation output is a recommendation list that includes what to make, when to make it, and how to make it. The recommendation list evolves continuously. Although the recommendation list should reflect the appropriate solutions for the manufacturing operations, the impact of each recommendation has been assumed equal. In real-life the impact is obviously different, however, for simplicity, the difference between impacts has not been accounted. Similarly, the threshold value for the comparison of the two parameters between the generated dataset and real-time data set should be different based on the operations. For implementation feasibility, the threshold point is kept the same for all the operations.

6 CONCLUSION AND FUTURE WORK

The digital twin can provide concrete value and help production managers take the key strategic decisions. A digital twin can have many applications across its life cycle depending on its context and purpose. It can answer the critical what-if questions more accurately in real-time. It is expected that the applications of digital twins can contribute to improved operations management, operations execution, resource utilization, lead times, and due-date reliability.

In this paper, an adaptive, simulation-based, digital twin has been implemented. The real, case study showed proof of concept. It further proves that digital twin needs to be use case specific. Specifically, this work targets a human-involved manufacturing process where automation is not completely available. It can be speculated that this approach will have instructional significance when manufacturing industries build or revamp a plant, arrange the facilities or staff, and polish up the process flow.

With more data and applications, further issues and challenges of the development, implementation, validation of the digital twin in real manufacturing environments will be identified. As a future activity, the authors would like to apply the approach to more manufacturing problems including a more detailed evaluation of the machine's health and the planning of the maintenance activities.

ACKNOWLEDGMENTS

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DISCLAIMER

In the case study, all data points and physical process maps are masked and do not represent the actual operations. Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose. No approval or endorsement of any commercial product by NIST is intended or implied.

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AUTHOR BIOGRAPHIES

HASAN LATIF works as a Sr. Manufacturing Engineer at Missiles & Defense Systems in Raytheon Tehnologies. He is a pasisonate researcher in the manufacturing domain. His research interest is in smart manufacturing, simulation, and industry 4.0, and he has relevant research experiences in the application areas of aerospace & defense industrty. He has a Ph.D. in Indsutrial Engineering from The NC State University. His email address is hhlatif@ncsu.edu.

GUODONG SHAO is a Computer Scientist in the Life Cycle Engineering Group in the Systems Integration Division (SID) of the Engineering Laboratory (EL) at the National Institute of Standards and Technology (NIST). His current research topics include digital twins; modeling, simulation, and analysis; data analytics; optimization; and model verification and validation for Smart Manufacturing. He holds a PhD in Information Technology. His email address is gshao@nist.gov.

BINIL STARLY is a professor in the Industrial & Systems Engineering Department at North Carolina State University. He directs the Data Intensive Manufacturing Laboratory (DIME Lab). His specific technical expertise is in digital design and fabrication, and cyber-physical systems in manufacturing. Binil has received the National Science Foundation CAREER award for research in multi-scale biological tissue scaffold systems built from additive manufacturing platforms. His email address is bstarly@ncsu.edu.