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NOVEL METHODS FOR TEACHING SIMULATION: STRENGTHENING DIGITAL TWIN DEVELOPMENT

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ABSTRACT

This article proposes new methods for teaching Discrete Event Simulation (DES) in manufacturing systems. Over the last four decades, numerous books have offered methods for teaching DES as what-if analysis tools for addressing stochastic problems. However, the emergence of the Digital Twin (DT) concept has posed challenges for such traditionally designed DES models. These models often struggle to evolve effectively into Real-Time Simulators (RTS). RTS are connected DES models embedded as kernels in the DT framework and synchronized based on real-time sensor data streams. Thus, the objective of this work is to introduce teaching methods that provide deeper insights into designing the needed high-fidelity DES models capable of evolving into RTS. It also illustrates how the Immersive Learning approach is employed to immerse students in a manufacturing environment through Virtual Reality (VR) experiences, allowing them to grasp key concepts such as granularity levels and synchronization challenges in deploying a DT.

1 INTRODUCTION

In recent years, the manufacturing industry has witnessed a transformative shift propelled by the integration of sensors and the Internet of Things. These advancements have revolutionized traditional manufacturing processes by enabling real-time data collection, analysis, and decision-making. As manufacturing systems become increasingly complex and interconnected, the need for Digital Twins (DT) of production systems has become imperative (Cimino et al. 2019). Specifically, in the context of production planning and control it becomes highly desired to embed Intelligent DTs based on Discrete Event Simulation (DES) models capable of monitoring and optimizing complex systems in real-time (Matta and Lugaresi 2023). For that purpose, many research works have focalized on proposing new frameworks that can be used to embed such Intelligent DT. The first works goes back to (Negri et al. 2020) and was based on parametric simulation-based optimization. More recently, to circumvent latency (Jaoua et al. 2024) opted to use the simulation-based control optimization by proposing a DT framework based on the Reinforcement Learning (RL). This framework is composed of two DES models. The first DES model is used for classic prediction during offline training of the RL algorithms. The second is a Real-Time Simulation model (RTS) which is a synchronized DES model evolving concurrently with the real manufacturing system. As stated by (Lugaresi and Matta 2018; Lugaresi et al. 2023) developing such RTS relies heavily on the accuracy of the designed DES model. Any discrepancy between the real and virtual environments can significantly degrade the DT real-time decision-making capabilities.

In order to be able to use DT in manufacturing company environments, research efforts should be directed not only at technological development, proof of concepts and implementation of the DT, but also at the proper training and skills development to have the people ready and able to use them. Until now, teaching in simulation is very much oriented to traditional what-if simulation (Lugaresi et al. 2023). It is lacking appropriate methodology to train for the DT design, RTS development and use in Industry.

Thus, the objective of this paper is to offer new developments on teaching methods for implementing high-fidelity DES models towards Intelligent DT for real-time decision in manufacturing environments. Specifically, the focus is on exhibiting the importance of modeling the detailed real system's process flow, resources dependencies and decision points for RTS models synchronization. For that purpose, we first propose a more comprehensive approach of introducing DES modelling without randomness. The authors let students, at first, address deterministic dynamic single-server queue with limited capacity before introducing stochasticity. This sequential method allows them to grasp the rationale behind this event-driven modeling approach and the internal system state evolution. Currently this state concept is underutilized and capturing it through simulation traces presents opportunities for real-time optimization (Nelson 2024). After addressing this simple introductory problem, we will explain how we immerse students in a Virtual Reality (VR) experience within a Learning Factory, enabling them to apply the DES modeling approach in real-world contexts towards a RTS embedment. In this activity, the authors will emphasize key concepts of granularity levels and the synchronization challenges in deploying a DT using an efficient RTS model. For that purpose, the Immersive Simulation Based Learning (ISBL) approach will be used (Ozden et al. 2020; Negahban 2024).

The remainder of this paper is structured as follows: Section 2 offers a Literature Review on the most common methods used for teaching DES modeling and the novel ISBL approach. In Section 3, the proposed method is presented, along with its learning outcomes. Section 4 discusses the implementation and synchronization issues through the use case of the Learning Factory. Finally, Section 5 concludes and suggests future teaching avenues.

2 LITERATURE REVIEW

During recent years, many research papers have focused on proposing DT frameworks towards production planning and control in manufacturing context. Wooley et al. (2023) conducted a comprehensive review of the proposed DT and their capabilities beyond traditional simulation models. When traditional simulation models were generally developed for what-if analysis, the DT evolved concurrently with real system synchronized through sensor data and capable to embed real-time decision. For that purpose, the DT is based on RTS model which is a connected DES model synchronized based on real-time sensors data streams. As presented in the framework developed by Jaoua et al. (2024) two DES models are required in an Intelligent DT, the traditional DES is used to predict system performances during offline training phase and the RTS, i.e. a connected DES, is used in real-time to establish the synchronization between the Cyber and Physical systems. In both of these DES models, it is crucial to represent process flows with the same level of detail. The main difference between these two models lies in their method of time advancement. In traditional DES model, the *Simulation clock* advances by jumping to the times of occurrence of future events scheduled according to the *random variates* drawn from probability distributions. Whereas, in RTS time advances continuously with the physical system using world wall clock time. In fact, in RTS the occurrence of events is not predicted based on a specific distribution but is triggered by sensor data. Thus, the RTS must rely on a high-fidelity model of the real system to ensure alignment between the physical components and their digital counterparts. The concern of requiring DES models that capture the essential details and dynamics of the physical system with high level of granularity for efficient DT deployment has been discussed in (Marquardt et al. 2021; Lugaresi and Matta 2021).

Over the past 40 years many books have proposed method to teach this DES modelling approach. Among the most frequently cited and seminal reference books in this context, we can mention “Discrete-Event System Simulation” (Banks et al. 2000) and “Simulation Modeling and Analysis” (Law and Kelton 2007). More recently, many other books have also addressed DES modeling from a practical perspective, focusing on the utilization of specific simulation software such as (Beaverstock et al. 2011; Rossetti 2015; Smith and Sturrock 2018). In all of these references, a common approach to introduce DES modeling based on the next-event time advance approach is to conduct a simulation by hand of a single-server queuing system. In this system, the interarrival and service times are independent and identically distributed (IID) random variables generated according to a Markovian or other probability distribution. These variables are supposed to be given by the instructors because at this stage the learner has not yet acquired the skills to manipulate random number generators.

The main weakness here arises from the simultaneous introduction of two novel concepts: random numbers and DES modeling. Introducing *random variates* alongside the unfamiliar concept of the simulation model's computer program and its complex components, such as the *Event list* and *Simulation clock*, could potentially overwhelm the learner. Therefore, the objective of this work is to adopt a sequential method that initially focuses the learner's attention solely on the DES modeling approach by manipulating the deterministic dynamic queuing system before introducing randomness.

Also, another area for improvement in these classic teaching DES books is the insertion of new chapters that address DT related concepts of RTS synchronization and on-line validation of DTs. Lugaresi et al. (2023) demonstrated that traditional methodologies based on confidence interval and hypothesis tests are not suitable for the new context of DT online validation. Also, for the RTS implementation, it is essential to capture the detailed operations of the real system in the DES with a high level of fidelity. A higher granularity of these models is required in order to be able to synchronize them with real-time data gathered from sensors. It is well known that the decision regarding the level of granularity in designing a simulation model is intrinsically tied to achieving the desired level of validity necessary to fulfil the study's objectives (Robinson 2014). This is why classic DES models designed primarily for what-if analysis often struggle to evolve effectively to an RTS. To tackle this issue, the authors propose to teach students how to develop such high-fidelity models towards efficient DT, using Immersive Learning.

The capability of VR to conduct verification and validation of DES models have been exposed in (Turne et al. 2016). More recently, the ISBL approach was applied for teaching different modules in many realistic contexts such as manufacturing assembly plan and hospital emergency, and its beneficial effects as a learning tool have been reported by Ozden et al. (2020), and Nowparva et al. (2021). Despite its great potential, Negahban (2024) criticizes that it is not yet integrated with learning theories in engineering education. Then, the objective of this paper is to explore the capability of ISBL in guiding students to gain a deeper comprehension of RTS model granularity by immersing them in a LF.

3 PROPOSED NOVEL DES TEACHING METHOD

As stated earlier, our objective is to employ a sequential learning approach, initially focusing on enabling students to grasp DES modeling for a deterministic and dynamic system before introducing randomness. We adopted this method in an Undergraduate Simulation course given for Industrial Engineering students. We have uploaded all models and materials for the assignments on GitHub. You can access them at the following link: https://github.com/neprev.

3.1 Teaching DES Modeling through a Deterministic Dynamic System

The proposed teaching methodology consists of two steps:

Step 1: Conducting a simulation by hand of a D/D/1/k queuing system.
Step 2: Exploring the internal system state and the balking effect.

For each step, there is a detailed description, followed by an exemplification case to ease the understanding.

3.1.1 Step 1: Conducting a Simulation by Hand of a D/D/1/k Queuing System

Description : this is a common exercise that serves to illustrate components of a DES program such as event list, simulation clock and data structures necessary for executing a simulation program. Nevertheless, the main difference herein is that the authors let students work with deterministic times rather than introducing random variables drawn from probability distributions of inter-arrivals and service times. Here, students focus on identifying the simulation time clock advancement associated with Arrival and Departure events, as well as the corresponding state changes in a Single-Server Queue with deterministic Arrival and Service times and limited total capacity equal to k, D/D/1/k. In order to observe queuing phenomenon, it is mandatory for this exercise to choose $\lambda > \mu$. Recall from, (Shortle et al. 2018), that in queue of limited capacity there is no restriction on having $\lambda < \mu$.

Application : an example of this queuing model could be the process of material handling, with an Automated Guided Vehicle (AGV), of a manufactured product from a workstation to a warehouse. The authors assume that an automated workstation delivers a product every 5 minutes, which corresponds to a deterministic arrival rate $\lambda = 12\ product/h$. Since this AGV, herein the Single Server, has a dedicated pathway its total service time is also deterministic and equal to 6 minutes, service rate $\mu = 10\ product/h$. If the AGV is busy, these products will be stored in a rack, herein the Queue, with limited capacity equal to 9 products, i.e. a D/D/1/10 queuing system. When the rack reaches its capacity, the product is redirected to a conveyor for alternative transportation mode, which aligns with the principle of balking in queuing theory.

In order to understand how DES modelling reproduces this queuing system state changing over time, students conduct a simulation by hand over a period of 30 minutes and to plot the number of products in the system at time t, $L(t)$, as depicted by Figure 1.

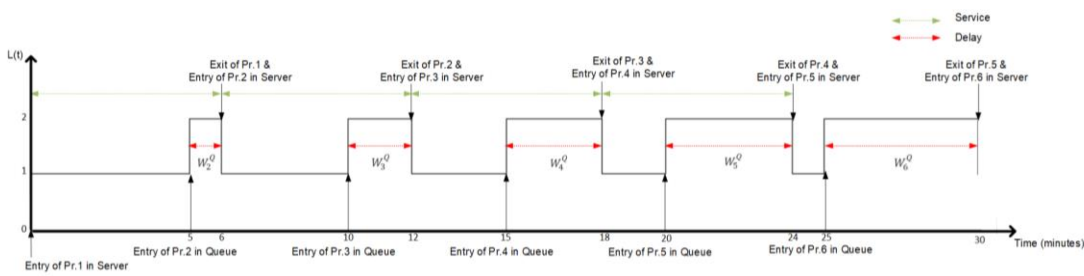

Figure 1: Number in system, *L(t)*, at time *t*.

This simulation by hand with simple deterministic values of Arrival and Service times allows students to manipulate, easily, basic concepts of collecting *System State*, manipulating the *Event list* and *Event routine* and advancing with the simulation *clock*. Also by observing this plot, Figure 1, students understand the concept of queuing formation and delay propagation through products in this deterministic dynamic system. Even though the service time is constant for all products but in this dynamic system, the second product will wait for 1 minute, $W_2^Q = 1\ min$, the third for 2 minutes, $W_3^Q = 2\ min$, and consequently, product 6 will wait for the cumulative waiting time of all preceding products plus 1, $W_6^Q = 5\ min$. This delay propagation is a common factor contributing to bottleneck formation in manufacturing systems, a phenomenon often erroneously attributed only to variability. With this next-event time advance approach the intricate dynamics of the queuing system and its different states is efficiently captured within a deterministic system.

Then after understanding the main components of a DES program, they are asked to deduce over this period of 30 minutes some classic performance measures of queuing theory, the time-weighted-average number of product in the system, denoted $\hat{L}$ given by equation (1), and the observed average time spent in queue per product denoted $\widehat{W_Q}$ given by equation (2).

$$\hat{L} = \frac{1}{T}\sum_{i=0}^{\infty} iT_i = \frac{1}{30}\int_0^{30} L(t)dt = 1.5\ products \tag{1}$$

$$\widehat{W_Q} = \frac{1}{N}\sum_{i=1}^{N} W_i^Q = \frac{W_1^Q+W_2^Q+W_3^Q+W_4^Q+W_5^Q+W_6^Q}{6} = 2.5\ minutes \quad (2)$$

This calculation is based on the plot and enables students to grasp the significance of these performance indicators. We then move to the next phase.

3.1.2 Step 2: Exploring the Internal System State and the Balking Effect

Description : once students are familiar with this DES modelling approach, the next step will be to let them explore the balking. Analyzing this balking phenomenon will allow them to understand the effect of delay propagation in realistic manufacturing context, i.e. with limited system capacity. This internal state changing is generally hidden when addressing the long-run average measures of performance of queueing systems. For that purpose, they will use a simulation software and model this deterministic dynamic system with different level of rack capacity. Then they will use the trace feature, provided by the simulation software, to capture the sample path of the system state. Finally, they are asked to plot the Average Waiting Time in Queue, W_Q when a product balks and the Delay per product over a pre-defined simulation period.

Application : the possible different levels of rack capacity were defined for the students as: 2, 3, 4 and 5. Recall herein D/D/1/5 corresponds to the case that the rack has a maximum capacity of four products. The pre-defined simulation period is equal to T =360 minutes, they are asked to plot the Average Waiting Time when a product balks and of the delay trace for each product ID. Plots are given in Figure 2-a and Figure 2-b.

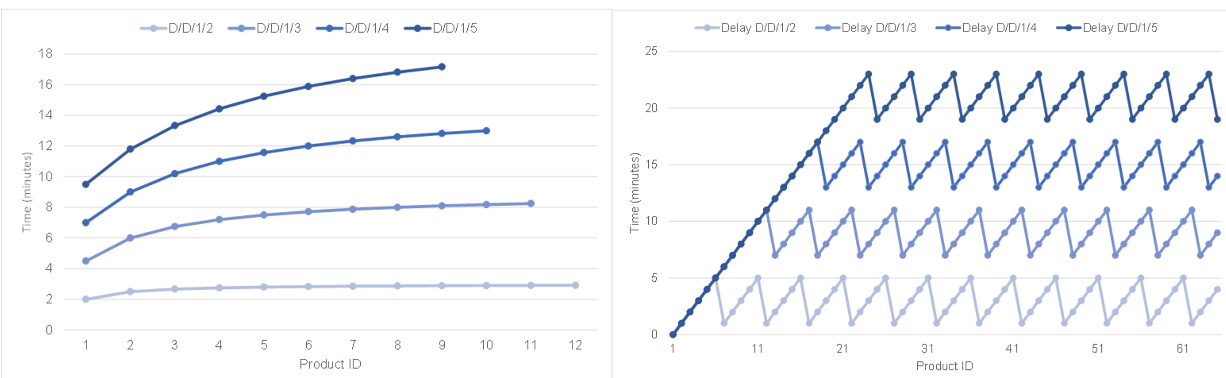

Figure 2: (a) Average Wait in Queue when Balking occurs, (b) Delay per Product ID (minutes).

Herein the first observation is that even though the throughput for all these models is equal to 60 served products, i.e. transported by the AGV, these models lead to different internal states. This state is related to the delay propagation behaviors dependently on the rack capacity. From the Figure 2-a, students can easily observe how the higher the rack capacity, the less product will balk. For the case of D/D/1/2, the W_Q is the lowest but 12 products balked. Whereas for the D/D/1/5, the Average W_Q reaches 17.16 minutes and only 9 products balked. Moreover, the trace for each Product ID, given in Figure 2-b, better exhibits the system state when this balking occurs. This plot indicates delay propagation through successive products until a product balks. Following the balking event, a periodic pattern occurs, depicted by a saw tooth waveform. This pattern shows delay increasing for consecutive products until a balking occurs. After the balking event, delay drops for the next product before resuming its increase for subsequent ones. For example, observing delays of products in D/D/1/5 this delay will propagate until the 24th product which will wait for 23 minutes, $W_{24}^Q = 23\ min$, then the 25th product will balk. After this balk the delay for the 26th product will decrease to $W_{26}^Q = 19\ min$. Then the delay propagates for the next four products until reaching its maximum of 23 minutes. This maximum delay corresponds to the time when the rack will reach its full capacity. This same behavior is observed for all the models where queue dissipation corresponds to a balk of an entity. This

Figure 2-b goes beyond the classic Average Outputs depicted by Figure 2-a, by providing a highly important state data which is the time spent by an entity in the queue.

This type of internal state data is highly valuable when it comes to use DES models to train Reinforcement Learning algorithm (Tiacci and Rossi 2024). As depicted in the Intelligent DT framework proposed by Jaoua et al. (2024) this state information is introduced as a node in the Input Layer of the Deep RL, which significantly enhances real-time decision quality. In fact, by supplying the algorithm with more comprehensive data about the environment, it can make better-informed decisions.

3.2 Insights from the Teaching Method

To summarize, this sequential learning method allows students to have a solid understanding of modelling deterministic dynamic systems through DES before introducing the concept of stochasticity. Specifically, the following outcomes are observed.

- Learners concentrate on comprehending the mechanism behind the next-event time advance approach by conducting simulations manually, using deterministic values for inter-arrival and service times, without manipulating assumed randomly generated variables.
- Learners analyze and understand that the concept of delay formation and propagation is inherent to the internal state of dynamic systems and is not necessarily due to stochasticity.
- Learners understand that DES allows to capture the internal, generally hidden, state by average long-run statistics. They also acquire the knowledge of utilizing simulation-generated data for future simulation-based control optimization in DT framework.

After understanding the basics of DES modeling on a simple queuing system the next step in the following section consists of addressing more realistic manufacturing contexts.

4 HIGH-FIDELITY DES MODELING OF A LF THROUGH APPLICATION OF ISBL

The ultimate objective herein is to teach students how to develop a DT for a Learning Factory (LF). The LF serves as an educational platform for the Master's degree program in NePRev https://neprev.com/ and also for the final-year undergraduate course in Industrial Engineering, titled 'Digital Twin for Smart Manufacturing', offered at the National Engineering School of Tunis, Tunisia. To achieve this, the instructors begin by introducing students to a real system. Then, they immerse them in a VR model, to teach students how to develop a high-fidelity DES model that is able to be evolved into an RTS. Once this DES model is developed the fundamental notion of synchronization with real-time data gathered from sensors is presented.

4.1 Description of the Learning Factory

At this LF, the Festo Modular Production System, MPS® system 403-1, from Festo® Didactic is used as an Industry 4.0 learning system. The MPS 403-1 is composed of three automated workstations: Distribution, Joining and Sorting, see Figure 3-a. The role of these workstations is to fulfil customer orders of workpieces received by the Manufacturing Execution System (MES), mimicking the make-to-order approach in the e-commerce context. The corresponding layout is given in Figure 3-b.

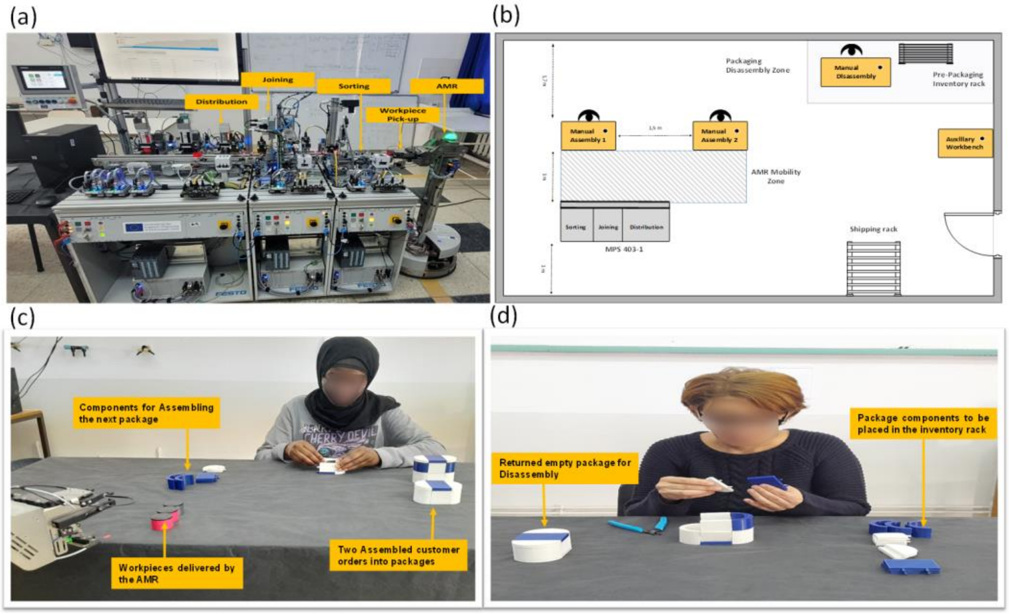

Figure 3: Learning Factory, (a) the MPS 403–1® with the Robotino®, (b) Layout of the LF, (c) Assembly operation, (d) Disassembly operation.

The workpieces are equipped with RFID chips and move between the three MPS 403-1 workstations using conveyor belts. Once these customized orders, which may vary in workpiece color and quantity, are produced by the MPS 403-1, they are transported to the Manual Assembly Station by an Autonomous Mobile Robot (AMR) named Robotino®, from Festo® didactic, Figure 3-a and Figure 3-c. The aisle colored in blue, Figure 3-b, is the AMR designated Mobility Zone. The AMR is programmed to navigate within this aisle for pickup from the MPS 403-1 and delivery to one of the two Manual Assembly workstations. At each Manual Assembly station, a worker assembles the appropriate modular package and places the customer orders inside, Figure 3-c. The packaged orders are subsequently placed in the Shipping rack. Since this LF is also a teaching laboratory for other courses, aiming to teach the Circular Packaging concept (Liu et al., 2023), the instructors have produced modular packages with Additive Manufacturing. These packages are adjustable for different order sizes and can be disassembled for reuse. In the LF, to mimic the reverse logistics principles, the instructors retrieve the finished order from the shipping rack to replenish the packaging disassembly area. A worker is assigned for disassembly operation, Figure 3-d. Once the package components are disassembled, they are placed in the Pre-packaging inventory rack, from which the Assembly operator will retrieve the components for packing the upcoming orders. This LF will be used as a case study for this section.

4.2 Teaching through ISBL High-fidelity DES modeling for RTS

The proposed teaching methodology consists of the following three steps:

Step 1: Immersing students in the LF to identify components of the DES conceptual model.
Step 2: Conducting Input data modeling and exploring the level of granularity.
Step 3: Deciding on the required level of details for RTS synchronization.

For each step, there is a detailed description, followed by an exemplification case to ease the understanding.

4.2.1 Step 1: Immersing Students in the LF to Identify Components of the DES Conceptual Model

Description : the instructors first introduce the students to the real LF by placing three of them at each manual workstation and launch 5 customer orders on the MES. This introductory step allows the students to observe the physical system, but it does not give them an overview of the different processes flows throughout the system's long-term operation. For that purpose, instructors recourse to the ISBL approach. The instructors gave to students an Immersive Simulation (IS) model that we preliminarily developed to mimic the described dynamics of the LF. It is worth mentioning that the model we provide can be used both in low immersive, i.e. 3D model, and high immersive, i.e. VR versions. We opted to let them use the VR headset to benefit from this immersion experience. The instructors have developed this IS model using Simio Simulation Software. To settle the high immersion mode, the Render to Oculus feature of Simio is used. Students use a VR headset, specifically the Oculus Quest 2, and they are asked to develop a DES conceptual model of the LF. Specifically, they have to identify based on the Tutorial provided by Robinson (2017) the following components: the objectives, the inputs, the outputs, the activities and their interconnections, assumptions and simplifications of the model.

Application : to create a more realistic flow in the LF, we introduce the following workspace constraint: each of the two Manual Assembly workstations can accommodate a maximum of three packages. Consequently, after assembling three customer requests, the operator proceeds to pack the subsequent order at the Auxiliary Workbench using components from the Pre-Packaging Inventory rack, Figure 3-b. The four Packed orders are then transported to the shipping rack. Subsequently the operator retrieves, from the Pre-packing inventory rack, the necessary package components for the next three customer orders before returning to his Manual Assembly workstation. Figure 4-a shows a student experiencing the Immersive mode and Figure 4-b presents a snapshot of the scene as visualized through the VR headset.

(a) (b)

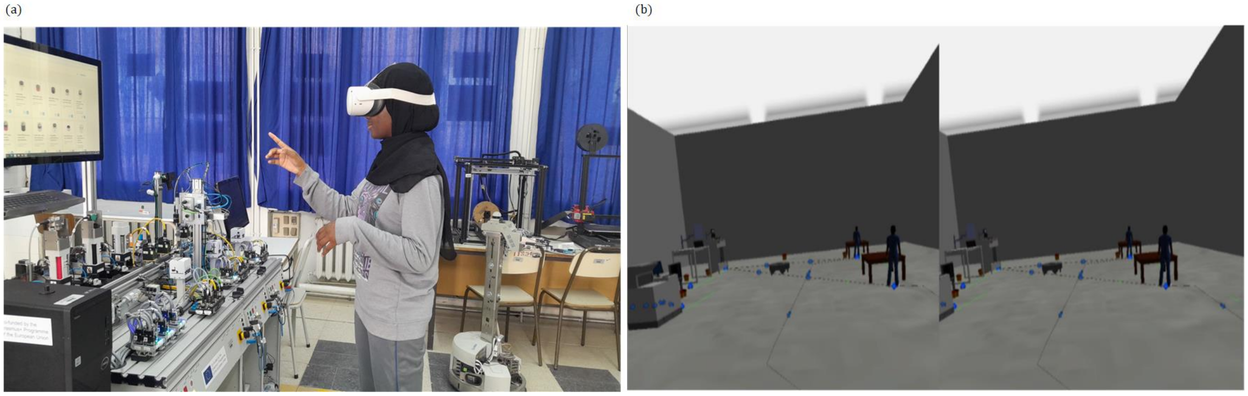

Figure 4: VR Immersion experience in the LF.

From the immersion experience students are asked to design two conceptual models with distinct level of granularity. The first, less detailed DES model does not consider space constraints and treats the Assembly activity for all orders as an aggregation of displacement and assembling operations. In contrast, the second model is a high-fidelity representation that replicates the periodic displacement required to perform the Assembly activity of the 4th orders at the Auxiliary Workbench. In the next step, *Input data modeling* will be conducted to fit these models.

4.2.2 Step 2: Conducting Input Data Modeling and Exploring the Level of Granularity

Description : Students must collect data corresponding to the different activities identified in the conceptual model. They first observe that the processing times of the three automated MPS stations: Distribution, Joining and Sorting is deterministic, and they do not need to collect sample for these processes. These data are extracted from the event log on the MES. Also, since the instructors fixed the AMR pathways, its transportation time is deterministic. However, they had to collect samples for non-deterministic Assembly and Disassembly processing times. To understand the previously discussed level of granularity, students are tasked with collecting a sample of Assembly times for 50 customer requests.

Application : using the VR headset, students collected the needed sample data, i.e. the Assembly time denoted A. Then they plot this sample and analyze the data. The corresponding plot is given in Figure 5.

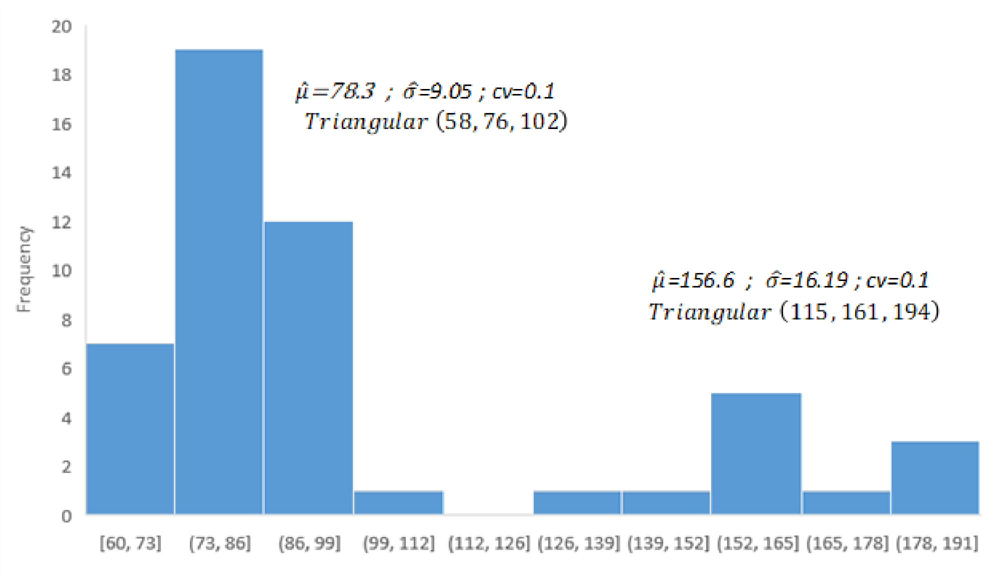

Figure 5: Histograms of Assembly times (minutes).

From this plot, Figure 5, students are able to detect that this Assembly time exhibits a bimodal pattern. The bimodality arises from the displacement due to space constraints, leading to periodic assembly of the 4th order at the Auxiliary Workbench. For these products, i.e. 25% of the sample, the empirical Mean Assembly Time is equal to 156.6 seconds whereas for the other 75% of assembled products it is equal to 78.3 seconds. They also observe that for both cases A exhibits low variability with a *coefficient of variation*, $cv = 0.1$.

Students are then asked to fit separately these data to theoretical distributions. The corresponding Triangular distributions parameters are given in Figure 5. Since this conditional behavior is already embedded in the high-fidelity DES model, the consideration of these Input data is straightforward. However, for the less detailed DES model, students have to fit this sample to a unimodal distribution since they aggregated the displacement with the assembly operations. Herein the KS Test accepts the hypothesis of fitting this sample to the following shifted Gamma distribution: $A \sim 60 + \Gamma(34.9, 1.12)$. They introduce this distribution to generate Assembly times random variates in their less detailed DES model and observe how they are inducing irrelevant stochasticity with considerable $cv = 0.36$. Students recognize that the simplification assumption in the less detailed model led to an inconsistency regarding stochasticity. While the stochastic variability in the real system is notably low, the DES model designed with low level of granularity introduces a higher variability, resulting in a discrepancy between the DES and the real system. From these experiments students conclude on the important aspect of model granularity to avoid discrepancy between the real and virtual environments. In order to use this DES model as an RTS it is essential to capture the detailed operation within the real system with a high-level of fidelity.

4.2.3 Step 3: Deciding on the Required Level of Details for RTS Synchronization

Description : finally, students are asked to identify the appropriate sensors data to capture in the developed high-fidelity DES model to use it as an RTS for DT synchronization. This exercise is aligned with the principle established by Lugaresi and Matta (2021), which emphasizes minimizing unnecessary updates of the RTS by avoiding capturing redundant sensor data.

Application : students detect that rather than tracking the workpieces continuous movement on the conveyor it is sufficient to track their corresponding events of entry and exit using the RFID readers placed at each station, i.e. Distribution, Joining and Sorting. However, capturing solely the event of delivery of packages by an Assembly operator on the shipping rack is insufficient to track the complex conditional flow. As they learned earlier, this aggregation of displacement and Assembly operations may lead to inconsistency between the RTS and the real system.

For an efficient RTS implementation, they conclude on the importance of tracking the AMR arrival and departure from the pickup to the delivery Manual workstations i.e. Manual Assembly 1 and 2. Finally, for Manual Disassembly, it is necessary to capture sensor data on both the Entry and Exit points to track the inter-arrival time between returned packages and the termination of the disassembly operation.

4.3 Insights from the ISBL Approach

To summarize, this ISBL approach allows students to acquire a good acknowledgement of developing highly detailed DES that can evolve to an RTS. Specifically, the following outcomes are observed.

- Immersion allows learners to effectively apply the conceptual modelling principles to design DES with different level of granularity for a real system.
- Learners gain proficiency in conducting input data modeling and the corresponding data collection step from the shop floor.
- The learners successfully identified which sensor data to gather in order to synchronize the high-fidelity DES model, enabling its integration as an RTS.

In conclusion, given the increasing complexity of the manufacturing context, the ISBL offers a highly potential approach to integrate with DES modeling and learning theories. Although we implemented this immersive learning only 2 years ago, we have observed a 13% increase in average test scores, indicating an enhancement in students' understanding. Indeed, this observed improvement must be confirmed with more in-depth statistical analysis with quantitative data comparing learning outcomes. As conducted in the investigation study by (Nowparvar et al. 2022), this can be achieved by dividing the learners into ISBL and control groups to assess the benefits of immersion. Also, employing the method proposed by (Li et al. 2022) to measure students' cognitive load during immersive tasks would be highly valuable.

5 CONCLUSION

In this work the authors have introduced new teaching methods for implementing high-fidelity DES models towards Intelligent DT for real-time decision in manufacturing environments. At first the authors have proposed a more comprehensive sequential approach of introducing DES modelling without randomness. This sequential method allows them to grasp the rationale behind this event-driven modeling approach and the complex notion of internal system state. For that purpose, the instructors let students manipulate the trace feature to capture the system's evolving state and delay propagation, which is often hidden by the averaged steady-state performances. After addressing this simple introductory problem, the instructors used the ISBL approach to immerse students in a VR experience within a LF and taught them steps towards embedment of an RTS. This approach allows students to develop a deeper understanding of RTS model granularity and the associated concepts of synchronization and determination of relevant sensor data to track.

The primary insight underscores the necessity for academia to produce updated educational resources tailored to the adoption of DT technology within the industry. This entails the integration of the discussed novel concepts specific to DT into educational materials. Additionally, the introduction of ISBL into Simulation Modeling curricula stands to significantly enhance learning outcomes. Even though in the application course the instructors had access to a real Learning Factory, immersion allowed students to observe the long-run behavior of a realistic hybrid manufacturing system with human operators. Ultimately, this proactive approach empowers future professionals to navigate and leverage DT effectively in real-world industrial settings. As a future works, the authors aim to continue providing updated educational content for academia for facilitating seamless integration of novel DT concepts in smart manufacturing. Additionally, a more in-depth comparative statistical analysis of learning outcomes under the immersive approach will be conducted.

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