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DISCOVERING SIMULATION MODELS FROM LABOR-INTENSIVE MANUFACTURING SYSTEMS

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ABSTRACT

Simulation modeling has become essential in industries for enhancing processes, improving efficiency, and mitigating risks within manufacturing systems. However, the automatic discovery of these models remains challenging, particularly in labor-intensive manufacturing systems (LIMSs), which are widespread in industries like food or apparel manufacturing. LIMSs are characterized by the central and direct involvement of human operators throughout the value chain. In this paper, we investigate state-of-the-art modeling approaches for capturing behaviors of human operators in LIMSs and examine their implications for extracting simulation models. Specifically, we use these insights to automatically extract a simulation model of LIMSs as a stochastic Petri net (SPN): this SPN explicitly models operators' fatigue and its impact on task durations. Our research contributes to laying the groundwork for developing Digital Twins for LIMSs. By automating model creation and ensuring continuous updates, our approach facilitates the automatic adaptation of simulation models to reflect changes in the system.

1 INTRODUCTION

Simulation modeling has emerged as an essential tool for industries seeking to improve processes, increase efficiency, and mitigate risk in manufacturing systems. Simulating different scenarios and predicting system behaviors provides invaluable insight for decision-making and performance improvement. Companies are recognizing the significance of simulation in optimizing resource allocation, scheduling, and throughput, ultimately leading to cost savings and competitive advantages (Kormin et al. 2021).

Typically, simulation models are developed manually in collaboration with domain experts. While effective, this approach can be labor-intensive and time-consuming (John and Heavy 2006). Furthermore, the static nature of manually developed models poses challenges in rapidly evolving manufacturing environments where adaptability is paramount (Robinson 2014).

To address these limitations, data-driven approaches to simulation modeling have gained traction in recent years (Tao et al. 2019). By leveraging operational data collected from various sources, such as sensors, Industrial Internet of Things devices, and production logs, and applying advanced analytical techniques, such as machine learning algorithms, statistical analysis, and process mining, these approaches enable automatic and continuous model discovery and updates (Reza and Behzadan 2013). These data-driven methods streamline the model development process and ensure that models accurately reflect the complexity and dynamics of the real world (Friederich and Lazarova-Molnar 2022). While manually developed models and data-driven approaches can achieve similar capabilities, the key difference is that data-driven models can be automatically updated, providing continuous adaptability to changing production conditions.

Labor-intensive manufacturing systems (LIMSs) involve production processes that heavily rely on manual labor for tasks where human operators form the backbone of value-generating operations. These systems often require human operators to perform intricate tasks that are difficult to automate efficiently. Industries, such as textiles, home fixtures and fittings, furniture, travel goods, apparel, and footwear are well-known examples of labor-intensive manufacturing sectors (Hanson 2021). Despite advancements in automation technologies, the unique characteristics of these industries still necessitate heavy human involvement. Consequently, data availability is restricted as human operators cannot be monitored as easily and freely as machines. This limitation arises from both data privacy legislation and the potential physical and psychological strain on humans, which likely will negatively impact performance, stress, work motivation, satisfaction, and behavior (Smith et al. 1992; Backhaus 2019). Additionally, sensors for collecting data points of human operators need to be as non-intrusive as possible, and their introduction should be communicated in a manner that fosters intrinsic motivation and support from the workers to mitigate the aforementioned issues. As a result, research on data-driven simulation model extraction in LIMSs has been scarce. However, the discovery of such simulation models could unlock the potential for labor-intensive manufacturing companies to enhance processes by factoring in human elements like motivation, fatigue, and emotional states. This informed decision-making facilitates efficient resource allocation, ultimately enhancing workers' well-being, productivity, and product quality (Götz and Lazarova-Molnar 2024). In this paper, we propose a data-driven methodology for discovering simulation models of LIMSs, focusing on integrating human factors like fatigue in the derived models.

The paper is organized as follows: In Section 2, we provide background information and review related work. Section 3 presents a detailed description of our methodology for extracting simulation models of LIMSs. We illustrate the application of this methodology through a case study in Section 4. Finally, we summarize our findings and outline avenues for future research in Section 5.

2 BACKGROUND AND RELATED WORK

In the following, we provide an overview of related work on modeling human operators in manufacturing systems and background on simulation modeling relevant to our approach discussed in Section 3.

2.1 Approaches for Modeling Human Operators in Manufacturing Systems

Modeling human operators in manufacturing systems is a complex task. Modeling involves, e.g., deciding on relevant features to be captured, setting up data collection for relevant aspects of human behavior, such as cognition, emotions, and interactions within a dynamic and multifaceted environment, as well as finding appropriate ways to model these aspects. This complexity is further increased in LIMSs, where humans play a central role in manufacturing processes. Therefore, accurate modeling of operators is essential for the simulations to represent the corresponding real-world systems correctly. Despite the inherent complexity and associated challenges, numerous efforts have been made to integrate human factors into existing simulation frameworks, as detailed in Table 1. In the table, we classify existing approaches to model human operators into three categories: discrete, continuous, and agent-based, providing modeling goals, data requirements, and key performance indicators (KPIs) for each approach. In the following, we describe each category and the corresponding approaches in detail. This informs us how the models have been adjusted and guides our research on what to consider to automatically discover these additional aspects from data.

2.1.1 Discrete Models

Certain methodologies involve representing human operators in a discretized fashion. This means that the behaviors of human operators are viewed through a series of events or state changes that happen at specific points in time, neglecting continuous changes that happen in between (Varga 2001; Borshchev 2013). E.g., fatigue can be segmented into three distinct categories: “fit”, “tired” and “fatigued”. However, when dealing with discretized factors or attributes, it is essential to acknowledge that introducing discretization to a continuous phenomenon, such as fatigue, inherently introduces error. If this error is significant or not, needs to be evaluated each time as it depends on both the discretization method employed and the specific context in which the discretized value is utilized.

Peças and Semeano (2019) explored the impact of worker performance variations on overall system efficiency in an industrial assembly setup using discrete event simulation. To ensure realistic representation of a worker’s performance, the authors drew on data from one of their previous industrial studies in which

Table 1: Approaches for modeling of human operators in the literature.

Modeling approach	Reference	Simulation/ Modeling Goal	Data Requirements	KPIs
Discrete Models	(Peças and Semeano 2019)	System Performance Analysis	Task Completion Times	System Cycle Times
	(Vilela et al. 2020)	System Performance Analysis	Task Completion Times	Throughput
	(Lämkull et al. 2009)	Evaluate Ergonomics Simulations' Accuracy	Anthropometric data, e.g., weight, height, and waist circumference	Volvo Car Corporations Ergonomics Requirements
Continuous Models	(Lassila et al. 2005)	Bottleneck Identification	Processing, transfer, setup, and rework times of products	Average Lead Time
	(Baines et al. 2004)	Improve Simulation Accuracy and Reliability	Human operator age, current shift length	Cycle Times
	(Perez et al. 2014)	Improve Human Operators Well-Being	Biomechanical, maximum endurance time, tasks durations, recovery durations	Cumulative Production
	(Abubakar and Wang 2019)	Human Operator Performance Analysis	Age, experience, cycle times, total count of units to be assembled	Task Completion Time
	(Ferjani et al. 2018)	Enhance Worker' Performance and Well-being	Number of task repetitions, and impact of environment and machines like noise levels or temperature	Satisfaction Level and Error Rate
	(Baskaran et al. 2019)	Analyze Ergonomic Impact	Biomechanical and anthropometric data of human operators	Human Operator Well-Being
Agent-based Models	(Liu et al. 2023)	Analyze the Impact of Fatigue on Productivity	Work duration, skill levels	Makespan
	(Sammarco et al. 2014)	Improve Production Performance through Dynamic Worker-Assignment	Work schedule, task durations, operators' skillsets	Production Rate, Flowtime, Utilization Mean Switch Rate

they observed workers in an assembly cell. They categorized the workers into four performance classes based on task completion time and its variance. Their findings indicate that poorer performing workers substantially slow down system throughput, while higher performing workers only marginally enhance productivity. In a similar study, Vilela et al. (2020) analyzed how the performance of human operators affects the efficiency of the assembly line. To accomplish this, the authors divided the workday into four periods, during which the speed of the workers would fluctuate based on the collective state of the workforce. Rather than relying on specific attributes, such as fatigue, this state was inferred from real-world data collected within a company. From this data, the authors derived various distributions to determine the working speed for each of the four distinct workday periods. Lämkull et al. (2009) investigated the predictive accuracy of ergonomics simulations for manual assembly tasks. They evaluated the economic implications of 155 simulation cases involving three distinct operators. Comparing the simulation results with data gathered from interviews, they concluded that the simulations effectively predict ergonomic challenges.

2.1.2 Continuous Models

Unlike discrete models where events or state changes occur at specific points in time, continuous models allow for state changes to happen continuously over a time interval. These changes are gradual, providing a more nuanced understanding of human behaviors and interaction dynamics since these phenomena are also continuous in nature (Borshchev 2013). It is, however, important to note that while continuous models provide greater precision, they can also introduce higher complexity. E.g., rather than representing fatigue as three distinct levels, it can be modeled as a continuous gradient from low to high.

An early effort in modeling human operators was made by Lassila et al. (2005) in which the authors tried to identify bottlenecks in a LIMS. For this reason, the authors modeled human workers as processes with scheduled availability and limited capacity. The resulting model showed that buffers between operations accounted for most of the product's lead time. Baines et al. (2004) tried to improve simulation accuracy and reliability by including age- and fatigue-related effects in the human model. To achieve this, the authors successfully implemented a circadian rhythm for fatigue and made the performance of the human operators dependent on their age. Similarly, Perez et al. (2014) tried to incorporate fatigue into their human operator model. They inspected four different equations proposed in the literature on how fatigue accumulates and dissipates based on maximum endurance times. In 2019, Abubakar and Wang (2019) presented an extension through which human elements could be integrated into a DES model. They showcased how the human elements significantly impacted the assembly time of their LIMS of interest. Their extension, AutoHmot, considers human operators' age, experience, cycle time, and total count of units to be assembled, to calculate their current task completion speed. Ferjani et al. (2018) propose a method for integrating fatigue into simulations. They successfully combine Discrete-Event Modeling, Multi-Agent, and System Dynamics into a single framework. This framework allows managers to comprehensively evaluate manufacturing systems by considering the evolution of human operator fatigue throughout their work, enabling informed decisions regarding work schedules, facility layouts, and rest periods. Human operators are modeled as agents and have a fatigue function attached that is modeled using differential equations. Baskaran et al. (2019) focused on analyzing ergonomics in an automotive assembly process. In the simulation of the assembly process they modeled human operators in a human Digital Twin using biomechanical, anthropometric, and ergonomic characteristics tables as basis. With this human Digital Twin, the authors analyzed how high the strain on the lower back is when doing physically demanding overhead assembly operations. With their study, Baskaran et al. could show that it is possible with their simulation to generate ergonomic reports based on which improvements in the work environment could be achieved.

2.1.3 Agent-based Models

Agent-based models (ABMs) use individual entities, termed agents, each featuring autonomous behavior and interacting within a simulated environment. ABMs aim to capture emergent phenomena stemming from the interactions among agents and enable the examination of system-level dynamics, driven by individual agent behaviors rather than hardcoded rules, resulting in a more realistic representation of real-world systems. It is, however, important to acknowledge that while ABMs offer high fidelity in capturing complex interactions, they can also pose computational challenges. This is due to the complexity of simulating numerous autonomous entities and their interactions with each other and the environment (Wu et al. 2023).

In relation to LIMSs, Lui et al. (2023) developed an agent-based model to simulate a production shop floor with multi-skilled workers and fatigue factors, aimed at investigating the hybrid flow shop scheduling problem, first formulated by Arthanary (1971). Worker agents in this model are characterized by two primary features: fatigue accumulation over time, and multi-skilled capabilities for performing multiple tasks within the manufacturing system. One notable result of the study is the demonstration that the constructed agent-based model can express the influence of uncertainty and dynamic factors better than conventional mathematical models. In another study, Sammarco et al. (2014) explored the outcomes of various dynamic worker-assignment strategies by developing an agent-based simulation, where workers, workstations (WSs), and products are modeled as agents. Additionally, Sammarco et al. implemented a set of rules that determined when and which worker is doing what task, when workers are available and which worker is doing the next task. Through their study, the authors could showcase that, e.g., depending on the employed rules, a reduction in mean flowtime of 15% to 30% was possible.

2.1.4 Findings

In our literature review, we observed that discrete-event models tend to be employed frequently for modeling higher-level or aggregate characteristics, by distinguishing, e.g., between high- and low-performance workers/teams. Conversely, continuous models and functions are predominantly utilized to describe specific attributes of individual human operators, such as fatigue or skill level. Generally, researchers tend to prefer continuous models over discrete ones when describing the characteristics or behavior of human operators. This preference seems logical since studying these characteristics is typically the focus of those studies. By selecting continuous attributes, researchers can avoid discretization errors or inaccuracies in the values, thereby strengthening the insights generated from these studies. Moreover, we discovered numerous studies that focus on fatigue and its impact on performance and productivity, exceeding the research on other related topics. This signifies a high demand for accurate fatigue models as part of more comprehensive LIMS models. However, many of these LIMS models are constructed manually rather than using data-driven approaches. Consequently, these manually constructed models often become outdated quite fast, particularly in fast-paced LIMSs' environments. Therefore, the goal of this paper is to provide an initial methodology to discover simulation models through data that not only describe the production system but also the effects of fatigue experienced by human operators throughout their shifts.

2.2 Data-driven Simulation Model Discovery

Simulation models, designed by domain experts with deep understanding, have historically delivered accurate representations of complex systems, however, demanding significant time, labor, and iterative refinements. The challenges of constructing simulation models become particularly pronounced in the context of highly adaptable systems, like manufacturing environments that demand rapid responsiveness to shifting requirements such as external demand changes or fluctuations in resource availability. In these scenarios, the hand-crafted simulation models face a diminishing validity period, raising questions about the proportional alignment of time and monetary investments with the resultant benefits.

To address these challenges, there have been a number of data-driven approaches for automatic model discovery. These approaches facilitate simulation models that adapt in (near-)real-time to changes in the corresponding systems, ensuring ongoing accuracy of the model in mirroring real-world conditions. Such changes may involve reconfigurations as well as significant changes to the systems, such as updating the material flow or introducing new WSs. These data-driven models can dynamically update their structures and parameters to match changed conditions in the systems. This adaptability not only enhances the robustness and flexibility of simulation models but also reduces the time and effort needed for model development and maintenance. Moreover, by continuously learning from new data and feedback, data-driven simulation models can refine themselves iteratively, improving their accuracy and predictive capabilities as they evolve. In this paper, we explore the utilization of process mining techniques to discover simulation models for LIMSs, as detailed in Section 3. Several studies have used process mining techniques in conjunction with event logs to discover simulation models, often in the form of various Petri net variants. Friederich and Lazarova-Molnar (2022, 2021) employed these methods alongside conditional data, describing machine states, to derive reliability models in the form of stochastic Petri nets (SPN). Maggi et al. (2014) extracted a hierarchical hybrid model by applying a context analysis algorithm to the event log, effectively distinguishing between structured and unstructured events. Furthermore, colored Petri nets mining has also been explored in (Knopp et al. 2023; Rozinat et al. 2008; Van Der Aalst and Van Dongen 2013).

3 METHODOLOGY FOR EXTRACTING SIMULATION MODELS

In the following, we outline our approach to extracting simulation models from event logs of LIMSs. In particular, we explore the impact of human factors, such as fatigue, on these systems. Building on our previous work in which we introduced our framework for creating Digital Twins for LIMSs (Götz and Lazarova-Molnar 2024), our approach consists of two main steps. First, we extract a *basic model* with key details about the manufacturing setup, including layout, process times, and dependencies. Subsequently, we enhance this model with fatigue models for the human operators, resulting in what we call a *human-centric model*. We validate our approach by comparing KPIs derived from the extracted simulation model to those from the original model using confidence intervals.

3.1 Data Requirements

Event logs constitute the foundational data source for process mining. In our case, a row in an event log contains a timestamp, an order ID, a resource, an activity, and an event. An excerpt of the used event log is shown in Table 2. Moreover, we need data outlining workers' shifts and breaks, specifically their start and end times, respectively. Ideally, these details are presented in a similar format as the event log data. Building on Friederich and Lazarova-Molnar's approach (2021, 2022), we also generate reliability models automatically. This involves maintaining an additional state log that records machine failure and repair events.

We utilize event and state logs for their common availability in manufacturing environments, eliminating the need for additional sensor installations. This streamlines the adjustment period and enhances workforce acceptance, as there is no need for adaptation to a new environment. This reduces the potential for psychological strain, as outlined in Section 1. Furthermore, this setup also eases data privacy challenges by abstaining from the use or storage of user-specific data that could be traced back to individual workers.

To enhance quality and completeness of the data, we excluded each order that lacked data on certain events, particularly if the storage events are missing as these are the last events tracked in our production process and indicate a full production cycle. These exclusions might occur if sensors are not working correctly, or the production process is not finished at the time the dataset was extracted. Furthermore, all shifts that have fewer or more tasks completed than predefined thresholds were also excluded as these shifts are outside of realistic task duration boundaries considering the typical time required to complete the tasks. This might be the case if machines fail, or the needed supplies are unavailable.

Finally, several additional key data points are derived from the event log. This involves calculating task durations using the timestamps of activity start and end events, determining the cumulative work time of each WS leading up to each event by summing previous process times within the corresponding shift and generating a binary-encoded column indicating whether a break occurred prior to each event.

3.2 Simulation Model Discovery

The simulation model extraction process extracts SPNs as *basic models* which are further enhanced with fatigue models in a subsequent step, resulting in more realistic *human-centric models*.

3.2.1 Basic Model

We extract *basic models* as SPNs from event logs using a customized version of the ddra library (Friederich 2023). First, we use the Alpha Miner (Van Der Aalst et al. 2004; Van der Aalst and van Dongen 2002) to discover Petri net of the LIMS, which primarily captures information about the production layout and dependencies. Next, we estimate probability distributions of transitions in the Petri net to capture task durations, thereby converting the Petri net into an SPN. This enables us to capture more detailed information about the manufacturing process. E.g., we can calculate the mean flow time of a production cycle, expressed in terms of KPIs like cycle time. Moreover, we can analyze whether the expected planned task durations align with the actual recorded task durations, facilitating a more comprehensive performance analysis.

To extract probability distributions for machine-only WSs, we can readily utilize the functionality of *ddra* with all available data points. However, for human-operated WSs, we developed a custom solution. For this, we combined Kolmogorov-Smirnov and Cramer-von Mises tests and considered only the first x data points, where x is a predefined threshold. We justify this approach by the assumption that the initial iterations contain minimal influence from factors such as fatigue, allowing us to extract process times that are relatively uninfluenced. Lastly, we utilize the *ddra* library to extract reliability models of machine WSs and integrate them through inhibitor arcs to the corresponding transitions.

3.2.2 Human-centric Model

After extracting a *basic model* that captures machines-related behaviors, our next step is to enhance it by incorporating fatigue models in the extracted SPN. Algorithm 1 shows our approach to extracting fatigue models. We assume that fatigue levels steadily rise throughout a shift and only reduce during scheduled breaks. Additionally, we assume that low levels of fatigue do not significantly influence overall task durations, whereas higher levels of fatigue do, increasing task durations (Abd-Elfattah et al. 2015). Our fatigue model extraction approach is split in two parts: 1. isolate effects of fatigue on tasks' durations (lines 4 – 13), and 2. train a polynomial model (lines 15 – 17) to capture fatigue given the cumulative task durations and if the break has occurred yet. To isolate the effects of fatigue on tasks' durations, we calculate the average duration of a predefined number of initial tasks for each shift (lines 4 and 6), assuming fatigue has minimal impact on these tasks, as discussed earlier. Then, we subtract this shift-specific average task duration from all task durations within that shift (line 7). The subtraction allows us to reduce the influence of the baseline task duration and focus on the effects of fatigue. The resulting values primarily reflect fatigue and are, hence, referred to as fatigue values. Note that fatigue values can also be influenced by other factors in real-world settings, such as operator mood, skill level, weather, or market demand. As our analysis is based on event logs, we lack the necessary data to refine our understanding of these values and proceed with the assumption that these values mainly represent fatigue.

Input : Event log as EL,
Set of identifiers for workstations with human operators as $WSH=\{WS_1, WS_2, ..., WS_n\}$,
Assumed number of process times with little fatigue as x_{pt},
Smoothing window size as x_{sws}
Output : Human operators' fatigue models aggregated per workstation as $FF=\{ff_1, ff_2, ..., ff_n\}$

1 **foreach** *workstationID* ***in*** WSH **do**
2 $EL_{ws} = EL$.select(workstationID == EL.workstationID)
3 **foreach** *shiftID in* $EL_{ws}.shiftID.unique()$ **do**
`// Isolate and smoothen fatigue values for each shift`
4 $EL_S = EL_{WS}$.select(shiftID isin EL_{ws}.shiftID)
5 $\overline{TD_{0-x_{pt}}} = EL_S.TD[0 : x_{pt}]$
6 $\overline{FV_{0-x_{pt}}} = \text{mean}(TD_{0-x_{pt}})$
7 $FV_{iso} = EL_S.TD$ - $\overline{F_{0-x_{pt}}}$
8 $EL_S.FV_s = FV_{iso}$.movingAvrg(window_size=x_{sws})
`// Fit logarithm function and transform fatigue values.`
9 EL_{SA}, $EL_{SB} = EL_S$.split($EL_S.hadBreak == 1$)
10 $logFunc_A$ = fitLogFunc(min($EL_{SA}.FV_s$), max($EL_{SA}.FV_s$), mean($EL_{SA}.FV_s$))
11 $logFunc_B$ = fitLogFunc(min($EL_{SB}.FV_s$), max($EL_{SB}.FV_s$), mean($EL_{SB}.FV_s$))
12 $FVA_t = logFunc_A(EL_{SA}.TD)$
13 $FVB_t = logFunc_B(EL_{SB}.TD)$
14 **end**
`// Train polynomial model`
15 $X = [EL_{ws}.TDcumsum, EL_{ws}.hadBreak]$
16 $y = EL.FV_t$
17 ff_{ws} = trainPolynomial(X, y, degree=4)
18 **end**

Algorithm 1: Extraction of fatigue models.

Subsequently, we preprocess the fatigue values to prepare the data for modeling. For this, we project the fatigue values onto a natural logarithmic space (lines 9 – 13). This transformation involves fitting a natural logarithm function for each shift to the fatigue values of the respective shift and applying it to the fatigue values. Specifically, we fit two logarithmic functions: one prior to the break and one after. Prior to fitting the logarithmic functions, a smoothing algorithm is applied to the fatigue values to mitigate the influence of outliers and extreme values (line 8). The smoothing algorithm calculates the mean within a predefined window size of 10 around each data point and replaces the original value with this smoothed value. Subsequently, the fitting of the logarithmic functions is done by using the non-linear least squares approach. For the first function, fitting is based on minimum, maximum, and mean fatigue values observed before the break, while for the second function, it is based on those observed after the break (lines 10 and 11). This ensures that each logarithmic function captures the relevant characteristics of fatigue within its respective phase of the shift.

The choice of mathematical model for representing fatigue, in our case the logarithmic one, is highly context dependent. Different contexts and types of fatigue may require different mathematical frameworks. E.g., experienced mental fatigue of office work might necessitate a different modeling approach compared to the physical fatigue encountered in construction work (Frone and Tidwell 2015). Therefore, the selection of the appropriate mathematical model should be guided by the specific characteristics of the assumed fatigue model and the trends present in the data.

Finally, with the fatigue values isolated, we train a n^{th}-degree polynomial model to predict fatigue (lines 15 - 17). This choice of model degree is determined through a grid search, ensuring its ability to capture the complexity of the fatigue data without overfitting. Our predictive model relies on two main features: the cumulative work duration at the time of fatigue prediction and a binary indicator for breaks. To improve the model's performance, we apply a logarithmic transformation to the cumulative work duration feature.

In conclusion, we developed an approach to capture fatigue in LIMSs. We assume fatigue levels rise steadily throughout a shift and decrease during breaks. After isolating fatigue effects on task duration, we preprocess fatigue values by projecting them onto a natural logarithmic space and fitting logarithmic functions. Finally, we train a nth-degree polynomial model using cumulative work duration and break status as features, ensuring robustness through grid search to prevent overfitting.

4 CASE STUDY

In the following, we demonstrate the effectiveness of the methodology outlined in Section 3 in extracting simulation models of LIMSs through a case study. We developed a simulation model of a LIMS based on insights gained from our project, where we collaborate with two companies that feature LIMSs. We use this model (which we term as original model) to generate data that we then use to re-discover the model.

4.1 Description of the LIMS Case Study

Our case study LIMS has four WSs on which either human operators or autonomous machines are working. In the first three steps, different assembly activities are performed and in the fourth step, the assembled goods are transported to storage by an AGV. Assembled items are transported from station to station via conveyor belts. WS1 and WS3 have one and three human operators working on them, respectively, and at WS2 and WS4, machines are used. Each WS's task durations follow different probability distributions (time unit is minutes). The assumed distributions are exemplary and have to be checked and adjusted to the given manufacturing context. E.g., human operator's tasks at WS1 have durations following a normal probability distribution with a *mean* of 10 *min* and a standard deviation (*std*) of 1 *min*. Furthermore, each 8-hour shift has one 45 *min* long break that occurs 4 *h* after the shift started. For human operators, task duration is influenced by their current fatigue level $F_i(t)$ which is utilized in the fatigue coefficient fc_i, as per Equations (1) and (2).

$$\mathrm{T}_i = fc_i * normal(mean, std) \tag{1}$$

The task duration T_i at task number *i* is calculated by multiplying the drawn base task duration of the normal distribution with the fatigue coefficient fc_i. This fatigue coefficient is determined as per Equation (2).

$$fc_i = \begin{cases} 1 & if\ F_i(t) \leq 0.25 \\ 0.75 + F_i(t) & otherwise \end{cases} \tag{2}$$

The fatigue coefficient fc_i is 1 if the current fatigue level $F_i(t)$ is less than or equal to 0.25, assuming low levels of fatigue have minimal influence on overall task durations. The current fatigue level ranges from 0 to 1, indicating no fatigue to maximum fatigue, respectively. If the current fatigue level is greater than 0.25, the fatigue coefficient is the sum of 0.75 and the current fatigue level.

The fatigue level calculations are derived from the work by Jaber et al (2013). For each operator, the new current fatigue level is calculated after he/she finishes a task using the following set of equations.

$$F(t) = 1 - e^{-\lambda t}, \tag{3}$$

where $F(t)$ denotes the fatigue accumulated by time t within the range of 0 to maximum endurance time (MET). MET refers to the length of time a worker can sustain a posture or effort before reaching the limits of their capability. Additionally, Equation (4) defines residual fatigue after a rest break of length $\tau_i > 0$.

$$R(\tau_i) = \mathrm{F(t)} e^{-\mu \tau_i}, \tag{4}$$

λ and μ represent fatigue and recovery parameters, respectively, which regulate the rate of fatigue accumulation and recovery. Lower values indicate slower fatigue accumulation or recovery, while higher values signify faster processes.

Notably, Equation (3) suggests that fatigue increases gradually over time *t*, beginning from an initial value of zero, indicating full recovery achieved during the previous rest break. However, real-world rest breaks between work repetitions are typically brief, not allowing complete recovery. Thus, residual fatigue $R(\tau_i)$ persists into the subsequent task repetitions, which is reflected in the updated Equation (5).

$$F_{i+1}(t) = R(\tau_i) + (1 - R(\tau_i))(1 - e^{-\lambda(t_n - t_i)}) \tag{5}$$

where t_n represents the production time at task number *i* and t_i is specified by projecting the value of $R(\tau_i)$ onto the fatigue curve as shown in Equation (6).

$$t_i = \frac{-\ln(1 - R(\tau_i))}{\lambda} \tag{6}$$

4.2 Results of the Model Discovery

To generate the necessary event log, we ran simulations for roughly 2000 á 8-hour shifts, generating around 382000 events and processing nearly 48000 orders. An excerpt of the generated event and state log as well as the predefined work schedule are shown in Table 2.

Table 2: Event and state log as well as the work schedule of the original model.

timestamp	orderID	resource	activity	event
14-02-2024 00:16:01	1244f84f-...	source	new_order	end
14-02-2024 00:16:01	1244f84f-...	Station1	assembly	start
14-02-2024 00:26:16	1244f84f-...	Station1	assembly	end
14-02-2024 00:26:16	1244f84f-...	Station2	assembly	start
14-02-2024 00:31:58	1893d6b4-...	source	new_order	end

a) Event log

timestamp	activity	event
14-02-2024 00:01:00	shift	start
14-02-2024 04:00:00	break	start
14-02-2024 04:45:00	break	end
14-02-2024 07:59:00	shift	end
14-02-2024 08:00:00	shift	start

b) Work schedule

timestamp	resource	state
14-02-2024 00:04:09	Station4	failure
14-02-2024 00:04:23	Station4	repaire
14-02-2024 00:05:44	Station2	failure
14-02-2024 00:06:08	Station2	repaire
14-02-2024 00:09:00	Station4	failure

c) State log

4.2.1 Basic Model

The extracted *basic model*, represented as an SPN, is shown in the dark grey part in Figure 1. This SPN encapsulates two primary components: the basic model component and the human-centric component. The main workflow is shown in the middle of the figure going from the (material) source through WSs 1, 2, 3, and 4. The fault loops of the machines are illustrated in the lower part of the figure. Above each transition, one to three aspects are outlined: the event, the extracted probability distribution, and for the tasks of human operators, fatigue functions are specified, which modify the drawn samples of the distribution during runtime. The fatigue functions are added during the enhancement of the *basic model* in the next subsection.

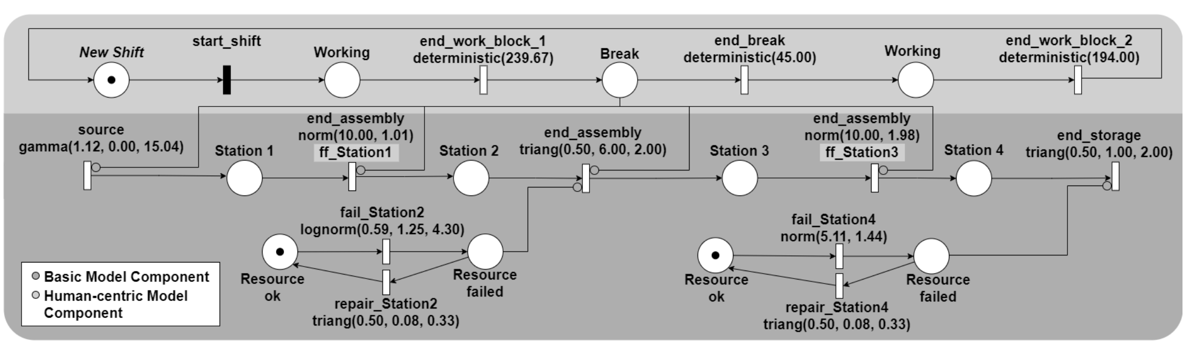

Figure 1: The extracted simulation model as an SPN.

4.2.2 Human-centric Model

We refined the *basic model* by incorporating human operators' fatigue and a break/shift loop in the SPN. The fatigue functions are attached to transitions related to WSs with human operators. For this, we trained a polynomial model to capture the extracted fatigue values. This model utilized the cumulative work durations of each worker and a binary feature indicating whether a break has occurred, as outlined in Section 3. After testing various functions, we concluded that the most suitable projection space for the fatigue values is a logarithmic one. Furthermore, utilizing grid search, we found that a 4th-degree polynomial model demonstrated the best performance. This resulted in achieving an average pairwise correlation score of 0.95 (Pearson) between the predicted fatigue values and the true recorded values along with a Root Mean Squared Error (RMSE) of 0.07. Figure 2 exemplifies the results of the fatigue function by displaying examples of three discovered fatigue functions for randomly selected work shifts. Finally, the break/shift loop and the fatigue functions, highlighted in light grey in Figure 1, are added to the SPN.

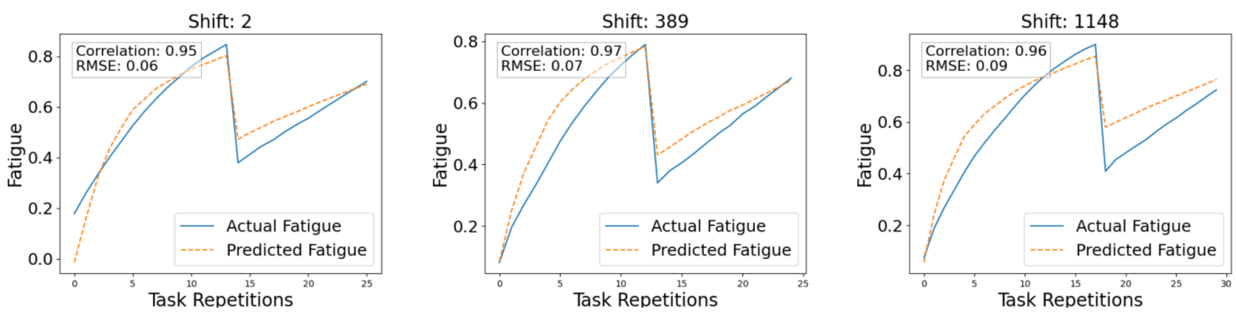

Figure 2: Comparison of three discovered fatigue functions with the original.

4.3 Evaluation and Discussion

In the following, we examine the results of our case study. Our main objective is to assess whether it is feasible to extract a valid model of LIMS that captures the fatigue of operators using limited input data.

Probability distribution fitting for task durations in the basic model, which includes human operators and machines, was successful. We fitted the normal distributions and their parameters from the original models, describing baseline task durations. Our results achieved an average p-value of 0.8. Consequently, our initial assumption that fatigue has a minor impact during the first x task repetitions holds. Moreover, the extraction of the fatigue model from cumulative task durations and break indicators produced promising results. With an average Pearson correlation score of 0.95 between the predicted and the true recorded values, along with an average RMSE of 0.07, the model proves effective in capturing fatigue.

The comparison of the entire extracted simulation model against the original model was done using confidence intervals of KPIs. The extracted Petri net model was run for the same number of shifts as the original model to generate synthetic data e.g. fatigue values. The generated data was compared against fatigue data from the original model. We calculated confidence intervals as $CI = \bar{X} \pm Z(\sigma/\sqrt{n})$, with $\bar{X}$ being the sample mean, Z the Z-score corresponding to the desired confidence level, σ the std and n the sample size. The confidence intervals calculated for task durations of both datasets overlapped, indicating consistency, and suggesting efficacy of the extracted model in capturing relevant patterns.

Acknowledging context-specific assumptions that we made is critical. E.g., preprocessing fatigue values is guided by the expected fatigue type, the corresponding mathematical model, and observable fatigue behavior in the data, if any. Moreover, it is essential to recognize that the values identified as fatigue are likely influenced by other factors such as mood or motivation. This raises the question of the extent to which these influences impact the observed fatigue levels. Given our approach with limited data, it is apparent that the dataset lacks the granularity to differentiate between these factors. Therefore, a more comprehensive investigation with additional data would be necessary to address these complexities effectively.

5 SUMMARY AND OUTLOOK

In this paper, we demonstrated the feasibility of deriving a model of LIMS that considers fatigue with minimal data requirements. Our methodology leverages event logs and work schedules to train a polynomial model that captures fatigue levels based on cumulative work duration and the occurrence of breaks.

Our approach offers several advantages. Firstly, it utilizes readily available data sources, circumventing the complexities associated with installing new sensors that may raise concerns regarding personal data protection legislation. Secondly, we employ simple polynomial models, enhancing interpretability and facilitating comprehension of the results. Thirdly, both the Pearson correlation coefficient and the RMSE indicate the model's efficacy in capturing fatigue accurately. Lastly, the model's ability to accurately replicate the LIMS is evidenced by its capacity to generate similar event logs.

However, some limitations have to be considered. Firstly, our approach relies on strong assumptions regarding the underlying mathematical fatigue model and the extracted fatigue values. Secondly, it predicts fatigue on a WS level, not of the individual operator. Our future research efforts will focus on addressing these challenges while also broadening the scope of considered human factors. For instance, we plan to include variables such as skill progression or mood into the model.

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