Industrial IoT integrated with Simulation – A Digital Twin approach to support real-time decision making

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Abstract

The industry faces more and more the challenge of deploying and taking advantage of evidence-based strategic decisions to enhance profit gain. In this research, the possibility of having a fully integrated system composed by a simulator and an IoT platform with the capability of collecting real-time data from the shop floor and returning performance indicators to support decision making is evaluated. The suggested approach involves a Manufacturing Executing System (MES) producing a production schedule, an IoT Platform composed by a message broker and a real-time database, a Simulator including simulation software and a wrapper, and a user application serving as an interface between the user and the IoT Platform and Simulator integrated system. A detailed analysis of the functionalities and integration of the Simulator and the IoT Platform will also be explored. To evaluate the approach, one use case of a production line in the automotive industry is used. The application of the integrated IoT Simulation system permits its validation and consequent future work.

Keywords
Discrete Event Simulation, Manufacturing Systems, Real-Time Decision Making and Internet of Things (IoT)

1. Introduction

Industry 4.0, also known as the 4th industrial revolution, is making industries more intelligent using advanced computational technologies. In this revolution, sensors, machines, devices and information technologies are connected along the value chain, making it possible to collect and analyze data from equipment, allowing faster, more flexible and efficient processes in order to produce high quality products at reduced costs (Rüßmann, Michael Lorenz et al. 2015), and support more efficient decision making strategies. According to Lidong et al. (2016), nine technologies are changing industrial production: simulation, augmented reality, autonomous robots, the industrial Internet of Things (IoT), the cloud, cybersecurity, additive manufacturing, horizontal and vertical system integration, and Big Data and analytics.
One of the most important technologies that will contribute to smart manufacturing is the industrial IoT (Thames et al. 2016). It is a ubiquitous network and a subset of IoT that connects industrial systems with "things", such as, sensors, robots, manufacturing devices and 3D printers in order to understand and control an industrial environment. IoT applications are present in many fields, including industry, agriculture, smart cites, etc. Despite the advance of IoT technologies in architectures, standardization and security, IoT is still in development. Additionally, IoT is based on integration of many standards and technologies with different sensing, connectivity, communication, storage, computational characteristics and capabilities. This diversity produces challenges in providing connectivity between all the technologies (Čolaković et al. 2018).

On the other hand, the increase in the number of IoT devices and data generated by them enables the development of sophisticated simulation models to allow online and effective decision making about manufacturing processes. Simulation, a promising technology in Industry 4.0, will allow the test and optimization of machines settings in a virtual production line before the physical changeover, and thus reducing machine setup times and increasing quality (Rüßmann, Michael Lorenz et al. 2015). Therefore, the integration of IoT data and simulation is a promising strategy in industry, since it allows more fast decisions, a direct connection to the production resources and automatic data insertion in simulation models. However, the integration of simulation tools and IoT platforms remains a challenge. For example, the acquisition of real time data coming from the IoT platform, and the conversion and inputting of the data into a simulation model are open issues in the literature (Tan et al. 2019).

In this paper, an architecture which integrates IoT platform and simulation software is proposed to support real-time decisions in manufacturing processes. More precisely, the IoT platform is used to ensure data collection in real-time directly from the shop floor and to enable distinct services communicating with each other. Simulation models are updated with the data gathered and present key performance indicators for user analysis. To demonstrate and evaluate the feasibility of the proposed architecture, a real use case, which represents part of a production line inside automobile industry, is proposed. The main contributions of this paper are: a data structure to develop simulation models, the description and proposal of an IoT platform integrated with a simulation software and the applicability evaluation of the proposed approach to a real use case.

This paper is organized as follows. Section 2 shows the relevant background literature of IoT technologies and simulation. Section 3 exhibits the proposed architecture which integrates IoT and simulation. Section 4 shows experimental use case and evaluates the proposed architecture. Finally, Section 5 provides the concluding remarks and future work.

2. Background

The process of monitoring production systems (such as, Manufacturing Plants and Supply Chains) is evolving due to the increasing digitalization of production and operations. Suitable data exchange – in terms of frequency and scope – is allowed using information and communication technology, which connects physical and information flows in cyber-physical systems. Cyber-physical interaction enables the acquisition of real-time system state data to support better monitoring and decision-making. Technological evolution pushes the boundaries of manufacturing systems and

supply chain towards an integrated and adaptive vision. The next subsections present the literature background regarding Industrial digital twins, Discrete event simulation and Hybrid commissioning-simulation methods.

2.1 Industrial Digital Twins

The ongoing technological evolution is characterized by increasing computational capacity, broadly applicable sensor technology and ubiquitous network structures (Lanza et al. 2015). The vision of the 4th industrial revolution describes the realization of the IoT within the context of the factory aiming to higher flexibility and adaptability of production systems (Wang et al. 2015). The increasing use of sensor-equipped collaborating machines enables the collection of data regarding the current system state in real-time and allows for up-to-date virtual representations of production systems (Wang et al. 2015; Terkaj et al. 2015; Lanza et al. 2015; Monostori et al. 2016). Current industrial facilities will evolve into smart factories, facing the challenges of shorter product life cycles, mass customization and an increasingly intense global competition (Monostori et al. 2016; Frazzon et al. 2018a, 2018b).

Technology and method-oriented drivers empower new possibilities for coping with the contemporaneous challenges (Lee et al. 2014). In terms of barriers, the capability of monitoring and decision-support methods to properly consider production, transport, inventory, and supply data stands out. This capability is paramount to properly advantage of forthcoming industrial digital twins representing the physical system virtually (Rosen et al. 2015; Schleich et al. 2017; Uhlemann et al. 2017). The proper combination of growing computational power, better industrial digital twins along with the evolving capability of decision-making methods will support an integrated monitoring and steering of manufacturing systems and supply chains (Monostori et al. 2016) within and across industrial companies limits.

In the realm of event processing and Big Data analysis, an interesting broker component is Apache Kafka. Kafka is a distributed streaming platform with a publish-subscribe protocol hosted by Apache foundation. Producers generate commits into topics, that can be read by any number of consumers. Outside the Kafka project, there are several independent open-source clients for various other programming languages and frameworks. Different from other types of brokers, events (log commits) can be read by subscribers at any time and as often as they like, since Kafka focuses on persisting its commits, only deleting them after a pre-configured period (Apache Software Foudation 2019). IoT events repository is needed to storage all the events exiting from Apache Kafka streaming tool. MongoDB is suitable for IoT applications and real-time analytics, by offering the flexibility, scale, and performance required by today's applications. MongoDB maintains the most valuable features of relational databases, such as strong consistency, expressive query language and secondary indexes. It also carries data model flexibility, elastic scalability, and high performance which are common qualities of NoSQL databases (DB-Engines 2019).

2.1 Discrete Event Simulation

Simulation models have become one of the most popular techniques used for the analysis of complex industrial systems with great potential for applications at the operational level. Simulation modeling in the form of discrete event simulation has evolved to become one of the most popular and economical means of analyzing complex systems. The technique of simulation of discrete events consists of developing a model of a system whose state changes at discrete intervals of time. Before one begins to apply simulation techniques to logistics and manufacturing systems, it is important to be aware of the problems that need to be overcome when attempting to provide solutions to real-world situations. The task of simulating a system is divided into several key items, each of which is difficult to perform satisfactorily. Over the years, many simulation-based tools have emerged that can be used to help novice simulators conduct a simulation study with confidence (O'Kane et al. 2000).

Simulation-based techniques can be used both to develop and to evaluate complex systems. In this way, aspects such as the physical configuration or operating rules of a system can be considered. Its applications have grown in all areas, assisting managers in the decision-making process and enabling a better understanding of processes in complex systems (Sakurada et al. 2009). The complexity of real systems is related to the large number of agents and interactions, both internal and external to the system. Historically, problem solving in complex systems involves modeling and simulation techniques (Longo 2010).

Simulation is a powerful tool for the analysis and evaluation of complex and stochastic systems, such as contemporary manufacturing and transportation environments (Lin et al. 2011). Simulation-based techniques can be used either to

develop or to evaluate complex systems. Aspects like the physical configuration or operational rules of a system can be considered. In the simulation process, the model represents the structure, the elements, their key characteristics, behaviors and functions of the selected physical or abstract system (Kück et al. 2016).

According with Pirard et al. (2011), the simulation has been identified as an effective tool to evaluate potential designs of a supply chain network according to several metrics (e.g. cost, service and lead-time). This technique makes it possible to consider the complexity and the dynamic behavior of the studied system and to consider the uncertainty related to its environment. Simulation also enables the decision maker to evaluate several control policies.

According to Banks et al. (2001), these techniques can also be used for the study of systems in the design phase. Thus, simulation models can be used as an analytical tool to predict the effect of changes on existing systems and as a design tool to predict the performance of new systems subject to different sets of circumstances. The integration of analytical and simulation models leads to hybrid models, representing a viable option to capture the best potentialities of both techniques.

Numerous replications of the simulation model, corresponding to several possible situations, can be performed to evaluate the robustness of the system. Simulation does not guarantee an ideal design. However, this technique gives the manager real help in establishing and evaluating the consequences of his or her decisions (Pirard et al. 2011).

In the simulation, the model represents the main characteristics or functions of the selected physical or abstract system. Simulation models address questions such as: What will likely happen over time and at which specific places if a particular design and/or operating policy are implemented? The model usually takes the form of a set of assumptions concerning the system operation (Banks et al. 2001).

Dias et al. (2017) presents a ranking of discrete event simulation software. Within top 10 of this ranking appears Simio, as one of the most used and with better simulation tools. Joines and Roberts (2013) demonstrates how to build simulation models using Simio software and offering the possibility of having a virtual representation through 3D objects.

2.3 Hybrid commissioning-simulation methods

New approaches that appropriately use available information, virtual commissioning models and enable real-time revisions as production and operations are a research opportunity with potential practical impact ready to be tested in industrial pilots. Indeed, new concepts, hybrid methods and smart technology-based approaches will fundamentally change the understanding of planning and control. This evolution impels the use of hybrid commissioning-simulation methods not only periodically to support planning at the strategic and tactical level, but also to allow for data-driven execution decision-making in real time, in the loop.

In this direction, Frazzon et al. (2018a) identified a gap regarding approaches capable of processing large amounts of data – generated with the support of physical and computational elements – and proposed a simulation-based approach for the integrated scheduling of production and transport processes in a supply chain. Complementarily, for job-shop manufacturing systems, taking advantage of always being able to get the current state of the system, Frazzon et al. (2018b) proposed and applied a data-driven adaptive approach that uses a simulation-based method and a data-exchange integration framework between a real system and a simulation model. The approach achieved a significantly higher performance than classical methods for a real-world application (Frazzon et al. 2018b).

Technological developments along with the emergence of Industry 4.0 allow for new approaches to solve industrial problems, such as the Job-shop Scheduling Problem (JSP), with gains in flexibility, scalability and efficiency (Leusin et al. 2018). Data-driven technologies in the Cyber Physical System era can bridge the boundaries of digitization and decision-making beyond the job-shop, including the company's remaining operations as well as its integration with other organizations (Leusin et al. 2018).

In this context, there is a huge potential for the proposition of tools that integrate physical processes and their virtual representation aiming at real-time decision-making capabilities. This topic embodies a timely practical opportunity with a relevant scientific impact. This kind of tool could take advantage of the communication between machines,

devices, sensors and/or products, supporting the automatic response to unexpected events with minimum human interaction.

3. Industrial IoT integrated with Simulation

According to the context described in Section 1 of this research and taking advantage of the key concepts defined in Section 2, the followed approach was defined. First, the concept is introduced and then the technical approach will be described using a sequence diagram to show the architecture solution and the interactions between the actors. The approach is explored further in the following section in terms of IoT platform and simulation role in the methodology and its integration.

3.1 Concept

The proposed approach is a Digital Twin that takes advantage of the data collected from the shop floor to feed virtual models to support decision making. Figure 1 presents the general concept diagram. The vertical integration starts in the physical resources of a production line and flows to the decision support system. The IoT Platform collects the resources status in real-time. The Simulation Model accesses the IoT Platform to gather the data and presents results for the Decision Support System analysis. Finally, the Decision Support System involves a computational part to provide decision suggestions and a human decision agent who validates the suggestions.

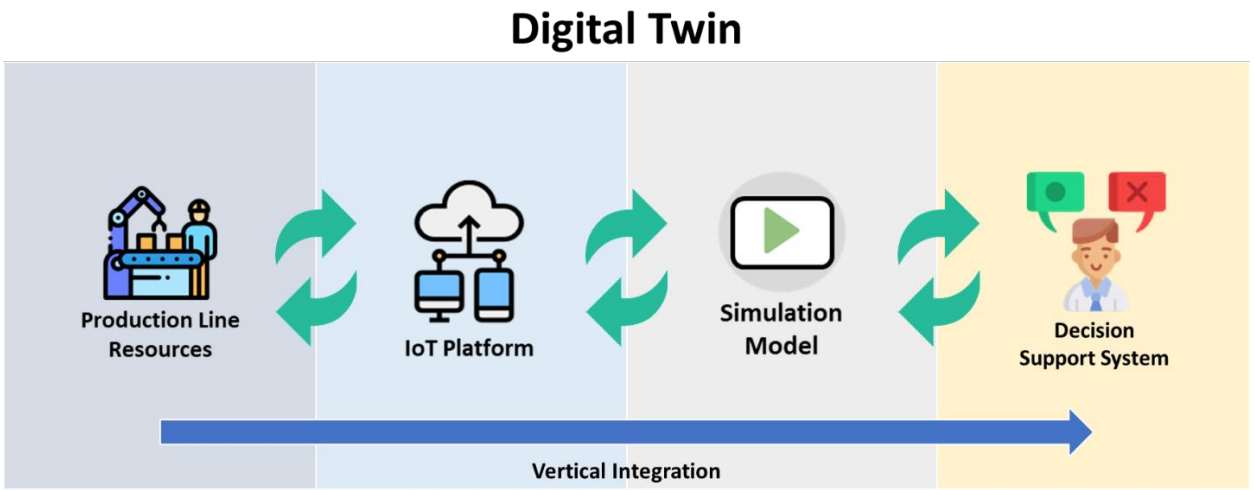

Figure 1. Concept diagram

3.2 Technical approach

In manufacturing systems, it is essential to have tools capable of supporting decision making, understanding the behavior of the production line and getting results' forecasts without wasting production line resources. Aligned with this perspective, the methodology developed (described in Figure 2) takes in consideration the advantage of accessing the production schedule produced by the Manufacturing Execution System (MES) and to have a simulation software gathering real-time data of the production line's resources to produce Key Performance Indicators (KPIs). To collect the production schedule and to trigger the simulation software, a user application was also included in the diagram. This diagram also includes the IoT Event Repository, capable of gathering and storing real-time data directly from the production line resources and all the messages between actors using the IoT Message Broker.

The approach presented in Figure 2 starts with the user requesting MES to produce a production schedule through the user application. Afterwards, the simulator is executed to obtain KPIs of the production line for a certain period of simulated time.

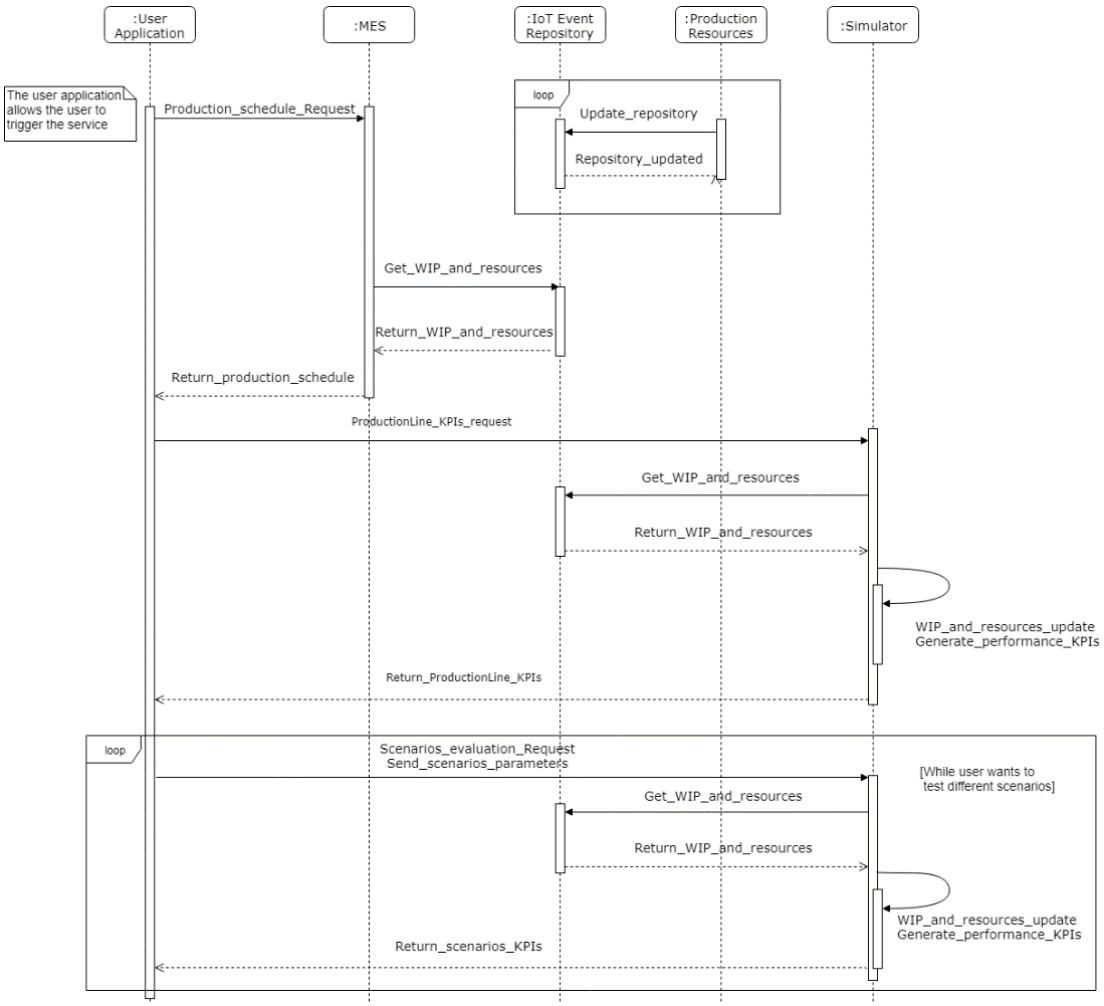

Figure 2. Sequence diagram of the technical approach

To ensure the execution of the request the following characteristics must be considered:

- The IoT Event Repository is connected to the production resources, updating the repository cyclically in real-time;
- The IoT Event Repository must store the production line resources status, the Work In Progress (WIP), detailing which tasks are being executed, and make them accessible to MES and to the simulator;
- The MES will have to access real-time data stored in an IoT Event Repository to produce the production schedule;
- The simulator will start the run to produce KPIs with the WIP of tasks and production line resources collected from the IoT Event Repository;
- The simulator must be able to present a dashboard containing relevant statistics for the user analysis;
- To synchronize the services, all the messages must be sent through an IoT Message Broker in real-time.

Respecting these characteristics, the user also has the possibility to perform tests in the simulated production line through the user application. The scenarios parameters must be defined in the user application and they could be, for example, the number of resources available or buffers capacities. To answer this request, the simulator must be flexible in terms of data exchanged by the user and start the run with the current state of the production line present in the IoT Event Repository. When the simulator ends running, dashboards must be displayed.

To have a fully integrated system capable of supporting decisions in real-time there is a necessity to explain the main functionalities of the components of the architecture and how they could be integrated. The exchanged messages through the IoT Message Broker will also be clarified.

3.3 Simulator

The Simulator is the tool to support the decision making, since it is responsible of evaluating the behavior of the production line and the production schedule according to the work in progress and the resources status collected in real-time. To add functionalities such as listening to requests and inserting data in simulation models, a simulation wrapper is included within the simulator.

Simulation models

To properly represent the real behavior in the models, it is necessary to ensure a preliminary work of gathering characteristics from the shop floor, such as the plant layout, the resources behavior, the products, and the production processes. After, this information is gathered and the processes is mapped, the simulation model needs to be flexible enough to allow small changes of the production line, like the insertion of a new product or a modification of buffers' capacities. To capture the characteristics of a manufacturing system, in Figure 3 the classes composing the simulation are represented using a Unified Modeling Language (UML) class diagram.

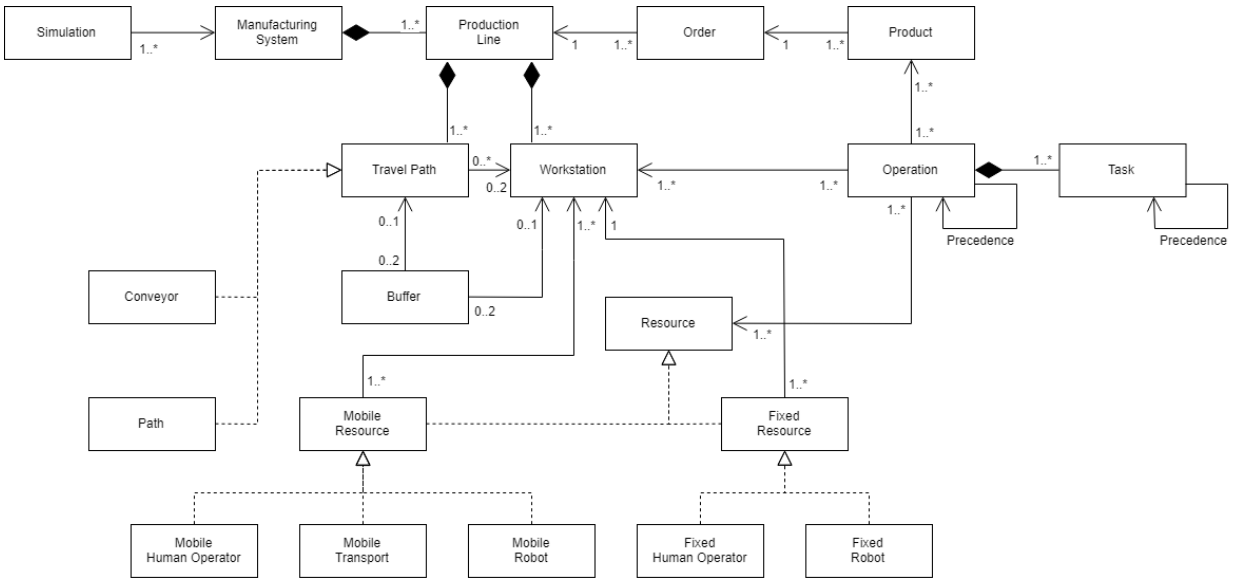

Figure 3. UML class diagram for simulation data in a manufacturing system

To a specific manufacturing system, for each class of the diagram presented in Figure 3, the attributes and methods should be defined. Each class is explained in the Table 1 and the following text explain the connections between the classes.

Table 1. Classes description

Class	Description
Simulation	Simulation model of the manufacturing system in study
Manufacturing System	Manufacturing system in study
Production Line	Production lines that compose the manufacturing system

Production Plan	Representation of the production plan that will be executed in its respective production line
Order (Production Order)	Representation of the orders requests that compose a production plan
Product	Representation of the products considered in the manufacturing system and gather all the information related to them
Operation	Set of tasks that will be executed on each workstation for each product
Task	Representation of the task to be executed and gathers all the information related to it
Travel Path	Representation of the transport of products/mobile resources between workstations/production lines
Conveyor	Representation of a travel path made by conveyors
Path	Representation of a travel path made by routes/accesses/passages/etc. A transport resource is required to move products through a path
Workstation	Representation of a work center of the production line, where the operation will be executed
Buffer	Representation of the place where the WIP is stored between Operations
Resource	Resources available in the manufacturing system, able to perform tasks on workstations
Mobile Resource	Resources with the capability of moving between different workstations to perform tasks
Mobile Human Operator	Mobile type human operator
Mobile Transporter	Resource used to make the transport tasks through the Paths
Mobile Robot	Mobile type robot
Fixed Resource	Resources allocated to one workstation to perform tasks
Fixed Human Operator	Fixed type human operator
Fixed Robot	Fixed type robot

The manufactory system at study could contain multiple Production Lines, each one composed of various Workstations, Buffers and Travel Paths. The Travel Paths are used to connect the Workstations/Production and Lines/Buffers between them and could be a Conveyor or a Path. Workstations can have Buffers and/or Travels Paths associated with them, while Travel Paths can have Buffers associated. A Production Line may be associated with one or more Productions Plans, each one with various Orders. The Orders have several Products associated. The Product to be produced require a set of Operations before its completion, which can have precedencies between it. Each Operation is composed of a set of Tasks. The Tasks can have precedencies, and some of them could be executed in parallel. To be executed, an Operation requires resources available in the production line. Some of the Operations can only be performed in some of the Workstations. There are resources in each production line, where some are Fixed and associated with only one Workstation; while others are Mobile and can execute Tasks on different Workstations. Both Mobile and Fixed resources can be Robots or Human Operators. Also, mobile resources can be of the Mobile Transports type, which are used to execute the transport tasks.

Simulation wrapper

The simulation wrapper plays the role of intermediary between simulation models and the IoT platform. This wrapper could be within the simulation software or an external code, depending on the software chosen. To properly send and receive requests, the wrapper needs to have the following functionalities:

- Internet connection;
- Web Socket Protocol;
- Simulation model's connection libraries;
- Microsoft Excel libraries;
- IoT platform libraries and connectors.

3.4 IoT platform

The IoT platform, in terms of the architecture of this research, is composed by the IoT Message Broker, the IoT Event Repository and a wrapper. To access the data stored in the IoT Event Repository, the wrapper deals with the connection between the IoT Broker and the IoT Event Repository.

The IoT Event Repository is a real time database, updating the events every time a change is detected. The IoT Message Broker is a framework to simplify the creation of connectors. In the IoT Message Broker the following connections are defined, according to the general architecture in Figure 2:

- MES – IoT Event Repository: this connection allows MES to gather real-time data from the IoT Event Repository and produce a production schedule with this data;
- User Application – MES: this connection enables the request and response of a production schedule;
- Simulator – IoT Event Repository: this connection allows the simulation models to use real-time data from the production resources, where the predefined simulation wrapper is used;
- User application – Simulator: every time the user wants, this connection allows the user to directly use the simulator to evaluate scenarios of production.

3.5 Simulator and IoT Platform interoperability

One of the objectives of this research is to evaluate how a simulator could be connected to the IoT platform in order to collect data directly from the shop floor, feeding the models with it and running them. The diagram, presented in Figure 4, is the solution generated in the followed approach to integrate both services.

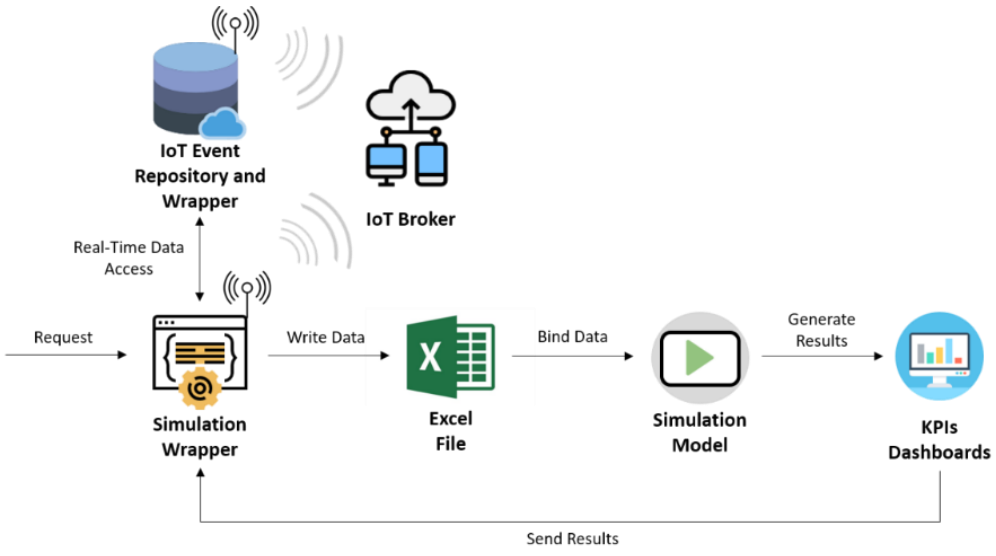

Figure 4. Integration diagram of IoT platform and simulator

In Figure 4, the connection made between each component of the simulator and IoT Platform is presented. To receive and answer requests, the simulation wrapper should start to listen when the user starts the request of a simulation. Once it starts, the following steps are executed:

1. The simulation wrapper is connected to the IoT Message Broker and receives the request from the user application;

2. The simulation wrapper sends an event with data request to IoT Message Broker;
3. The wrapper connected to the IoT Event repository receives the message through a function handler, gets the real-time data gathered from the shop-floor and publishes the response event in the IoT Message Broker;
4. The function handlers of the message in the simulation wrapper are triggered and the data is received;
5. The data is saved into a predefined flexible structure in an Excel file;
6. Data collected is updated in the simulation software structure using binding options with Excel;
7. The simulation model starts to run;
8. At the end of the run, dashboards are presented for the user analysis;
9. The simulation wrapper sends a message to the User Application, connected to the IoT Message Broker, with the relevant results.

The reason behind using an Excel file to do the data interface is the simplicity of binding information in Excel to the simulation software. Another reason is that the end users of the platform are familiar with Excel and know how to visualize and manipulate data in this software.

4. Application case

To evaluate the methodology, one experimental use case was considered. For this study, the main goal is to determine whether the IoT connection to the simulator is possible. First, the characteristics of the use case will be detailed, specifying the context and the components that will be part of the simulation model, and then, it will be described the approach applied to the use case.

4.1 Use case description

The use case chosen for the approach evaluation is a small production line in the automotive industry sector. This production line produces two types of engines. It is composed by one table containing piston's engine and one Automated Guided Vehicle (AGV) transporting the piston from the table into one conveyor. In the conveyor, there are three workstations, a fixed robot executing screw and unscrew tasks, one human worker reversing the engine and one mobile robot executing tasks between the first and the last workstations. The production plan followed is random and with a production ratio of 50% of each type. There are common tasks for both engines, but there are also specific tasks to the type and depending on this, the processing time is also different. The use case was developed to solve the resource sharing problem, since the mobile robot executes tasks on a different workstation and has distinct functions according to the type of engine in production.

4.2 Application of the Industrial IoT integrated with Simulation to the use case

Once the use case was defined, the integration between the simulator and the IoT platform was evaluated. For the simulator, first the simulation model was developed using the proposed UML class diagram (Figure 3) as a base and then the simulation wrapper was designed. For the IoT platform, development tests were made to send and receive messages containing fictional data, with the same structure as the data to be stored in the IoT Event Repository.

<u>Simulator</u>
The model present in figure 5 is the 3D model of the use case in Simio software. To enable data insertion in the model and to use the data with the structure defined in the approach, Excel tables were bound to Simio software. To start to run the simulation model, a wrapper was developed with Microsoft Excel library embedded (Microsoft.Office.Interop.Excel library). This enables the wrapper to write in the same Excel file as the simulation model, changing the input data dynamically.

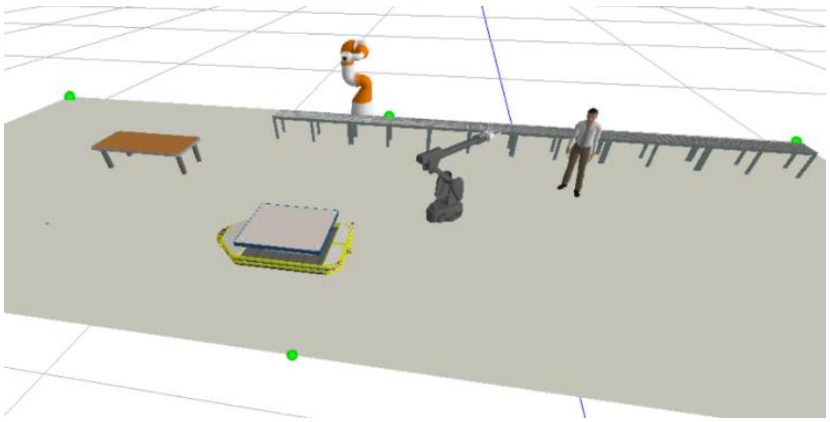

Figure 5. Simio simulation model of the use case

IoT platform application

Based on the architecture designed, Kafka and MongoDB were chosen to play the role of IoT Message Broker and IoT Event Repository, respectively. In Kafka, the connections defined in the approach were built. Because of confidentially policies, MongoDB, functioning as real-time event repository, were fed with fictional data.
To ensure the communication and integration between Simio and this platform, another wrapper was created between Kafka and MongoDB, including Kafka and MongoDB libraries and connectors.

The integration of Simio with Kafka and MongoDB was also implemented following the next steps:

- The simulation wrapper connected to the simulation model input data and to Kafka is executed and stays connected;
- One request of data is sent from the simulation wrapper to Kafka, specifying the topic of the message as Simulator-MongoDB-Request;
- The wrapper connected to the IoT Event Repository handles the request from Kafka and returns a message containing the data with the topic MongoDB-Simulator-Response;
- The simulation wrapper receives the message with the data and inserts it in the Excel file with a predefined structure of input data;
- The simulation wrapper calls Simio model to run;
- Simio opens with the input data updated and allows the user to run the model, and presents dashboards with the KPIs.

5. Conclusions

This research presents an integrated system composed by Industrial IoT and Simulation to support decision making in the industry sector. The advantage of this approach is to have a fully integrated system capable of connecting two worlds, the physical and the virtual one. Besides that, it also allows the automatic insertion of real-time data on simulation models using an IoT platform. This means that the simulation models can be fed more quickly without wasting human resources on data exchanges.

The implementation to the use case was considered fundamental to check the followed approach applicability. It was chosen specific software, Simio to model the production line and Kafka and MongoDB to represent the IoT platform. To accomplish the full integration two wrappers were also defined. The success of the technical approach implementation permits its validation and enforces the usability of this kind of approach as the future of the industry companies in order to support their decisions.

As future work, a deep analysis, containing comparison of a real use case in its “as is” state and with the proposed approach integrated, is considered fundamental to explore the gains in terms of key performance indicators of its manufacturing processes.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement Nº 777096 and from SEPIN/MCTI under the 4th Coordinated Call BR-EU in CIT.

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