Journal of Simulation

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tjsm20

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JOURNAL OF SIMULATION
https://doi.org/10.1080/17477778.2023.2174458

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A new teaching approach exploiting lab-scale models of manufacturing systems for simulation classes

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ABSTRACT
Teaching in higher education is often challenging for the lack of practical implementation and difficulties in student involvement. In engineering classes, students are often deeply involved in computer laboratories and projects in which they are challenged with decision-making problems. The lack of the real system that is being modelled may hinder the effectiveness of the teaching activities. In this paper, we propose a new teaching approach based on the student's interaction with lab-scale models of manufacturing systems. Students have the possibility to make observations, collect data, and implement improvements to a system, all within a course duration. The flexibility of the proposed approach enables its application to a wide range of courses, for instance manufacturing system engineering, production management, Industry 4.0. As case study, we target a course on simulation of manufacturing systems for industrial and mechanical engineering, in which students are asked to build, validate, and use a discrete event simulation model of a production system. The application of this project methodology changed the way of teaching simulation in the course and significantly improved students' evaluation and satisfaction.

ARTICLE HISTORY
Received 5 May 2022
Accepted 28 December 2022

KEYWORDS
manufacturing systems; discrete event simulation; learning factory; learning-by-play; LEGO

1. Introduction

Teaching in higher education is often challenging for the lack of practical implementation and difficulties in student involvement. Although laboratories are considered fundamental to fill this lack and widely present in the educative process, the limited access to real systems for many disciplines may represent an issue for student learning. Indeed, industrial and systems engineering disciplines often involve the comprehension of complex manufacturing systems and the resolution of problems based on a proper model of the real system. Complex descriptions of industrial cases are widely used on course material (e.g., lecture notes, technical notes, books and papers) and the laboratory experience often relies on a case study analysis which is surely significant for the deep comprehension of the problem. Nevertheless, students almost never face with practical aspects of a project, such as observation, data collection, and implementation constraints.

Several recent works sponsor the introduction of more interactive activities for teaching purposes (Sterman, 1989). The role of a realistic experience has gained particular attention in higher education (Buckley et al., 2017; Padilla et al., 2017), and it could help to provide students with better problem solving abilities while facing the challenges of a practical application. In addition, the more the interactive projects are aligned with their passions, the better the result achieved. Quoting (Resnick & Robinson, 2017): *"Creativity doesn't come from laughter and fun: it comes from experimenting, taking risks, and testing the boundaries"*. Following the *constructionism* idea, learning through play can positively contribute to build a new awareness based on pre-existing knowledge of students (Papert, 1980). Also, (Padilla et al., 2016) considers games as an effective tool to learn complex topics because *"students use the game as an experimental setting just like one would a simulation"*.

In this work, we propose a new interactive teaching approach making use of lab-scale models of manufacturing systems. These systems are replicas of portions of real factories in scale, where certain phenomena (e.g., parts routing, machine breakdowns, maintenance policies) can be reproduced, observed, and studied in a controlled environment. Also, we describe in detail the approach application to a simulation course for industrial engineering where the lab-scale models are built with LEGO[1](Souza et al., 2018). The application of such innovative teaching approach proved successful for master degree students. The main improvements compared to traditional teaching of simulation have been observed (1) in the modelling phase, in which the observation of the real system is fundamental for developing abstraction and data complexity skills, and (2) in the implementation phase, in which it is possible to physically see the results of decisions made

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with the support of simulation tools. Further, based on the experience of the teachers, the application of the proposed approach resulted in a higher student engagement compared to the similar projects presented and pursued through frontal classes.

The remainder of the paper is organised as follows: Section 2 revises the most related literature. Section 3 gives an overview of the main components of lab-scale models used in this work. Section 4 outlines the proposed laboratory experience. Section 5 presents two relevant case studies from the author's experience. Finally, conclusions and final remarks are presented in section 6.

2. Related works

Several innovative works claim the key impediments to the rapid implementation of Industry 4.0 are its perceived complexity and abstractness. In section 2.1, significant literature contributions are listed in the context of interactive teaching with simulation. Section 2.2 summarises the main contributions that address the innovative teaching of industrial engineering concepts using lab-scale models. Finally, section 2.3 outlines the main contribution of this paper with respect to the related works.

2.1. Interactive teaching with simulation

In the context of interactive teaching with simulation, it is important to distinguish between regarding simulation (1) as a tool to reach a learning outcome and (2) as a part of a learning outcome itself.

2.1.1. Simulation as a Tool

Courses that use simulation as a tool aim at reaching the students' understanding of the mechanisms of real systems, such as production systems and supply chains. These systems usually present issues, e.g., concurrency of events, conflicts in resource's selection, congestion in routing, which are complicated to understand and difficult to solve using only intuition. In order to facilitate understanding, physical visits to manufacturing plants are often organised alongside conventional teaching approaches. However, logistical issues often arise when organising a visit. Among other issues, we may note the difficulty in observing specific events during a visit, its limited duration, and the unpredictability of its effectiveness. Last but not least, some visits may result costly to organise every academic year. Thus, simulation models of the systems of interests are developed in the preparation phase of teaching and students interact with already-built simulation models, for instance using them to play games. Much experience of teaching falling in this category can be found in literature (Greenwood, 2017). Mustafee and Katsaliaki (2010) presented a business game to simulate the supply chain of blood units from donors to patients. The goal was to make students understanding the complex principles behind a supply chain and to give them tools to make decisions in complex situations. Indeed, the teams could easily test the implication of their decisions and the outcomes of their supply policies. Klug and Hausberger (2009) set up an interactive lab in which each student had a production planning problem to solve. Tobail et al. (2011) developed an interactive business game in which participants mimic real life decision making processes by playing a managerial role in the automotive supply chain. The game enabled students to learn the impact of strategic decisions on other portions and players of the supply chain. A similar game was developed by Lee (2011), with the goal to make practitioners exercise the *"science and art of making tradeoffs between schedule, scope, cost, and quality while solving project management problems"*. Hübl and Fischer (2017) designed a web-based business game in which gamers could act as purchasing, production, sales and finance managers, with the target to identify sales and production volumes for the next planning periods.

2.1.2. Simulation as a Learning Objective

Courses that use simulation as a learning objective aim at providing students the skill of simulation modelling and the ability to conduct analysis based on simulation. Among significant contributions, Padilla et al. (2016) used interactive teaching to capture the attention of students in classes of discrete event simulation modelling. Students were required to develop simulation models which were described as a game in which the activities resulted in changing the input parameter values of the model. Martin (2018) designed classes by performing a real-life simulation study at a cross-dock, where students interacted with the company. Students had to test the effect of a possible reorganisation of the docks layout and balance the workers workload. The goals of the experience were to perform a simulation project within a realistic business context and to learn how to use raw data files from an industrial information system.

2.2. Interactive teaching supported by lab-scale models

Recently, other forms of teaching have emerged, to take advantage of easy-to-build, lab-scale models of real systems that can be used to replicate realistic behaviour in a controlled environment, and being used for improving teaching effectiveness. In this context, LEGO has been increasingly used as an educational tool for teaching in several engineering subjects such has robotics, computer programming, and control. The design philosophy of the LEGO instructional material is based on the concepts that students should construct the knowledge by themselves and that effective learning is established through play (Hussain et al., 2006; Iturrizaga & Falbel, 1999). As reported in the literature, the exploitation of LEGO in engineering projects successfully improved students' motivation, involvement and enriched their competences (Behrens et al., 2010).

Several applications of LEGO-based systems for teaching purposes can be found in the literature. Among others, successful teaching projects have been done in embedded systems (Kim & Jeon, 2006), robotics (Behrens et al., 2008; Grandi et al., 2014; Papadimitriou & Papadopoulos, 2007), control theory (Gomez de Gabriel et al., 2011; Wadoo & Jain, 2012; Y. Kim, 2011), computer science (Iversen et al., 2000; Klassner & Anderson, 2003), and data acquisition (Cruz-Martín et al., 2012).

In general, the adoption of LEGO in Industrial and Mechanical Engineering courses that focus on manufacturing systems is less common, however some contributions can be found. Sanchez and Bucio (2012) based a course on a manufacturing system realised with LEGO to teach the principles for controlling discrete event systems to postgraduate students and to allow them to gather hands-on experience with an automated system. The project goal was the design and realisation of a hierarchical supervisor for the physical model. The physical system was a closed-loop line composed by two workstations, two feeding systems, two dispatchers and a conveyor belt system. Production planning was done in compliance with the ISA-S88 standard for industrial batch control. Students were required to design a modular-hierarchical coordination architecture capable of supervising the execution of the production schedule of the LEGO system, and to design controllers to supervise the resource allocation tasks during production. The development of a model for performance evaluation was not required. Syberfeldt (2010) described a practical exercise to teach simulation-optimisation using a LEGO-based factory simulating the refinement of raw materials. The system was a three-stations flow line with dedicated controllers. The main purpose of the course was to make students understanding the benefits of performance evaluation, and to provide them with an additional tool for learning and understanding simulation-optimisation. Indeed during the project work, students were asked to find the best system configuration with the aim of maximising the profit by changing either the product mix or the buffer capacity allocation along the line. An Artificial Neural Network was used for performance evaluation as surrogate model of the physical system. Jang and Yosephine (2016) developed a LEGO-based flow line consisting in one feeder and two machines with an intermediate buffer. The machines were programmed to simulate failures of different duration. Hence, the system was affected by blocking of the first machine and starvation of the second. The course had three main goals: understanding the processing times and failure rates by collecting data, modelling the system with the objective to optimise the throughput, the cycle time, and work-in-progress, and designing the system in terms of buffer allocation. The LEGO-based project proved to be effective in motivating students. Thanks to the developed system, students have been able to learn and understand the basic concepts of stochastic modelling, production planning, and scheduling. The authors also showed that the students' understanding of the issues of dynamic behaviour of manufacturing systems was improved more effectively than with traditional lecture-based learning. Markov-chains are used as system performance evaluation method. Lugaresi et al. (2020) designed an interactive teaching experience in which students can learn manufacturing systems integration using LEGO models. The students are divided into groups, each group is dedicated to the design and building of a part of a complex manufacturing system model. The final goal is to integrate the results of each group in a single working model.

2.3. Paper contribution

In this work, we propose a new approach for teaching discrete event simulation exploiting the student interaction with lab-scale models of manufacturing systems. The approach includes laboratory experiences using a physical system where the students can learn from the system, analyse system behaviour, and face with the challenges of a real data collection. As a consequence, the proposed approach fills the lack of a real manufacturing system to be studied. The approach is applied to a course presented in this work where simulation modelling and analysis play a dominant role. This paper contribution is articulated into three main parts: (1) we are proposing a teaching scheme that can be flexibly applied to many different courses; (2) we are describing a lab-scale manufacturing system designed not only to support interactive teaching but also to be used as laboratory demonstrator of research outcomes; (3) two case studies within a course for Industrial and Mechanical Engineering are described in detail so to be easily replicated.

3. Lab-scale manufacturing systems

This section introduces lab-scale models of manufacturing systems. The goal of such systems is to be able to replicate the main phenomena that define the behaviour of a manufacturing system. For instance, routing of parts to different stations, queues and priorities, as well as machine failures.

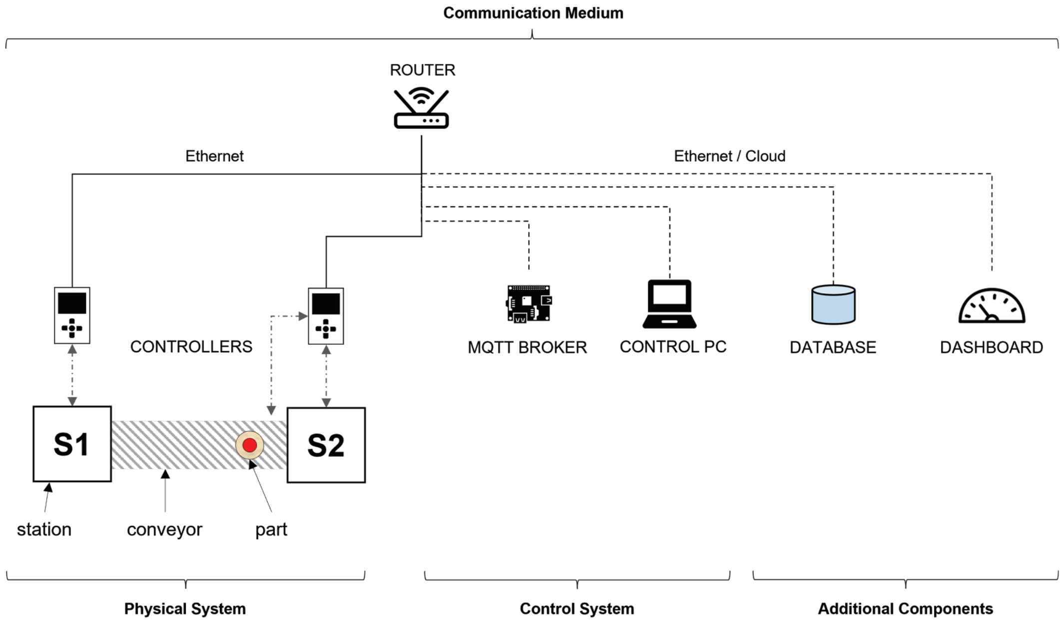

Figure 1. Building architecture of a 2-station lab-scale model.

The assembled models can be used to replicate the behaviour of a real production line by moving parts such as spheres or discs along a proper route and reflect operation times by letting parts wait in a station for an appropriate time span. Figure 1 shows the architecture of a two-station lab-scale model built with LEGO. We may divide the architecture in four main parts (1) the physical system, (2) the control system, (3) the communication medium, and (4) additional components. The following sections briefly introduce each part of the architecture.

3.1. Physical system

The physical components include both structural pieces such as beams, shafts, conveyor belts, and actuators, sensors and PLCs. Without loss of generality, this work refers to physical models built with LEGO MINDSTORMS. Next, the common components of the proposed lab-scale manufacturing system models are presented:

- The **material flow** is represented by wooden discs (diameter 35mm). The discs may be tagged in different ways depending on the level of traceability required: (1) without any identifier, the parts can be identified by the sensors using the intensity of light; (2) by using coloured tags it is possible to represent different part types, for assigning the setup and processing times accordingly. (3) by using single code identifiers (e.g., bar-codes or quick-response codes), this way enabling a single-piece flow production (i.e., different production recipe for each part).
- **Conveyers** are controlled by dedicated electrical motors and compose the transportation system that moves the parts from one station to another. Each conveyor can be set to run at a specific speed, which can be changed at runtime. Conveyers also constitute the inter-operational **buffers** between two stations. It is possible to define a specific buffer size through the position of the downstream sensor of each station (e.g., Sensor 3 in Figure 2a). The maximum allowed buffer size is limited superiorly by the length of the conveyor.
- **Stations** are represented by dedicated areas which hold parts for an amount of time that mimics the setup and processing operations on the parts as well as production disruptions such as failures. A station can be in either one among three states: (1) working, (2) idle, and (3) blocked. Figure 2a shows an example of a station built with LEGO. A station is composed by a controller, three optical sensors, a part-entrance system and a motor. The part-entrance system is in front of each station. Referring to Figure 2a, a beam is driven by Motor 1 and blocks the parts in front of the station to avoid the entrance of more than one part at a time. Figure 2b summarises the workflow of a station. Sensor 1 lies over the part-entrance system to recognise if a part is waiting to be worked. When the station is idle and a part is available, the part-entrance system pushes the part inside the station. The motion is provided by Motor 2. Sensor 2 is placed in the middle of the station structure to check if a part has entered the machine and to distinguish the product type. As soon as the part has entered, Motor 2 is stopped and the station is set to working state.

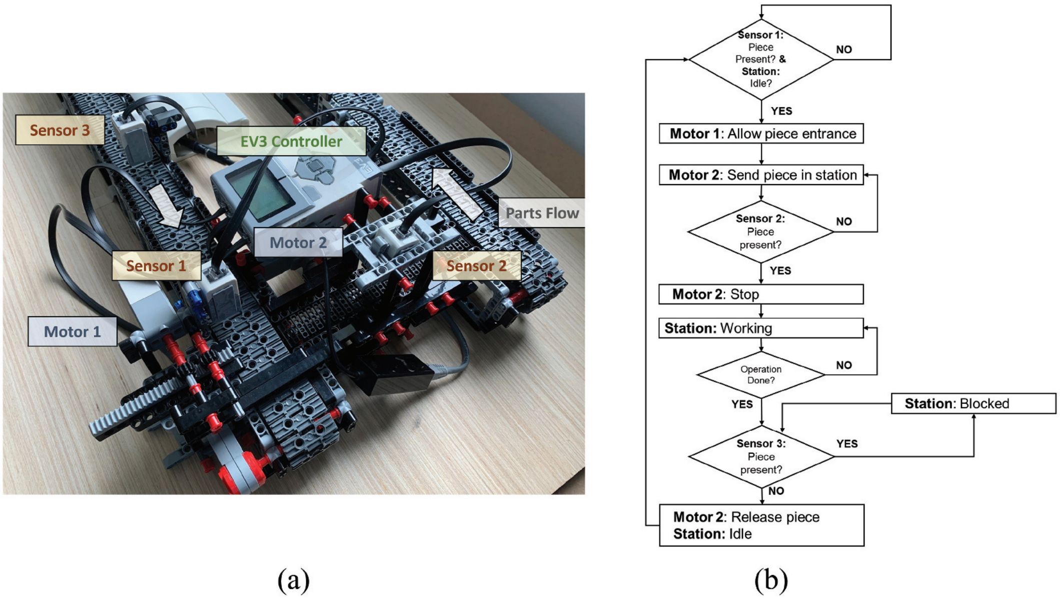

Figure 2. Example of a station: (a) physical model components, (b) logical workflow.

Sensor 3 is installed on the downstream conveyor and determines if the downstream buffer is full. When the operation is done, if there is enough space on the downstream conveyor, Motor 2 is used to download the part and the station is set to idle state. On the other hand, the station is set to blocked state if and until the downstream buffer is full. The station model exploits three optical sensors to control the part flows.

3.2. Control system

The stations are controlled by LEGO EV3 intelligent bricks, which are programmed using customised python scripts. In this work, EV3DEV OS[1]https://www.ev3dev.org/ (Accessed on 24-08- has been used. This open-source operating system is based on Debian Linux and allows the execution of *python* scripts[2] for controlling the sensors and motors through dedicated libraries. Each controller is assigned an IP address in a local network and can communicate with a centralised controller. Each station has its own script that is run locally such that different distributions of the processing times can be assigned to different stations.[3] A production activity on the i-th part on station s is represented by the time $p_s(i)$ that a station must hold the part before being allowed to release it towards the downstream conveyor. Some stations can be modelled as unreliable and may fail with probability f_s. If a failure occurs, the part is held by the station for an additional amount of time r_s, which accounts for the station repair. The quantity $\phi_s(i)$ represents the whole time that the i-th part spends in a station, and its realisation can be expressed as follows:

$$\phi_s(i) = \tilde{p}_s(i) + \tilde{I}_s(i)\tilde{r}_s(i) \tag{1}$$

where $\tilde{I}_s(i)$ is an indicator function which is 1 if $u(i) < f_s$, 0 otherwise. $u(i)$ is a random number in the interval $[0, 1]$. All stochastic quantities are sampled each time a part enters a station. The expression (1) can be easily extended to a multiple part-type case. Specifically, by using the index t to indicate the part-type, the processing time of the i-th part of type t is $\phi_s(i,t) = \tilde{p}_s(i,t) + \tilde{I}_s(i,t)\tilde{r}_s(i,t)$.

The station conditions of working (i.e., a pallet is loaded onto the machine), starvation (i.e., upstream buffer is empty), and blocking (i.e., downstream buffer is full) can be supervised and logged by the control system. Additional state-based conditions can be applied. For example, sending a stop message to an upstream station of a resource that goes in maintenance state, with the goal of energy efficiency.

3.3. Communication medium

The stations are connected through a local network and a PC through the Secure Shell Connection (SSH) protocol. The communication between the software levels is possible thanks to an IoT infrastructure based on the Message Queue Telemetry Transfer (MQTT) protocol. This allows the PLCs to send and receive messages to any kind of IoT-compatible device connected to the network. Hence, it is possible to share and store data from the real system and the architecture levels exploiting the message-based communication protocol. The messages are written in the JavaScript Object Notation (JSON) format. Depending on the message contents, specific actions can be designed accordingly to specific system

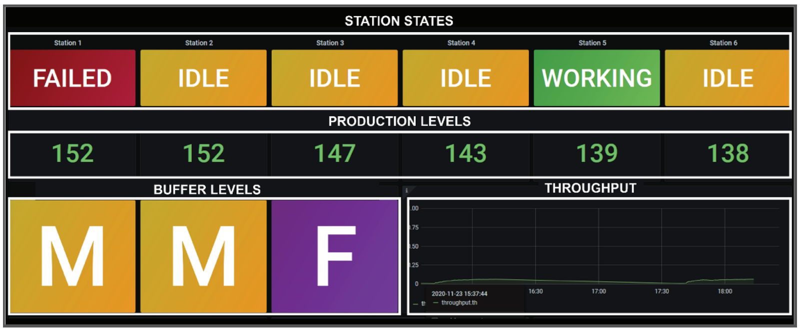

Figure 3. Example of real-time dasboard connected to the lab-scale system data infrastructure.

requirements (Lugaresi et al., 2021). For instance, a message content is a JSON object containing the motor name, the name of the EV3 that controls it and a value that describes the speed at which the motor should run.

3.4. Additional components

The architecture may additionally include software components that exploit data from the system to perform several high-level operations. In this paragraph, we list a significant yet non-restrictive list of applications. Databases allow the storage, manipulation and query of the acquired data for obtaining useful information: for example, the time series of a machine state may be used to derive both availability and reliability indicators. Real-time dashboards can be used to query data in real-time from most databases. Hence, they can be used for showing both raw data and aggregated indicators derived from the system logs (e.g., station sojourn time, system time). As a result, they represent a useful tool to show an overview of the system status at anytime. Figure 3 shows an example of a real-time dashboard that has been developed for the system of section 5.2. The developed architecture allows to communicate the data measured on the shop-floor, hence it is able to infer the system status and use it as initial condition for simulation models. It is thus possible to couple the system with a real-time simulation model, to be used to simulate different production and management policies online (Lugaresi et al., 2021). Depending on specific laboratory convenience, the aforementioned components may reside either in different devices or in the same one, either locally or in the cloud.

4. Simulation project

In this work, we take as reference the course *"Integrated Manufacturing Systems"* offered by Politecnico di Milano to students of M.Sc. in Industrial and Mechanical Engineering[2]https://tinyurl.com/polimi-ims (Accessed on 24-08-2022).. The contents include the description of automated manufacturing systems and basic theory of discrete event simulation (DES). The course consists of lectures, classwork modules, and a semester project. Lectures allow students to have the basic knowledge and understanding of: (1) the main elements of integrated manufacturing systems and their relationships; (2) the basic principles of discrete event simulation; (3) the basic analysis methodologies in the context of simulation. Classwork modules are taken in computer laboratory sessions and allow students to apply knowledge and understanding through the following activities: (1) modelling several types of manufacturing systems using DES software, e.g., manufacturing lines, assembly lines, flexible manufacturing systems; (2) building DES models with data input analysis techniques; (3) understanding the system behaviour with data output analysis techniques; (4) ranking and comparing alternative manufacturing systems using simulation outputs.

4.1. Project learning objectives

The goal of the semester project is to improve the performance of a given manufacturing system. As far as simulation content, students are required to observe the manufacturing system, build a model, validate it with statistical techniques, and execute experiments in order to choose a proper solution that can improve a performance metric of interest. From an educational perspective, the simulation project aims to stimulate students to apply the theoretical contents learned during classes to an industrial and system engineering problem, in which information is not fully available and the problem statement is not perfectly defined. The project activities allow students to:

- Autonomously analyse and design an integrated manufacturing system in a context of partial information. Students are required to retrieve information from observations of the physical system. Besides, they are asked to decide which data to collect and to complete data collection within a limited time period. This is to mimic the realistic cost of data collection.

- Obtain data and acquire knowledge from experiments in a physical laboratory. Indeed, data collection is often a complex and time-consuming task. The use of data physically generated from the lab-scale system helps to touch the real problems encountered by simulation practitioners in this phase. Among others, the need to cope with incomplete data sets, the excess of details on a portion of a system, the need to aggregate or reformat data, and the choice of data granularity level.
- Choose the modelling level of detail from the physical system to the conceptual model. The step from the system observation to the development of the conceptual model requires abstraction capabilities. This is usually difficult to reach in educational projects due to the unavailability of a real system. In practice, this lack is often compensated by a text describing the real system using words and layouts. However, dealing with a realistic system is much more effective for students who have to understand the system dynamics, to decide which elements to include in the conceptual model, and to choose which assumptions to introduce.
- Choose computer coding strategies for building simulation models in a software platform.
- Summarise and present the results with technical documents and oral presentations.

As a result, students develop the ability to handle the complexity of manufacturing systems, to integrate the knowledge acquired in other courses on production systems and industrial plants, to formulate judgements with incomplete and uncertain data, to study in a manner that may be largely self-directed and autonomous. Students also develop the ability to communicate their choices and conclusions to specialist audiences.

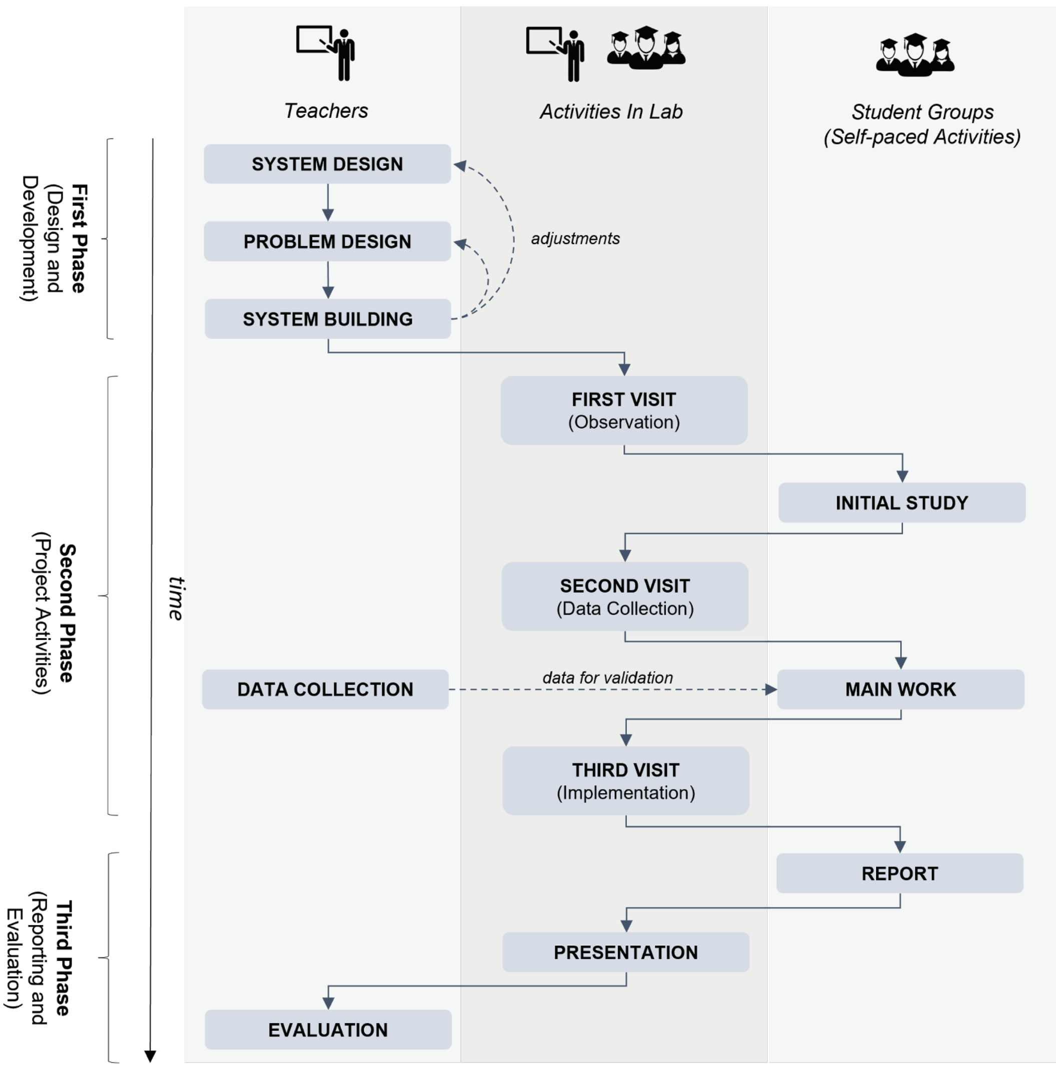

Figure 4. Map of the main activities of the proposed simulation project.

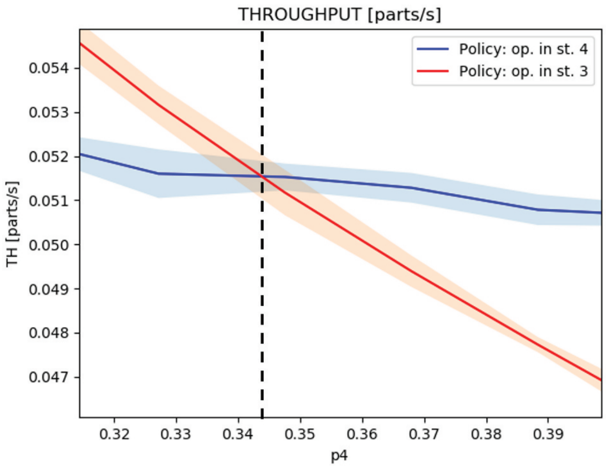

Figure 5. Example of dependency of the throughput on two system parameters: the operator's default position and the probability of failure on a station, the colored area is the 95% confidence interval obtained by five independent replications via a DES model of the system.

4.2. Project development

The project aims at involving students in observing, modelling, analysing, and improving the performance of a production system. Figure 4 outlines the main steps of a project. Each project is characterised by three main phases: (1) design and development, in which the main features about the real system are determined and the main problem is outlined, (2) project-specific activities, in which students interact with the lab-scale system and perform the main analyses, and (3) reporting and evaluation, which is the phase that concludes the project. The following sections further elaborate on each project phase.

4.2.1. First phase: design and development

The first phase is related to the design and development of the manufacturing system that will be subject of the study. The goal is to build a physical system that replicates a realistic manufacturing system, and it allows for its study and improvement of specific aspects. The design of the system can be inspired by the most common manufacturing systems, such as flow lines, flow shops, and flexible manufacturing systems. The teachers expertise in lab-scale model building may also be taken into account in this phase. In general, the construction of closed-loop systems facilitates the management of the material flow.

Secondly, but not less important, is the design of the main system parameters. In order to ensure that enough data can be acquired to fit statistical distributions during the visit, short processing times can be assigned to each stations. For instance, in a system producing around 5 parts per minute, a 30-min visit will allow to collect more than 100 data points, which is enough to estimate the statistical distribution of the processing times in each station.

Once the main real system features are decided, the main problem that can be addressed by the students can be decided. This phase is particularly important because it determines the complexity and viability of student activities along the project. A too complex problem may hinder the reachability of the learning objectives, while a trivial one may result in a loss of interest by the students. Figure 5 explains how this phase decision can be addressed, using as example the parameters of the manufacturing system described in section 5.2. In the figure, it is shown the behaviour of the system throughput depending on the probability of failure on station 4. The results have been computed via a preliminary discrete event simulator and show that the throughput behaviour changes depending on the default position of the operator (i.e., either in front of station 3 or 4). In this problem, students are asked to determine a state-based policy to dictate the operator's position depending on the system status. Hence, it is suggested to design the failure rate of station 4 within a range such that no trivial solution exists, namely $p_4 \in [0.34, 0.35]$. This means that the students will need to take into consideration other aspects of the manufacturing system, such as the buffer levels, to determine the optimal position of the operator.

After the system features, parameters, and main problem have been defined, the system lab-scale model can be built. It is worth to notice that this phase may result in the need to modify the system design. For instance, the length of a conveyor may be adjusted to give enough space for a controlled buffer, since the control implies the presence of a higher number of sensors. Finally, the duration of this phase strictly depends on the dedicated effort. Based on the authors experience, this effort ranges from 20 to 40 man-hours. It is suggested to contain it within a 1–2 months period.

4.2.2. Second phase: project activities

The main project activities alternate visits to the laboratory with self-paced group activities. At the beginning of this phase, students may visit the lab and observe the physical system. In the first visit, students should observe by themselves the layout, the pallet number, the actual buffer capacity, the blocking after services rule, the unreliability of automatic stations. Students are provided with a descriptive document with nominal information about the system. Also, the format of the log files extracted from the system database is described. Each log file is a data table with four main columns: date-time timestamps, part identifiers, activity identifiers, and activity-related tags (e.g., distinguishing if the timestamp indicates the start or the finish of an activity on a station). Table 1 presents an extract of event log that has been used for one group.

After the first visit, students are divided into teams. Each team can start to study the system main features,

Table 1. Example of an event log provided to students (extract).

Time-stamp	Part-ID	Activity-ID	Tag
2020-11-23 16:37:40	1	1	start
2020-11-23 16:37:44	1	1	finish
2020-11-23 16:37:47	2	1	start
2020-11-23 16:37:51	2	1	finish
2020-11-23 16:37:52	1	2	start
2020-11-23 16:37:54	3	1	start
2020-11-23 16:37:57	1	2	finish

making assumptions about its behaviour, constructing a conceptual model, and deciding the type of data to collect in the second visit to the lab. Also, the interaction and the division of labour along the project can be decided autonomously by each group.

During the second visit, each team can collect data for building the simulation model while the system is working. A log file in the format of Table 1 is extracted from the system database. Further, extra sensors are provided to the students, as they can place them anywhere in the system to collect additional data. Besides, they are also allowed to perform manual acquisitions. For instance, by using stop watches or video shooting. This data acquisition activity normally lasts for between 30 and 60 min. It is worth to note that – depending on the specific project – some design parameters of the system may not be shown to students (e. g., processing and failure time distributions, maintenance policies, failure rates). They need to observe the system and collect data during the visit. Hence, given the limited amount of acquired data, the distributions fitted by students may be biased due to the sampling noise. Also, students interactions with the system might affect the number of records they can get. For instance, some teams might move pallets while the system is running or might interrupt the service at a certain station to study starvation and blocking conditions.

After the second visit, each group must complete the development of a discrete event simulation model that can be used for the as-is system analysis. In order to facilitate this phase, students obtain additional data so that they can validate the simulation model using the techniques acquired in the course. Specifically, a data set acquired during a 2-h production interval is provided for simulation model validation. This data set is for validation purpose only, hence it contains aggregated performance measures such as throughput and system time.

During the following self-paced activities, students are expected to properly apply the knowledge and techniques taught in the lectures and extract relevant insights from their analysis. The students are also invited to exploit available techniques from the literature, and are not restricted to any specific methodological constraint.

During the third and last laboratory visit, each team may implement the chosen solution onto the physical system and acquire new data for 45 min. The performance obtained from this visit should be compared to that obtained from the DES model (i.e., validation) and the one obtained in the second visit (i.e., comparison with the as-is situation).

Overall, the second phase may last between 1 and 3 months.

4.2.3. Thirdphase: reporting and evaluation

The last phase of the project consists in the preparation and presentation of the work done by eachgroup. The project has three main outputs:

(1) a valid DES model able to reproduce the current system behaviour;
(2) the evaluation of the system performance, which includes the identification of the system elements that determine this result (e.g., bottleneck, critical resources), and the analysis of the relationship between certain parameters and the system performance (e.g., how the number of circulating pallets might affect the throughput);
(3) a new system configuration such that the system production rate increases compared to the initial situation (e.g., a new buffer space allocation).

The deliverable for evaluation consists in a 15-page technical report and a 10-min presentation, together with the developed DES model. The technical report should contain all methodologies and techniques used to obtain the results. The following report structure is provided to guide the students: (1) introduction; (2) modelling of the as-is system; (3) analysis of the as-is system; (4) system improvement; (5) conclusions. The use of proper methods as well as students' understanding of the numerical results are considered in the evaluation. In particular, the project is graded according to the following criteria:

(1) system modelling and validation including the conceptual model of the system, the implementation in simulation software and input analysis (35/100);
(2) performance analysis using DES according to project requests, i.e., model validation, bottleneck identification and pallet analysis (25/100);

(3) selection of alternatives and validation of the final choice after a proper problem definition (25/100);
(4) communication of results in terms of clearness, language, and logic of project report and students' presentation (15/100).

The third and last phase usually lasts around 2 weeks.

4.2.4. Note on teachers role

Teachers and tutors are involved during all the project phases. Hence, their role is essential for a correct and successful project development. Herewith, we briefly summarise their functions.

In the first phase of the project, the instructors have the responsibility to design the lab-scale manufacturing system of interest. Their expertise in other projects can represent a valuable asset for it helps to reproduce a realistic and relevant situation. Also, tutors are essential for a proper design of the industrial problem. Preliminary analyses need to be conducted, such as estimations of the system performance and preliminary evaluations that can hint which modifications could improve the system performance. Therefore, it is preferable that the assistants that have built the system and designed the industrial problem will also be guiding the students.

During the second phase, the advisers lead the students during the visits to the laboratory. Tutors may help each group with a different degree of involvement, depending on the level of expertise of the participants. In general, self-management of student groups is encouraged. During the visits, the teachers effectively take on the role of plant managers and operators that master the system as-is configuration. Hence, students are free to ask them any information regarding the system dynamics and configuration. Nominal parameters of the production system may also be shared by the instructors.

During the last project phase, the teachers have the responsibility of evaluating each group. Hence, the evaluation phase consists in reading their reports and assisting to the presentations. The teachers apply the criteria listed in section 4.2.3 to produce final grades.

5. Case studies

In the following, two relevant case studies are reported, which refer to projects done within two consecutive academic years. The first case study is presented in section 5.1, it is a seven-station closed-loop production line, and the main project objective is to solve a Buffer Allocation Problem (BAP) (Demir et al., 2014). The second case study is described in section 5.1, it consists in a six-station closed-loop production line, in which the main goal is to determine an optimal state-based maintenance strategy. Finally, section 5.3 collects the lessons learned after these two experiences.

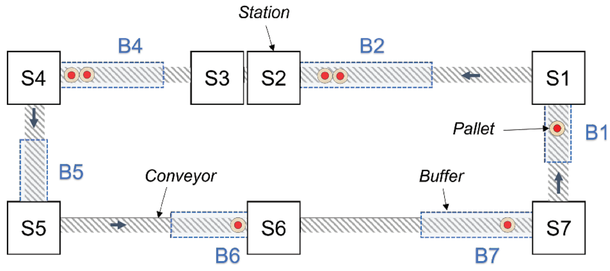

Figure 6. Case Study 1 - logical schema of the production system.

5.1. Case study 1 - flow line

5.1.1. Manufacturing system

The physical system is a closed-loop production line composed by $S = 7$ stations with intermediate conveyers that operate also as buffers, as shown in Figure 6. Denote with b_s the buffer capacity after station s such that $\mathbf{x} = \{b_s\}|s = 1, \ldots, S$ is the vector representing system layout. Blocking after service rule is applied. Each wooden disc represents a pallet and a fixed number of pallets ($n = 25$) circulates into the system. It is assumed that station $s = 1$ is the load/unload station and a large number of unprocessed parts are waiting in front of the first station. Also, we assume that a finished part can immediately leave the system. One station can process only one part at the same time. Stations $s = 2$ and $s = 3$ work in sequence with no intermediate buffer (Figure 7a). Therefore, these stations could be modelled as one single station in the simulation model.

Stations $s = 1, 4, 5$ represent manual operations and their processing times are stochastic, while stations $s = 2, 3, 6, 7$ represent automatic stations such that their processing times are deterministic. All stations are perfectly reliable except for stations $s = 6, 7$ which may fail. For these stations, the production is affected by a failure probability of 0.35. In the event of a failure, the operation time on a station s is increased by r_s, in accordance with Equation (1). It is worth to notice that high failure probabilities are set to increase the amount of failure data that students can collect during experiments. Table 2 reports the processing times of the stations, the distributions of the repairing times for stations 6 and 7 and the as-is buffer capacities b_s. The loading/unloading times are deterministic and equal to $3s$ each, although affected by natural noise. These times are not negligible compared to the processing times and vary between 1.2 and 2.5 s depending on the structure of

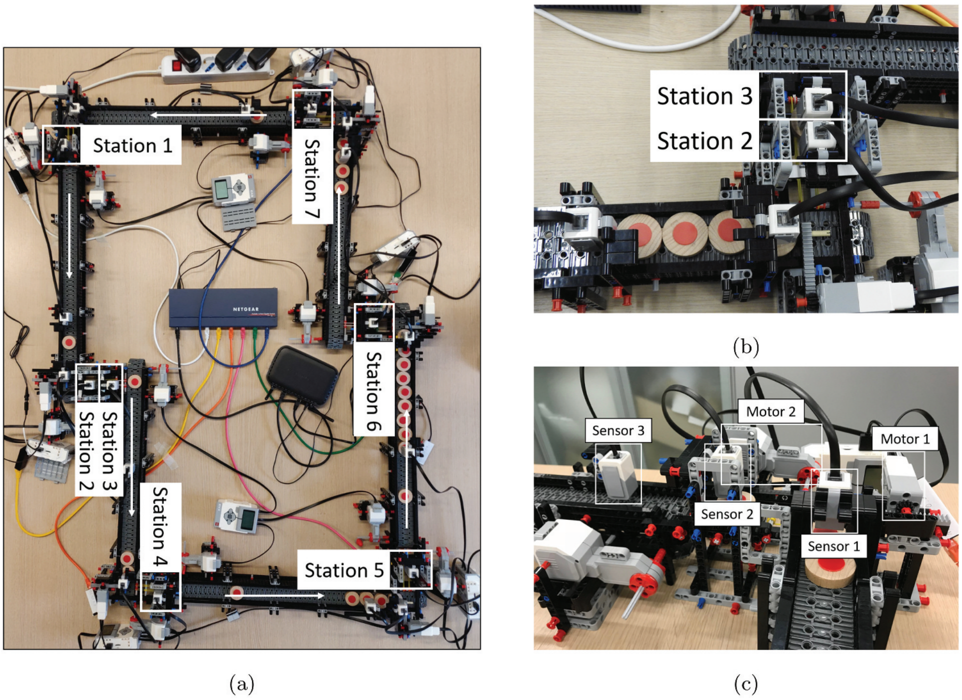

Figure 7. Case Study 1 - overview of the lab-scale system used for the didactic project.

Table 2. Case Study 1 - manufacturing system parameters (TR: Triangular, WB: Weibull, UN: Uniform).

Station s	1	2	3	4	5	6	7
Processing Times p_s [s]	TR(2,4,6)	2	2	WB(5,2)	WB(6,1.5)	2	2
Repairing Times r_s [s]	-	-	-	-	-	TR(8,9.5,11)	UN(10,13)
Failure Probability f_s	0	0	0	0	0	0.35	0.35
Buffer Capacity b_s	5	0	9	3	9	3	13

the stations. Moreover, all the conveyers have a speed of $v = 7$ cm/s. The system is unbalanced and it has been designed to allow a potential increment of the system performance by adjusting the buffer capacities along the line.

5.1.2. Proposed problem

In this project, each team had to face with the BAP. Buffer capacity $b_s | s = 1, \ldots, S$ needs to be allocated along the line in order to maximise the system throughput $\psi(\mathbf{x})$, respecting maximal total buffer space allowed $B_{\max}$ and the domain of each single buffer capacity $[L_s, U_s] \cap \mathbb{Z}$ which are limited by the length of the conveyers and the location of the sensors. We obtain the following BAP:

$$\max\left\{\psi(\mathbf{x}) | \sum_{s=1}^{S} b_s \leq B_{\max} \ ; \ L_s \leq b_s \leq U_s\right\}$$

In the project, $B_{\max}$ is equal to 42, and L_s and U_s are equal to 2 and 15 for all $s = 1, \ldots, S$, respectively, except for stations $s = 2$ and $s = 3$ that cannot be separated (i.e., $L_2 = U_2 = 0$). Students were required to identify a set $\mathbb{X}$ of candidate solutions $\mathbf{x} \in \mathbb{X}$ and, then, choose the best among the candidates. A DES model was used to evaluate $\psi(\mathbf{x})$. The inclusion of other performance indicators of interest (e.g., system time, queue levels) for the decision-making was encouraged.

5.2. Case study 2 - flow line with operator-assisted stations

5.2.1. Manufacturing system

The physical system is a lab-scale closed-loop production line composed by six stations with intermediate conveyers that operate as buffers. Figure 8 shows the logical schema of this system. Blocking after service rule is applied. Pallets are represented by wooden circles tagged with a red plate, and a fixed number of pallets ($n = 20$) circulates into the system. It is assumed that station 1 is the load/unload station and a large number of unprocessed parts are waiting in front of this station. Also, we assume that a finished part can immediately leave the system. Each station can process only one part at the same time. Pallets are held by a station for an amount of time that represents a physical process (e.g., milling, turning). Failures may

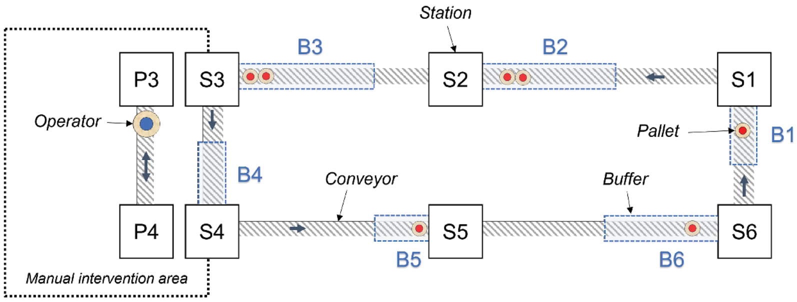

Figure 8. Case Study 2 - logical schema of the production system.

Table 3. Case Study 2 - manufacturing system parameters (UN: Uniform, EX: Exponential, N: Normal).

Station s	1	2	3	4	5	6
Processing Times p_s [s]	1	1.5	1.1	1	Max(2, N(2, 10))	2.5
Repairing Times r_s [s]	UN(5,60)	UN(5,60)	EX(1)	Max(0.5, N(4,2))	-	-
Failure Probability f_s	0,15	0,1	0.35	0.34	0	0
Buffer Capacity b_s	4	3	6	6	2	4

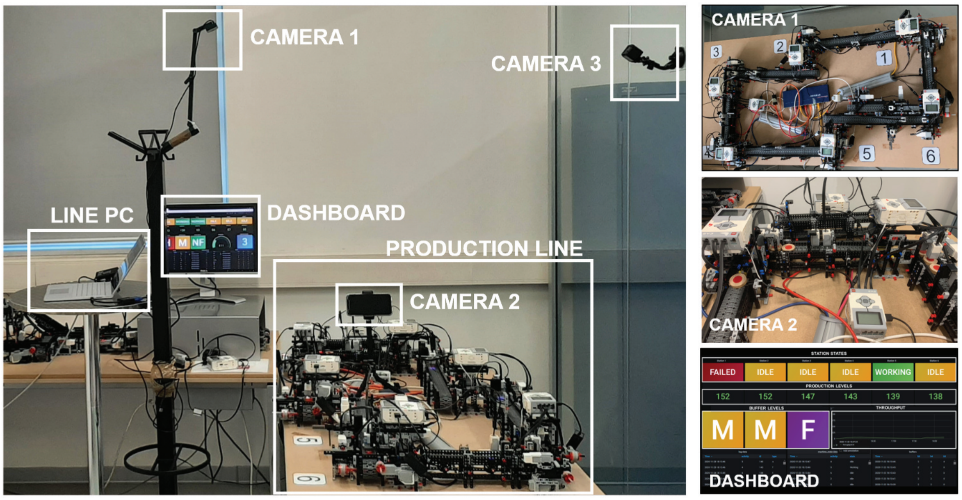

Figure 9. Case Study 2 - laboratory setting used in this project.

occur with a certain probability that is different for each station. Stations $s = 3$ and $s = 4$ are supervised by operators, which are modelled by blue discs. Each operator stays in the corresponding position, P3 or P4. If a failure occurs in either station 3 or 4, the station cannot be fixed unless an operator is at the respective position. In addition, the levels of buffers 3, 4, and 5 are constantly monitored and streamed in a time-series database. The parameters of the manufacturing system are available in Table 3.

Figure 9 shows the laboratory setting that has been developed for the project. This setting allows for both in-presence and remote observation of the system. The laboratory is composed by the following items: (1) the physical lab-scale model of the manufacturing system; (2) a dashboard, which allows for the real-time visualisation of the current system state; (3) three cameras: cameras 1 and 2 are used to give a bird view and a closer view of the system, respectively, while camera 3 is only used for offline video recordings and high-quality videos upon request; (4) a line PC, that allows not only the control of the system by a supervisor, but also the seamless sharing of the cameras and the live dashboard via remote connection.

5.2.2. Proposed problem

The proposed production problem is the definition of an operator allocation policy. It is assumed that a manufacturing company would need to reduce the number of operators assigned on the production line. As a consequence, stations $s = 3$ and $s = 4$ can be served by a single operator, instead of dedicated ones. This means that if a failure occurs on a station while the operator is not supervising it, the travelling time must be accounted in the repair duration. Specifically, assuming the operator is positioned in a generic location l, the repair time on station s will be

Table 4. Case Study 2 - example of state-based operator allocation policy (extract; $s(s)$ indicates the state of the s-th station).

Operator position	b_3	b_4	$s(3)$	$s(4)$	Action
4	4	1	DOWN	DOWN	P4
4	4	2	DOWN	DOWN	P4
4	4	3	DOWN	DOWN	P4
4	4	1	DOWN	UP	P4
4	4	2	DOWN	UP	P4
4	4	3	DOWN	UP	P4
4	4	1	UP	DOWN	P3
4	4	2	UP	DOWN	P4
4	4	3	UP	DOWN	P4

corrected as $r_s^{'} = r_s + t(s,l)$, where $t(s,l)$ represents the time to reach the station from the location l. In this problem, $t(3,4) = t(4,3) = 30\,s$.

With less operators, it is essential to establish a protocol on how to maintain the machines. The protocol could involve the position of the operators, their schedule, or reaction rules based on a set of inputs from the system. The students are asked to design an operator allocation policy that can take advantage of the real-time knowledge about the location of work-in-progress in the system, i.e., the number of parts in the buffers in front of stations $s = 3$ and $s = 4$. The teams must provide a rule that the customer company will need to follow to continue with the regular production. Table 4 reports an extract of a sample policy.

5.3. Lessons learned

In this section, some remarks on the experiences are listed. Also, a summary of observed outcomes with respect to main project learning objectives is in Table 5. Specifically, project objectives 2 and 3 (Table 5) could not be based on real system without the laboratory.

In the author's experience, all teams were well organised for the visits, and a high variability of approaches has been observed in this phase. For example: some groups preferred to label pallets so they are easier to be tracked, some brought a camera to record specific stations that they think should be noted, some used chronometers to record timing. Also, each team member was assigned tasks before the second visit.

During experiments, the students were free to decide the initial state of the system (i.e., the positions of pallets along the line) and to interact with the running system, e.g., by moving pallets in the system. As a consequence, students interacted with the system in order to focus the attention on peculiar behaviour of stations. For example, students manually accumulated several pallets to check the blocking conditions of machine. Also, students used additional sensors to record additional information, e.g., the conveyor speed, the blocking time.

Students encountered difficulties in choosing the level of detail of DES model. At the beginning, they have tried to model unnecessary details of the physical system including white noise of processes and rare events (e.g., pallet congestions, conveyor variable speed). The modelling of conveyers was particularly critical. Indeed, in the physical model, conveyers have two functions: part handling and part holding. Students analysed different conceptual models for conveyers and selected the most appropriate according to different criteria: some prefer the reduction of computational time and chose to model the holding function only, others modelled also the transportation time using the buffer length and the conveyor speed by representing the transportation time as a linear function of buffer occupancy. All students faced with the trade-off among the model detail level and the simulation execution time. Compared to a real setting, students found it harder to calibrate the importance of different elements. For example, some students focused with the same level of detail on load/unload, processing times, and failures.

Due to the unreliability of some sensors, students faced with data-post-processing issues. They needed to distinguish between acquisition errors and natural variability. Further, each team dealt with the trade-off between the uncertainty of measures taken manually (e.g., chronometers and video recording) and the magnitude of modelling approximations. Also, it might happen that the physical system suffers of real failures

Table 5. Summary of the observed outcomes with respect to the project learning objectives.

Project Learning Objective	Observed Outcome
1. To apply theoretical contents.	Better understanding of learned methods. Correct selection of the method(s) to be applied.
2. To analyse the observed system.	High student interaction with the running system. Intensive Q&A.
3. To acquire and process data.	Autonomous organisation of activities with different approaches. Self-assigned roles to team members in advance.
4. To design DES models.	Understanding of the trade-off among level of detail, execution time, and estimation accuracy.
5. To integrate knowledge.	Autonomous application of methods/tools not included in course contents to solve problems.

because of natural unreliability (e.g., motor overheating). The students were able to handle such variability with the teacher's support.

Overall, the interaction with a physical system and its observation increased student involvement. Further, students were satisfied to implement their own solution and to verify that the system performance was improved. The groups applied competences learned in other courses without specific request, e.g., design of experiments, queuing theory. Also, additional software and tools have been used autonomously by the students to perform the analyses, such as *Microsoft Excel*, *Matlab*, and *python*.

Last but not least, the remote setting allowed for a smooth organisation of the project activities during pandemic lock downs. Despite analysed from remote locations, all the groups were able to gather the important information. This is proved by the fact that all the proposed policies were compliant with the system configuration (i.e., with no deadlocks).

6. Conclusions

In this paper, we have presented the experience of an innovative mode to teach discrete event simulation for manufacturing systems. The proposed approach enables practical experience within realistic settings, that is not guaranteed in traditional teaching approaches. The results of two successful experiences demonstrated that students can be faced with realistic problems in model building and input analysis phases more effectively than with traditional lecture-based learning. The approach can be replicated in learning factories with real industrial equipment. Indeed, the most important activities in the lab are the system observation and data collection. Further, in addition to interactive teaching, the lab-scale models can also be used as demonstrator of research activities, thesis works, as well as scientific and industrial projects. Indeed, the proposed laboratory has proven to be a successful tool for the testing of digital twins and IoT architectures (Lugaresi et al., 2021). Hence, it is reasonable to assume that also courses related to the topics of Industry 4.0, industrial automation, and production digitisation could benefit from a similar lab-scale framework and project structure.

The case studies highlighted some limitations of the proposed approach. Although the lab-scale manufacturing systems have potentially no limits in terms of complexity and realistic production dynamics to be reproduced, they will always represent only a portion of a real system behaviour. The same concern is valid for the synthetic data that are provided to the students. The choice of level of detail and data tables to be provided brings along validity concerns on the approach. For instance, rare events may be synthetically reproduced and observed in a lab visit. The utility of this inclusion is questionable, as it renders the experience less realistic. In general, the proposed approach does not convey the same experience of a real site visit, and a proper trade-off has to be made between the effectiveness of the teaching and the effort required in building and managing the laboratory. The choice of which system behaviours to reproduce in lab-scale is not trivial, and no systematic guidance is available at the moment. In this paper, the evaluation of the advantage of applying the proposed approach in opposition to traditional frontal classes has been based on the experience of the teachers and tutors. The quantitative evaluation of the advantages requires further research and dedicated experiments. Last but not least, the success of the learning experience strictly depends on the possibility to organise activities in a laboratory. This is not always guaranteed, especially in light of the recent global restrictions (Lugaresi & Matta, 2021).

Future research should investigate the possibility to bring some activities outside the laboratory, perhaps through the design of smaller lab-scale models that can be easily transported and re-built. Also, in the proposed approach the student's interactions with the physical system are limited to data collection and observation. Next projects could explore the possibility to provide a direct connection to the physical setting, and allow students to directly change the system behaviour online. In the future, the flexibility provided by LEGO-based models will be further exploited for replicating different manufacturing systems. Specifically, the effort will be devoted to create models of complex production systems where other decision-making problems can be experienced, e.g., machine loading rules, routing of pallets, scheduling.

Notes

1. LEGO and LEGO MINDSTORMS are trademarks of the LEGO Group. ©2022 The LEGO Group®.
2. The choice of *python* as programming language is not restrictive and the proposed architecture can be extended to other languages.
3. The basic *python* code of a station is available in the following repository: github.com/giovannilugaresi/lab_scale_manufacturing_systems.

Acknowledgments

The research has been partially funded by Sme.UP Group. The authors also thank the Italian LEGO Users Group (ItLUG) for their contribution in physical model building.

Attachments

The instructions to build a two-station lab-scale manufacturing system with LEGO and the python code to be used on a simple station are available in the following repository:

github.com/giovannilugaresi/lab_scale_manufacturing_systems.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Behrens, A., Atorf, L., Schwann, R., Ballé, J., Herold, T., & Telle, A. (2008). First steps into practical engineering for freshman students using matlab and lego mindstorms robots. *Acta Polytechnica Journal of Advanced Engineering*, *48*(3), 44–49. https://doi.org/10.14311/1007

Behrens, A., Atorf, L., Schwann, R., Neumann, B., Schnitzler, R., Balle, J., Herold, T., Telle, A., Noll, T. G., Hameyer, K., & Aach, T. (2010). Matlab meets lego mindstorms—a freshman introduction course into practical engineering. *IEEE Transactions on Education*, *53*(2), 306–317. https://doi.org/10.1109/TE.2009.2017272

Buckley, C., Nerantzi, C., & Spiers, A. (2017). Enhancing learning and teaching with technology. In C. Scales (Ed.), *An introduction to learning and teaching in higher education: Supporting fellowship, chapter 7* (pp. 107–116). Open University Press.

Cruz-Martín, A., Fernández-Madrigal, J. -A., Galindo, C., González-Jiménez, J., Stockmans Daou, C., & Blanco-Claraco, J. -L. (2012). A lego mindstorms nxt approach for teaching at data acquisition, control systems engineering and real-time systems undergraduate courses. *Computers & Education*, *59*(3), 974–988. https://doi.org/10.1016/j.compedu.2012.03.026

Demir, L., Tunali, S., & Eliiyi, D. T. (2014). The state of the art on buffer allocation problem: A comprehensive survey. *Journal of Intelligent Manufacturing*, *25*(3), 371–392. https://doi.org/10.1007/s10845-012-0687-9

Gomez de Gabriel, J. M., Mandow, A., Fernandez-Lozano, J., & Garcia-Cerezo, A. J. (2011). Using lego nxt mobile robots with labview for undergraduate courses on mechatronics. *IEEE Transactions on Education*, *54*(1), 41–47. https://doi.org/10.1109/TE.2010.2043359

Grandi, R., Falconi, R., & Melchiorri, C. (2014). Robotic competitions: Teaching robotics and real-time programming with lego mindstorms. *IFAC Proceedings Volumes*, *47*(3), 10598–10603. https://doi.org/10.3182/20140824-6-ZA-1003.00222

Greenwood, A. G. Striving for ubiquity of simulation in operations through educational enhancements. In W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, & E. Page, Eds., Proceedings of the 2017 Winter Simulation Conference, pages 4252–4263, Piscataway, New Jersey, 2017. IEEE.

Hübl, A., & Fischer, G. Simulation-based business game for teaching methods in logistics and production. In W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, & E. Page, Eds., Proceedings of the 2017 Winter Simulation Conference, pages 4228–4239, Piscataway, New Jersey, 2017. IEEE.

Hussain, S., Lindh, J., & Shukur, G. (2006). The effect of lego training on pupils' school performance in mathematics, problem solving ability and attitude: Swedish data. *Journal of Educational Technology & Society*, *9*(3), 182–194.

Iturrizaga, I., & Falbel, A. (1999). Study of educational impact of the lego dacta materials. *4*, 2004.

Iversen, T. K., Kristoffersen, K. J., Larsen, K. G., Laursen, M., Madsen, R. G., Mortensen, S. K., Pettersson, P., & Thomasen, C. B. Model-checking real-time control programs: Verifying lego mindstorms tm systems using uppaal. In Proceedings of the 2000 Euromicro Conference on Real-Time Systems, pages 147–155, Piscataway, New Jersey, 2000. IEEE.

Jang, Y. J., & Yosephine, V. S. (2016). Lego robotics based project for industrial engineering education. *International Journal of Engineering Education*, *32*(3), 1268–1278.

Kim, Y. (2011). Control systems lab using a lego mindstorms nxt motor system. *IEEE Transactions on Education*, *54*(3), 452–461. https://doi.org/10.1109/TE.2010.2076284

Kim, S. H., & Jeon, J. W. Educating c language using lego mindstorms robotic invention system 2.0. In Proceedings of the 2006 IEEE International Conference on Robotics and Automation, pages 715–720, Piscataway, New Jersey, 2006. IEEE.

Klassner, F., & Anderson, S. D. (2003). Lego mindstorms: Not just for k-12 anymore. *IEEE Robotics & Automation Magazine*, *10*(2), 12–18. https://doi.org/10.1109/MRA.2003.1213611

Klug, M., & Hausberger, P. Motivaton of students for futher education in simulation by an applied example in a related other course in engineering education: A case study. In M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, & R. G. Ingalls, Eds., Prooceedings of the 2009 Winter Simulation Conference, pages 248–255, Piscataway, New Jersey, 2009. IEEE.

Lee, W. -L. Spreadsheet based experiential learning environment for project management. In S. Jain, R. Creasey, J. Himmelspach, K. White, & M. Fu, Eds., Proceedings of the 2011 Winter Simulation Conference, pages 3877–3887, Piscataway, New Jersey, 2011. IEEE.

Lugaresi, G., Alba, V. V., & Matta, A. (2021). Lab-scale models of manufacturing systems for testing real-time simulation and production control technologies. *Journal of Manufacturing Systems*, *58*, 93–108. https://doi.org/10.1016/j.jmsy.2020.09.003

Lugaresi, G., Frigerio, N., & Matta, A. (2020). A new learning factory experience exploiting lego for teaching manufacturing systems integration. *Procedia Manufacturing*, *45*, 271–276. https://doi.org/10.1016/j.promfg.2020.04.106

Lugaresi, G., & Matta, A. (2021). A remote laboratory experience in teaching discrete event simulation modeling for manufacturing applications. *SSRN Electronic Journal*, *3857933*. https://doi.org/10.2139/ssrn.3857933

Martin, N. Bringing students to practice: Performing a real-life simulation study in an introductory simulation course. In M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, & B. Johansson, Eds., Proceedings of the 2018 Winter Simulation Conference (WSC), pages 4014–4025, Piscataway, New Jersey, 2018. IEEE.

Mustafee, N., & Katsaliaki, K. The blood supply game. In B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, & E.

Yücesan, Eds., Proceedings of the 2010 Winter Simulation Conference, pages 327–338, Piscataway, New Jersey, 2010. IEEE.

Padilla, J. J., Lynch, C. J., Diallo, S. Y., Gore, R. J., Barraco, A., Kavak, H., & Jenkins, B. Using simulation games for teaching and learning discrete-event simulation. In Roeder, T. M. K., Frazier, P. I., Szechtman, R., Zhou, E., Huschka, T., and S. E. Chick, Ed., Proceedings of the 2016 Winter Simulation Conference, pages 3375–3384, Piscataway, New Jersey, 2016. IEEE.

Padilla, J. J., Lynch, C. J., Kavak, H., Evett, S., Nelson, D., Carson, C., & Del Villar, J. Storytelling and simulation creation. In 2017 Winter Simulation Conference (WSC) Las Vegas (USA), pages 4288–4299. IEEE, 2017.

Papadimitriou, V., & Papadopoulos, E. (2007). Putting low-cost commercial robotics components to the test-development of an educational mechatronics/robotics platform using lego components. *IEEE Robotics & Automation Magazine*, *14*(3), 99–110. https://doi.org/10.1109/MRA.2007.901322

Papert, S. (1980). Mindstorms: Children, computers, and powerful ideas. Basic Books, Inc

Resnick, M., & Robinson, K. (2017). *Lifelong kindergarten: Cultivating creativity through projects, passion, peers, and play*. The MIT Press.

Sanchez, A., & Bucio, J. (2012). Improving the teaching of discrete-event control systems using a lego manufacturing prototype. *IEEE Transactions on Education*, *55*(3), 326–331. https://doi.org/10.1109/TE.2011.2173688

Souza, I. M., Andrade, W. L., Sampaio, L. M., & Araujo, A. L. S. O. A systematic review on the use of lego® robotics in education. In 2018 IEEE Frontiers in Education Conference (FIE), San Jose (USA), pages 1–9. IEEE, 2018.

Sterman, J. D. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management science*, *35*(3), 321–339. https://doi.org/10.1287/mnsc.35.3.321

Syberfeldt, A. A lego factory for teaching simulation-based production optimization. In Proceedings of the 2010 Industrial Simulation Conference, pages 89–94, Ostend, Belgium, 2010. EUROSIS-ETI.

Tobail, A., Crowe, J., & Arisha, A. Learning by gaming: Supply chain application. In S. Jain, R. Creasey, J. Himmelspach, K. White, & M. Fu, Eds., Proceedings of the 2011 Winter Simulation Conference, pages 3940–3951, Piscataway, New Jersey, 2011. IEEE.

Wadoo, S. A., & Jain, R. A lego based undergraduate control systems laboratory. In Proceedings of the 2012 IEEE Long Island Systems, Applications and Technology Conference, pages 1–6, Piscataway, New Jersey, 2012. IEEE.