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SIMULATION AS A SOFT DIGITAL TWIN FOR MAINTENANCE RELIABILITY OPERATIONS

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ABSTRACT

This paper lays out a framework for using modeling and simulation to build a "soft digital twin" (SDT) and demonstrates its efficacy by modeling the maintenance task processes within a real-world mission-critical facility. Such crucial infrastructure systems, such as nuclear power plants, rely on the efficient completion of maintenance tasks (MTs) to achieve high reliability with minimal downtime. Managers often wish for a "crystal ball" that can enable them to configure their resources optimally. However, the MTs are inevitably encountered by various uncertainties rooted in intrinsic equipment failures, endogenous factors (e.g., staffing), and exogenous factors (e.g., supply chain disruptions). Thus, it is challenging to manage these tasks. The proposed SDT can serve as a "crystal ball" to gain insights into resource configurations, staff planning, and task scheduling, thanks to the versatility of simulation. This feasibility study uses both a data-driven framework and stochastic modeling methods to construct the SDT. Initial results indicate the SDT can produce reliable results comparable to the test dataset retrospectively, and it can be used to minimize the time in system of the MTs, while maximizing the throughput within a specific time frame.

1 INTRODUCTION

In mission-critical facilities, such as nuclear power plants or hospitals, it is crucial to maintain high reliability of the system with minimal downtime. In such facilities, any downtime or failure may lead to catastrophic results. High availability of the services requires the efficient maintenance of the equipment and structures by completing maintenance tasks (MTs). Intelligent maintenance strategies can offer tremendous benefits (Errandonea, Beltrán, and Arrizabalaga 2020). However, it is often difficult to manage such MTs because of the multi-step interconnected processes and various uncertainties within, rooted in intrinsic system failures, endogenous factors (e.g., staff turnover), exogenous factors (e.g., supply chain disruptions and natural disasters), and so on.

Due to the aforementioned difficulties and uncertainties, management often seeks to have a "crystal ball" providing insights into the optimal employee mixture to streamline the MTs. Recently, digital twins (DTs), or as close as possible approximations of physical systems in digital form, have been used to find optimal resource allocation and maintenance management strategies that allow for experimentation and exploration (Graessler and Poehler 2018; Wang, Zhang, Guo, and Zhang 2021). In this paper, we demonstrate a simulation and modeling framework to construct a "soft digital twin" (SDT) that mimics relevant portions of a real-world MT process instead of the process in totality as seen in a regular digital twin. Simulation has been utilized to give a better visualization of the process. Along with that simulation is very flexible and allows for a stochastic elements to be incorporated into the model. Utilizing data obtained from an undisclosed source, an analysis of a real-world MT process's structure and statistical behavior was conducted to generate datasets for the construction of an SDT. Both data-driven models (DDM) and stochastic models (SM) are built. Next, the real-world MT structure and statistical behavior are simulated to produce the SDT that accurately models the processes. Finally, the SDT simulates the MT process and searches for optimal crew mixtures, with the goal of minimizing overall time in the system (TIS) while maximizing the number of MTs completed in a restricted time window.

The remainder of the paper is organized as follows. The next section details a literature review of related work. We then provide a mathematical description of the problem, along with the general framework for constructing an SDT. Next, we analyze the SDT with discussions, leading to conclusions and future work.

2 LITERATURE REVIEW

Constructing an MT simulation that is reliable, efficient, and resembles real life can be a daunting task, given the fact that simulation is known for handling complexity, stochasticity, and non-linearity. Researchers have been using computers to simulate the structure of MTs, aiming to gain a deeper insight into how resources should be utilized for maximum efficiency (Muchiri, Pintelon, Gelders, and Martin 2011). Mjema (2002) simulated the processes of finding an appropriate staffing policy that would minimize the throughput of maintenance orders. It tackled the problem of personnel capacity planning and analyzed the relationships between the MT steps and the priority of the work (Mjema 2002). Such a simulation model has many similar properties to an SDT. To lay the base of the simulation analysis, both MTs must analyze the flexibility of the personnel, the amount of personnel, exchangeability of personnel, priority, and type of maintenance (Duffuaa, Ben-Daya, Al-Sultan, and Andijani 2001). A major priority of the simulation is to reduce the TIS for high-priority jobs while still allowing for a smooth flow of lower-priority jobs. Key performance indicators (KPIs) used by Mjema (2002) were the utilization of personnel and the average downtime in the system, while an SDT may have more KPIs, including TIS of each step and a better understanding of the utilization of each resource. Mjema (2002) showed that the system was not perfect, which could be seen in the results of the resource utilization data. The utilization might start low and then skyrocket, exhibiting that the time in the system would most likely begin to increase heavily (Mjema 2002). This phenomenon also happens in the SDT and it has been noticed by researchers, which in turn leads to Muchiri, Pintelon, Gelders, and Martin (2011) and the ideas of simulating real-world systems. Muchiri, Pintelon, Gelders, and Martin (2011) stated that creating a work structure simulation was extremely difficult and most often nearly impossible to implement all the stochastic tendencies of humans (Muchiri, Pintelon, Gelders, and Martin 2011). This is often times a con of using simulation as the purchasers of the simulation often want a ”crystal ball”. The simulation will give a deep insight but it will not be perfect. Simulations do not need every step, it only needs the relevant information. This is often not realized.

In essence, an SDT is a simulated version of some real-world processes to assist in predictive maintenance (Liu, Meyendorf, and Mrad 2018). By creating a digital twin, researchers can mirror real-world situations quickly and efficiently while learning and accurately measuring the system (Boschert and Rosen 2016). Taking measurements and KPIs are critical to a successful SDT, because KPIs can be analyzed and optimized (Mjema 2002). The SDT developed by He, Chen, Dong, Sun, and Shen (2019) was created using visual system modeling. The SDT was developed by using a multi-block PLS process, which breaks down a much larger system into small units that would then be modeled and eventually combined to represent the whole system (He, Chen, Dong, Sun, and Shen 2019). Constructing an SDT is beneficial in many ways as it not only enables one to see what is happening in the system, but also collects data that can be utilized to continuously improve the system.

Creating a successful MT simulation generates automation and a more intuitive model for a very complex process provides managers an advantage that they may never have had before (Paz and Leigh 1994; Alabdulkarim, Ball, and Tiwari 2013; Xing, Chen, and Yang 2009). an SDT may help increase predictive measures, create a better production schedule, and optimize the process. It is key to find the optimal sequences of steps within a massively complex process (Stoop and Wiers 1996). Many companies do not have a sound MT system, and each day it is evaluated by hand, which often leads to under-maintenance or over-maintenance (Muchiri, Pintelon, Gelders, and Martin 2011). This calls for in-depth research on constructing DTs for better decision-making, strategically and operationally.

Many maintenance-based operations are focused on preventative maintenance rather than day-to-day maintenance. an SDT will likely involve stochastic maintenance, which is challenging to simulate with high fidelity. In contrast, others like Paz and Leigh (1994) took a straightforward preventative maintenance approach, which is easier to simulate because each piece of equipment will have a distribution to match its life cycle and provide an estimate of when it should be updated or re-calibrated. This task is not stochastic, so it is much easier to look into the future and come up with estimates (Paz and Leigh 1994). Another age-old question of humans vs. machines is one of the most significant differences between most MT processes. Looking to simulate people is very difficult because they are stochastic, which creates lots of variabilities that are hard to account for. This work provides the framework to build an SDT based on real-world MT processes to find the optimal configuration of resources.

Simulation is the most significant analysis engine used within an SDT. In comparison, others, such as Al-Harbi (2000) used a system called data envelopment analysis (DEA). The objective of DEA is to determine the level of efficiency of decision-making variables using input and output data (Al-Harbi 2000). In addition, Kao and Lee (1996) implemented a regression analysis to analyze the system. Regression analysis of the manpower demand needs to follow a time series to satisfy all times in the future. Others used time-series analysis to best find patterns within the data and optimize to create a very efficient system allowing to forecast the future work (Bandt and Shiha 2007). These are only a few of the many ways to analyze a system (Al-Harbi 2000). As a feasibility study, this work focuses on simulation-based analysis with an SDT.

3 PROBLEM DESCRIPTION

A general description of the maintenance task process is as follows. There are some sets of MTs that need to be completed. They arrive independently and must pass through a multi-stage process before completion (see Figure 2). Each stage requires administrative employee resources, some number of labor employee resources, or both. Administrative employee resources include approvers, planners, prioritization agents, supervisors, facility administrators, and schedulers. The specialized skills of labor resources are required to complete the MTs. These resources include pipe-fitters, laborers, painters, electricians, carpenters, and machinists. The administrative resources are tied to a specific location. In comparison, the specialized more labor-intensive resources can be tied to a specific location and crew group, or they can be treated as a pool of resources the different locations can utilize to maintain the facility. Each of the seven stages (request, approval, prioritization, planning, scheduling, execution, and completion) takes time measured in days. This time consists of the resource-dependent time required for the employee resources to complete the task and some amount of intrinsic time that is just an intrinsic part of the stage, not relying on any resources. Some MT stages are processed daily, while others are processed weekly. Each MT is assigned a priority, tied to a specific location, and requires a specific number of employee resources, with higher priority MTs getting precedence when requiring crew resources. These business logic rules are extracted from an undisclosed mission-critical facility that can represent a generalized MT process.

4 MATHEMATICAL MODEL OF THE MT PROCESS

The problem can be described mathematically using the sets, indices, parameters, and variables as in Table 1. The facility must maintain some set of locations F by completing MTs. There is a set of MTs $M_{f,p}$ each corresponding to a certain location f in the set of locations F and having a priority value p. There is a set of employee resources $R_{j,f}$. Each employee resource has a specified job type j, and a location f that determines which MTs they interact with. Each location f has a number $E_{j,f}$ of each resource type j for location f that processes MTs at each step s within the MT process set S. Two major objectives are to minimize the average TIS (Equation 1) and maximize the throughput (Equation 2) in a given time

Table 1: Sets, Indices, Parameters, and Variables for Resource configuration problem.

Sets and Indices	
F	Set of locations where MTs must be completed, {1, ... G} $f \in F$
$M_{f,p}$	set of MTs where f is the location and p is priority
J	Set of employee roles or jobs, j *in* J
S	Set of steps for maintenance task process, s *in* S
$R_{j,f}$	employee resource of role j for facility f
Parameters	
P	Set of MTs possible priorities, {5, 4, 3, 2, 1}, $p \in P$
B	budget for cost of additional resources that must not be exceeded
$K_{j,f}$	maximum number of employee resources j at facility f
H_j	hourly cost for resource j
Variables	
$E_{j,f}$	number of employee resource type j at facility f
$X_{j,f}$	+ or - adjustment to the number of employee resource type j at facility f
N	number of completed MT's in given time window
M_j	maximum number employee resource j that can be added
T	average TIS
$\Delta_{m,s}$	total time in step s for maintenance task m
D_m	total duration in system for maintenance task m
C	total hourly increase (&/hour) for additional employee resources added

window by deciding the optimal adjustments to the employee mixtures $X_{j,l}$. The additional cost of employee resources must not exceed the budget for additional hourly costs due to added resources (Equation 3) or exceeding the employee resource limits (Equation 4). The average TIS is the average time in the system for all of the N workers that are completed in the time frame (Equation 5). The total cost for the additional employee resources is the sum of the amount of additional resource j times the hourly rate for that type of resource (Equation 6). Each MT m will require a non-zero amount of time $\Delta_{m,s}$ (Equation 7) in each stage s. The total time an MT m spends in the maintenance task process D_m across all stages S is expressed in Equation 8. Since each m must remain in the system for some non-zero amount of time, the summation of TIS for all completed MTs must be non-zero as well (Equation 9). To get the optimal T and N values the optimal employee resource changes $X_{j,f}$ are required to allow the system to operate efficiently. Please note the model is not intended to be used to solve it mathematically via commercial solvers as the intrinsic dynamics of the processes are nonlinear and stochastic in nature. Rather, we describe the problem as a base to be used by the simulation-based SDT.

$$\min : T \tag{1}$$

$$\max : N \tag{2}$$

$$C \leq B \tag{3}$$

$$0 \leq \sum_{l}^{|L|} X_{j,l} \leq M_j, \, \forall j \tag{4}$$

$$T = \frac{\sum_{m=1}^{N}(D_m)}{N} \tag{5}$$

$$\sum_{l}^{|L|}\sum_{j}^{|J|} X_{j,l} * H_j = C \tag{6}$$

$$\Delta_{m,s} > 0, \; \forall \; m,s \tag{7}$$

$$D_m = \sum_{s=1}^{|S|}(\Delta_{m,s}), \; \forall m \tag{8}$$

$$\sum_{m=1}^{N}(D_m) > D_m > 0, \forall m \tag{9}$$

5 SIMULATION-BASED FRAMEWORK

This work aims to create a framework for generating an SDT of the MT process and its various stages. The SDT focuses on modeling the aspects of the process that allows the model to mimic the throughput, average time in stages, and TIS for the real-world process to be used for optimization. The digital model of the process is then used to simulate and optimize the employee resource configuration to minimize overall TIS and maximize the throughput while maintaining a set budget for the additional hourly cost of acquiring new employee resources. The framework consists of data analysis to quantify the stochastic and statistical behavior of portions of the process and discussions with the subject matter experts (SMEs) with first-hand experiences. The analysis and discussions allowed the pertinent portions of the process to be identified and modeled.

5.1 Modeling the Structure and Behavior of a Maintenance Task Process

The process of developing the SDT is illustrated in Figure 2. Data provided from a real-world MT process for a mission-critical facility is analyzed for descriptive statistics, fitted distributions, and frequency ranges for various attributes. This information is used to generate a data set that mimics its structure and statistics. The statistical findings are used to model stochastic processes in the SM, where the features of the MT agents are drawn from these statistics and distributions. This dataset is used in DDM. Many of the timing statistics such as arrival rates and TIS follow long-tail distributions such as that seen in Figure 1 meaning that while many may pass through the system in a few days or months, some will be in the system for over a year. Such long-tailed distributions often make the task of planning for the MTs very difficult.

In order to gain deeper insights into the MT process from those SMEs, an iterative process is adopted for interviews and discussions. We then break down the detailed MTs of each sub-process and the steps and resources required. After iterations of data analysis, process mapping, model construction, simulation, and verification, the SDT gradually takes shape. The analysis of the results of the simulations and further discussions allow adjustments based on insights and understandings not found through data analysis. Over time, the model encompasses enough details that are closer to the structure observed in the real-world process and becomes an SDT. This work models the sequential stages of *request*, *approval*, *prioritization*, *planning*, *scheduling*, *execution*, and *completion* as illustrated in Figure 2. Figure 2 also shows a visualization of the high-level process for constructing the SDT.

The following section describes the model architecture, followed by the simulation settings.

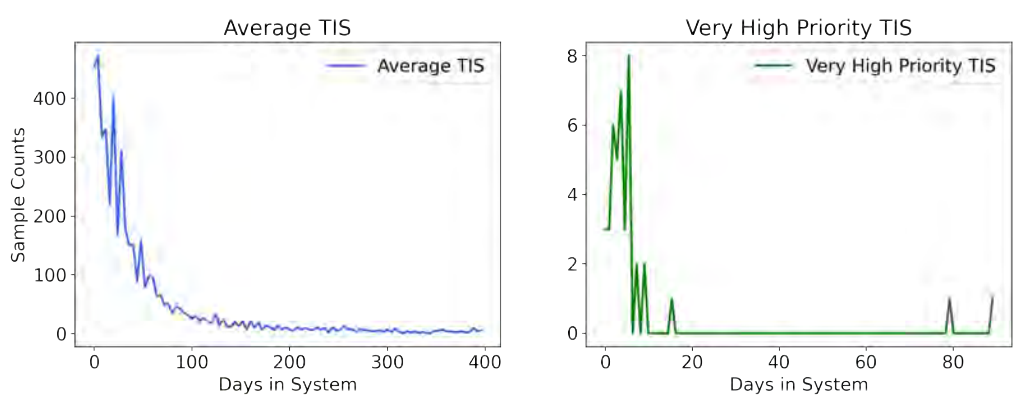


Figure 1: TIS distribution for overall TIS (right) and for very high priority MTs (left)

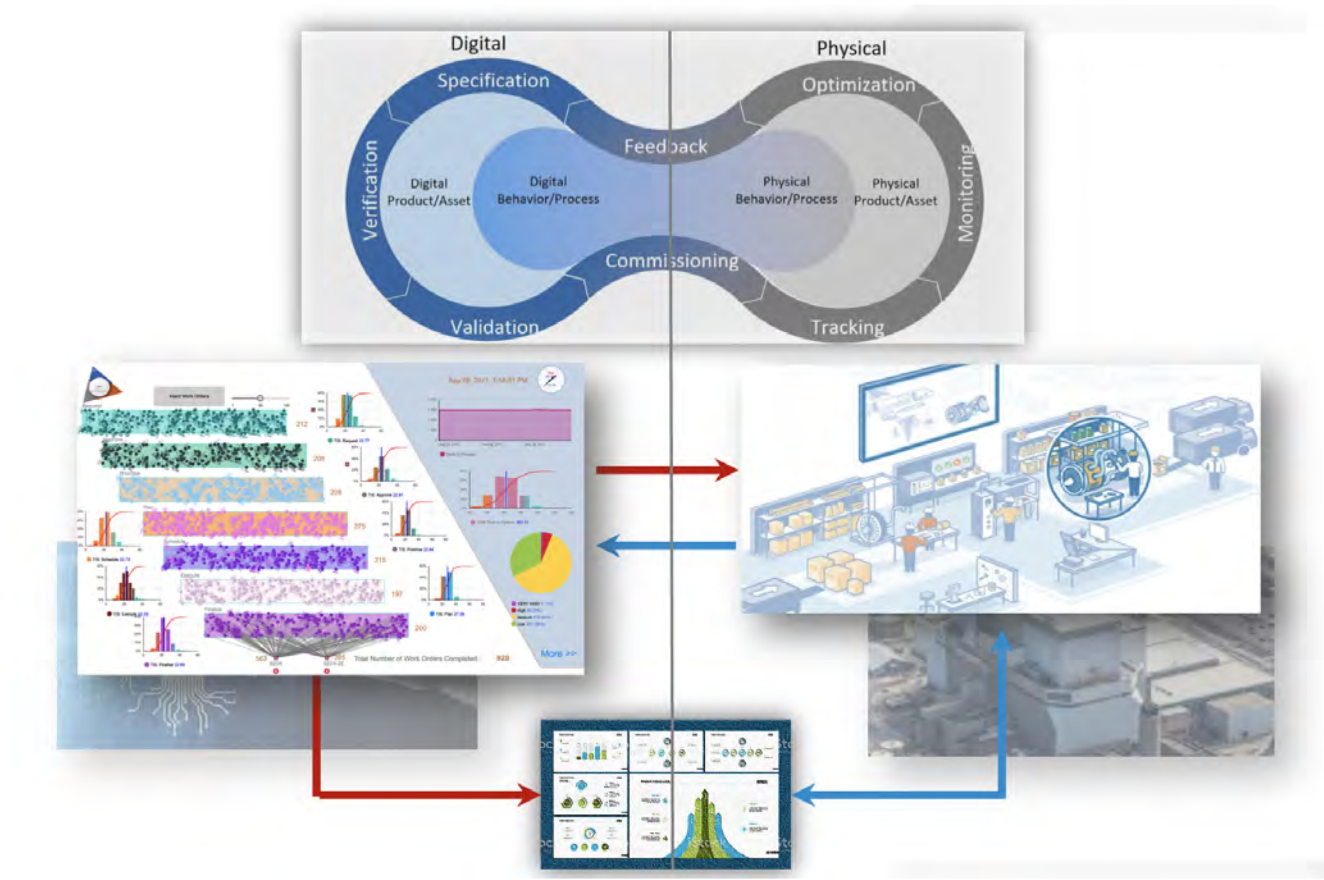


Figure 2: Illustration of MT process simulation model as an SDT: MT process and data are obtained to construct the simulation model, which guides the management to make operation decisions. Actual system operational data are collected to feed and update the simulation model. Such an iterative process continues to improve the overall SDT.

5.2 Model Architecture

For each stage of the process, as the MTs arrive, they are placed in a queue for that stage. From the highest to lowest priority, the MTs will attempt to acquire the necessary employee resources and have them process the MT. If the resources are available, the MT will seize them. Employee resources can only process one MT at a time. The MT will undergo a delay for the stage based on the MT agent. For the DDM, MT agents have individual times for each stage determined by the data. For the SM the time is generated based on the distribution for that stage, either through bootstrapping or a fitted distribution. The overall time in each stage is split between resource-based processing time and the time that is intrinsic to that stage. Once this time is complete, the MT is passed on to the next stage's queue.

The model treats the MTs and employees as agents. Hence, the simulation model is in fact a hybrid of discrete event and agent-based model. The MT agents have characteristics that drive their path through the process, such as timing rates, assigned locations, and priorities. The employees are represented as agents that process MTs at each stage based on their role, which determines which MTs and at what stage they interact with them. The nature of the MT characteristics depends on which of the models is the subject of discussion. For the DDM, the majority of MT attributes come directly from the data, while for the SM, the MTs are generated at simulation time with attributes based on the statistical analysis results.

There are two main types of employee resources or agents in the model. First, the administrative employees are resources for the non-labor stages of the process. These resources are utilized in financial approval, prioritization, planning, scheduling, and completion stages. Second, the labor workers' employee resources model the specialized and physical laborers who must complete the MTs. Each MT requires one or more labor agent resources of varying specializations determined by the MT.

The model consists of the MT and employee agents and a network of stages through which they interact. The steps in the MT process are modeled as a network such that each is moved from the request, approval, prioritization, planning, scheduling, execution, and completion stages in sequential order while allowing for cycles at the approval and execution stages (Figure 2).

At each stage, the MTs agents interact with the employee resources for that stage. The approval, prioritization, scheduling, and completion stages require some amount of administrative employee agents to be processed. The planning stage requires at least some administrative agents and possibly some craft or labor resources as well; but for the SDT, this aspect is only modeled as a time delay and planner resource acquisition. Finally, the execution stage uses labor agents, and during this stage, each MT agent must be processed using some amount of each of the differing types of labor agents based on the plan created during the planning stage.

5.3 Model Approaches

The DDM and SM both share the same structure for modeling the process. The multi-stage process and logic for possible cycles are shown in figure 2 in the left panel of the figure. While both the DDM and SM models share the above described MT process structure, the differences lie in the processing of the MT at the various stages. For the DDM, the arrival date, location, resource needs, priority, and time in the planning, execution, and completion stages come directly from the data that mimics real-world MT data. For the SM, the arrival rates, time in planning, execution, and completion stages are generated using the best fitted and bootstrapped distributions using the data that drives the DDM. DDM is used as for model verification and validation. SM can be used for prediction, multiple runs, and optimization as it has incorporated the embedded stochasticity.

5.4 Simulation Settings

The simulation utilizes a roughly 3-year time window that is based on real-world data. The original start and end dates for the simulation are based on the earliest, and latest complete MT data. The time window is reduced by three months for the optimization experiment to maximize the throughput of MTs in a reduced period. The simulation only allows for queue processing during a 10-hour per day, 4-day work week, and outside of these times, queues are not processed except in the execution stage when there are very high-priority MTs queued. The employee agent resource counts match closely the real-world employee resource information and the "normal" work hours are based on the facility we received the data from. For the comparison of the models, the model was seeded with the same random number seed to compare the results in similar situations. For the crew resource experiments, the simulations are allowed to be randomized, and the average behavior of the resulting simulations is used. During the simulation, the maximum number of additional employee resources of any type is set to 10, and the additional hourly budget is set to $2,000. These numbers are chosen based on the discussions with the SMEs. The hourly costs for the various labor resources are based on the local area's average hourly rates.

6 SIMULATION ANALYSIS METHODOLOGY AND RESULTS

6.1 Simulation Analysis Methodology

The comparison of the SM and DDM models shows that the DDM most closely models the behavior of the MT process based on the number of MTs completed in the time frame, the average overall TIS, categorical

(a) Execution time vs crew size. *N*+craft means *N* extra agents for all craft types.

(b) completion time vs crew size. *N*+craft means *N* extra agents for all craft types, *PN* indicates *N* extra planners.

Figure 3: Sensitivity analysis of execution time and completion time

distributions such as that of the MTs across the different locations, and priorities present in the process. Therefore, the final model used for the optimization analysis uses most aspects of the DDM, with some stochastic elements for rates of MTs processed in the prioritization and scheduling weekly stages.

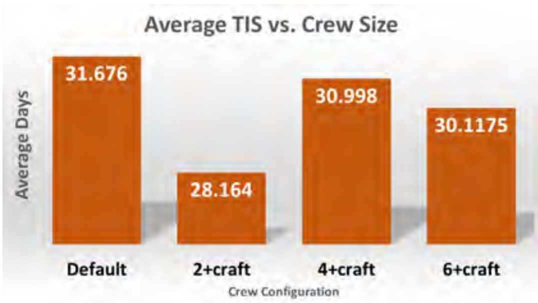
The first set of experiments tests the sensitivity of the average TIS, time in execution, and time in completion as the number of each labor agent type is increased by units of 2 up to 6 more of each of the machinists, pipefitters, painters, laborers, carpenters, and electricians. Next, the same increases in labor agents are performed along with the increases to the planner resources of units of 2 up to 4 additional planners. Finally, the effect of these blanket resources on timing characteristics over five randomized simulations is averaged, compared, and analyzed. The execution and planning stages were focused on because those were some of the known bottlenecks according to the SMEs.

There are two optimization experiments performed using the OptQuest Optimization Engine provided with AnyLogic. The optimization experiments are intended to test the models' ability to independently optimize the numbers of the various labor and planner agents to find the optimal amount of each. The first goal is to optimize the labor and planner mixture to minimize average TIS compared to the systems default distribution. The second optimization task involves comparing the default employee mixtures amount of MTs completed in the full simulation time to optimize the labor and planner agents to maximize the number of MTs completed within three fewer months. For the former optimization, an objective of minimizing the average TIS is set, and for the latter, an objective of maximizing the throughput is set as the objective. The optimizations vary the number of the additional employee resource types from none to ten to find one that optimizes the objectives.

6.2 Analysis Results

The simulation results show interesting relationships and how increasing the available resources for one stage can affect the next. Figure 3 shows the results on average execution (Figure 3a) and completion (Figure 3b) times as the number of labor crew are increased by units of 2. The variance of the results for all execution time tests is less than a day with a maximum of .3 for the default settings and a minimum of .004 for the +6 settings. The completion time tests show the variances of .02 for the default and +2 configurations, and .04 and .03 for the +4 and +6 configurations. Figure 3a demonstrates how increasing labor resource sizes reduces average execution times, while figure 3b shows the opposite effect on the time spent in the completion stage. The results show that as one increases the throughput for the execution stage, the completion step has to deal with the increased rates of MTs to process and, as a result, see an increased average completion time.

Figure 4a depicts the results of changing the labor agent sizes by units of 2 on the overall TIS. The averages reported in Figure 4a are associated with variances of around 2 days for all but the +4 version

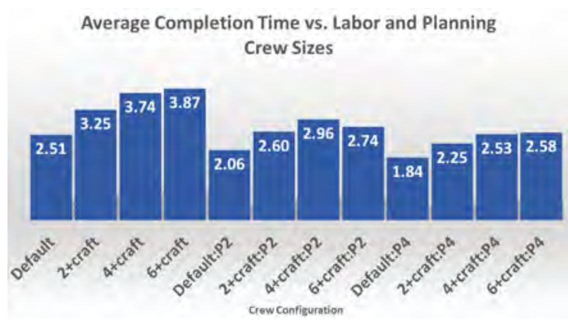


(a) Average TIS vs. crew size comparison. *N*+craft means *N* extra agents for all craft types.

(b) Average execution time comparison for increased labor and planner agents. *N*+craft means *N* extra agents for all craft types, *PN* indicates *N* extra planners.

Figure 4: Sensitivity analysis of TIS and average execution time

(a) Average planning time vs. crew & planning resource increases. *N*+craft means *N* extra agents for all craft types.



(b) Average completion time vs. crew & planning resource increases. *N*+craft means *N* extra agents for all craft types, *PN* indicates *N* extra planners.

Figure 5: Sensitivity analysis of average planning & completion times to crew and planning increases

which has a variance of .3. These results suggest that while the +4 does have a smaller overall average, the +6 version can end up with higher TIS in some cases. While increasing the crew sizes of the specialized workers by 2 does see a decrease in the average TIS, further increases see smaller decreases. The cause of this can be seen in Figures 3a and 3b. When only increasing the craft agents and thus the throughput through the execution stage, there is an increase in completion time. Thus, the increased TIS overall is due to the increased completion time as discussed above. This result leads to testing the sensitivity of the execution, planning, completion, stage times, and average TIS to increased labor and planner resources.

The experiments comparing the average TIS, execution, planning, and completion times resulting from increased labor and planning agents can be seen in Figures 4b, 5, and 6. Figure 4b shows that increasing planner agents has no appreciable effect on the average execution time and that only the increases in labor agents result in a reduction. For these tests, the variances are less than a day for all but the “+6 craft:P2” which has a variance of around 3 days. Figure 5a shows that increasing the number of labor resources has no effect on the planning stage and that only increases to the planners’ decreased time in the planning stage. Figure 5b shows that increased labor agents do increase completion time with the default number of planners as before, but when the planners are increased, the effect is reduced. The variances for both the planning and completion time tests are all below one day (.008 to .02 days).

Figure 6 details the change in average TIS as both labor and planner agents are increased. The trend line on the figure does indicate a downward trend in average TIS but the results indicate that the decrease is relatively small and fairly non-linear. Potentially this comes from the fact that only two of the stage resources are modified. The variances in TIS for the tests seen in the figure are all-around 2 to 3 days except for the configuration with no additional planners and 4 additional craft resources which is 1 day.

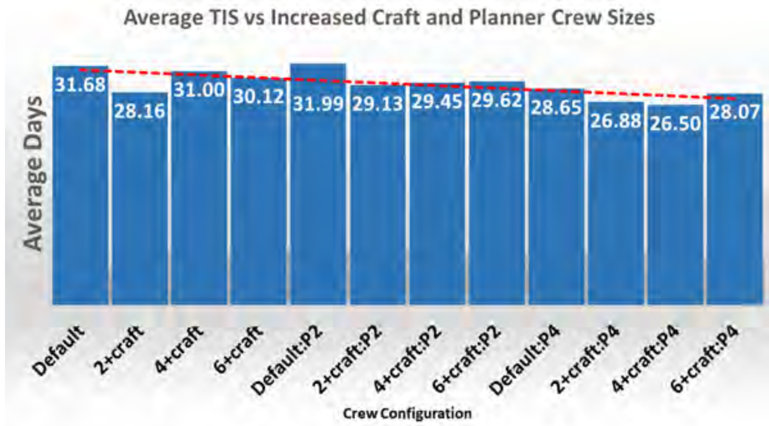


Figure 6: Average TIS vs labor & planner size comparison. *N*+craft means *N* extra agents for all craft types, *PN* indicates N extra planners.

Table 2 details the results of running optimization experiments for deciding on the correct number of each type of labor resource individually. The results indicate that by increasing various crews, as seen in Table 2 a reduction of nine days for the TIS can be achieved at the cost of an additional $761.09/hour of the labor resources. For the optimization to maximize the throughput of MTs with a reduced time frame, seen in Table 3, a decrease of 4% can be achieved. However, this reduction requires an additional $1014.73/hour of labor resources. While these results are preliminary and illustrative, they have been verified by the SMEs. Detailed data with MTs and crew mixture utilization are being collected that could be potentially used to update the SDT for greater granularity.

Table 2: Comparison of base crew sizes and optimal crew sizes for minimizing TIS (days)

Agent Type	**Optimal Size**	**Base Size**	**Increase**	**$/hour Increase**
machinists	5	5	0	0
pipefitters	13	8	5	139.25
painters	12	2	10	196.80
laborers	16	9	7	117.10
carpenters	11	2	9	209.61
electricians	20	16	4	98.32
Crew Size	**TIS**	**Decrease (days)**		
Optimized	14.936			
Base	24.168	9.23		
Additional $/hour	761.09			

7 CONCLUSIONS

The framework laid out in this work details the process of modeling a maintenance task process with both data-driven method and stochastic modeling approaches to constructing a modeling and simulation tool as a "soft digital twin". The analysis and modeling methods can be applied to any maintenance process to build an accurate system model capable of providing a "crystal ball" for management to reveal the optimal crew configurations. Initial simulation experiments show that the SDT can be used to find the optimal

Table 3: The difference between the amount of MTs completed with the original simulation time and a 3-month reduced simulation time and how the crews differ.

Agent Type	Optimal Size	Base Size	Increase	$/hour Increase
machinists	13	5	5	186.48
pipefitters	15	8	13	194.95
painters	11	2	2	177.12
laborers	15	9	7	100.38
carpenters	12	2	9	232.90
electricians	21	16	17	122.90

Crew Size	MTs Complete	% Decrease
Optimized Reduced	4813	
Base Time Span	5008	4%
Additional $/hour	1014.73	

crew configuration and it can also be utilized to experiment with different process structures as "what-if" analyses. Simulation results also reveal how increasing the amount of a given crew type may affect the MT stages and how alterations in one stage may affect the preceding stages in the system, indicating the strong interconnectivity among the MTs process.

The optimization experiments indicated that the average TIS could be minimized, and the throughput under time constraints can be maximized when the appropriate crew mixture is utilized with a certain cost. Management can then utilize the framework to build their own SDT of a similar process and search for the optimal employee resource configurations. The construction of the SDT requires the analysis and exploration of the MT process. In return, the SDT can provide insights into possible bottlenecks and root causes of inefficiency in the process. Thus, the construction of the SDT not only provides a tool to help optimize the process and increase reliability but also helps gain a deeper understanding of the system itself.

There are a few limitations to the study. First, the SDT was built around a specific real-world case. Although it is somehow representative of MT processes, it may not be applied to other facilities without significant modification to the model. Second, this is a preliminary feasibility study of using simulation as an SDT. More rigorous evaluation, verification, and validation are still needed to be conducted. Future work for this framework includes incorporating mechanisms for adjusting the structure of the process, such as modifying the rate of weekly stages, allowing for cost minimization while maximizing the number of MTs completed, or minimizing average TIS or some combination of the three. Further granular operations of the MTs can be added to the SDT.

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