TOWARDS A DIGITAL TWIN BY MERGING DISCRETE EVENT SIMULATIONS AND THE INTERNET OF THINGS

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Short Abstract: This work proposes the integration of discrete event simulation (DES) in the environment of the industrial internet of things. A simulated process is defined for which its parameters are stored in a remote server. A local computer with an internet connection runs a DES which performs a request that updates the input parameters of the DES simulation to the latest data. With that, the results of the cycle time, the number of parts a day, and other indicators are obtained. Future work includes optimization and implementation in a real factory environment.

Keywords: Discrete event simulation, Industry 4.0, IoT, digital twin.

1- Introduction

The fourth industrial revolution is linked to the concept of the Digital Twin (DT). The DT is a concept under discussion and for which there are several conceptions **[KK2]**. A simple definition of the DT "refers to a virtual representation of the real physical system that mirrors its state and behavior" **[KJ1]**. The virtual representation requires models (that can be simulated) of the data, functionality, and communication interfaces **[SA1], [SR1]**. According to Kunath and Winkler, the DT constitutes the Cyber part of the Cyber-Physical System (CPS) and in order to obtain the real-time virtual representation of the physical part, the latter must be digitalized, or in other words, produce data through sensors and communication systems **[KW1]**.

Discrete Event Simulation (DES) is widely used in the manufacturing sector to research energy consumption **[RE1]**, reduce bottlenecks **[IY1]** and assembly line optimization **[KJ1]**. DES has been around since the 50's however, with the application of recent technologies, new opportunities to generate value has been found, for example, the integration of virtual reality and DES **[TH1]**. The integration of automated data generation to serve as inputs of the DES was studied by Ingemansson et al. **[IY1]**. An evolution of this idea is shown in a research about an Internet of Things (IoT) platform that monitors an assembly line and feeds information to the DES **[KJ1]**. Both of these works rely on the gathering of information for several days and then, based on this information run the DES for analysis and optimizations.

The contribution of this work is to present a DES that has the capability to continually updating its results with real-time data stored remotely. The data can be generated by machines equipped with sensors in an Industry 4.0 or smart factory environment as expressed in the diagram of Figure 1. In the Figure, the DES is integrated into a CPS to contribute to generate the real-time DT of physical objects in the plant. This work provides a case study of a theoretical machine simulated in a remote server. The DES simulation makes an internet request at a fixed time interval to query the last parameters and update the results. This work is organized as follows. Section 2 shows the setup of the DES and the simulated machine. Section 3 offers the results of the full implementation, and Section 4 provides the conclusions of this study and the future direction of research.

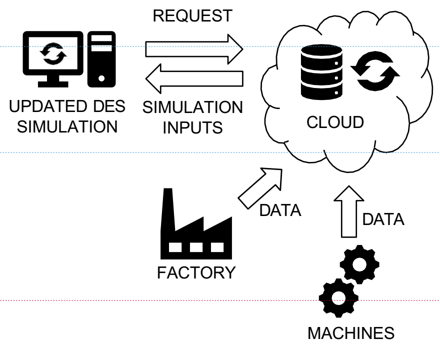

Figure 1: Concept of the DES simulation updated by real time data from smart factory.

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2. – Setup of the Case Study

This section is organized as follows. The first part of this section contains the explanation of the study case through the presentation of the relevant details of the operation of the simulated machine. The second part of this section includes the details of the DES and the update function.

2.1 – The simulated process

A simulated process that works according to Figure 2 is presented. While the process is theoretical, it is generic enough to be adaptable to many possible cases. The process starts with a nominal-volume material storage chamber (SC). SC is filled with material. Filling the storage chamber take t_F time. Before the machine is turned on, a setup stage is required, which takes t_s time. When the setup stage is completed, the machine is turned on (takes t_{ON} time), and the material is transported to a manufacturing chamber where an item is produced (taking t_P time). While this is happening, some of the material could not be added to the product and it is sent to a recovery chamber (RC). When the item is complete, the machine is turned off (time t_{OFF}) and a process of removing and stacking the item starts (time t_R). If the recovery chamber reaches the Upper Limit capacity (RC_{UL}), it will be emptied (time t_E); if not, a check is made if storage chamber has reached its Lower Limit volume (SC_{LL}). If that is not the case, the setup process starts again.

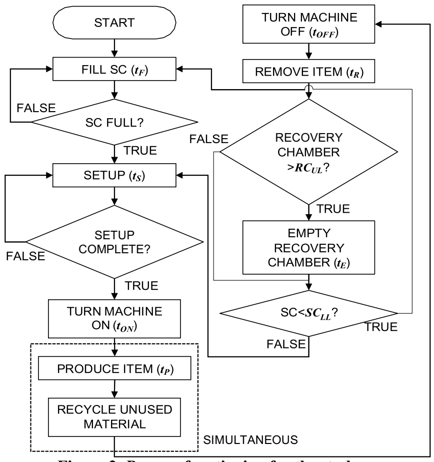

Figure 2: Process functioning for the study case.

The process considers an operator participating in all the activities (e.g. filling the storage chamber, the machine setup, supervise item production, etc.).

2.2 – The automatically updated DES.

The DES takes as input parameters of the process the times described in the previous subsection. In a smart factory environment, these times can be updated real-time. Historical records can be used to calculate a mean and standard deviation of these times. A remote request to a remote server with a web app coded to store the machine parameters retrieved the latest update of the mean and standard deviation of important times. The RC_{UL} and SC_{LL} are part of the setup of the process and they are also variables that can be adjusted in order to modify its behavior. The DES was coded using the SimPy framework and executed in a local computer with an internet connection. The remote request was implemented using HTTP with the GET method. The input parameters related to the times were obtained in the response. The general architecture of the software is presented in Figure 3. The number of items (N_i) produced in a day depends on the cycle time, which in turn is a function of the process parameters (the previously described times) and the limits on the setup according to equation (1). The times of each step are a function (normal distribution) of the mean and standard deviation as exemplified in equation (2).

$$N_i = f(t_F, t_s, t_{ON}, t_P, t_{OFF}, t_R, t_E, RC_{UL}, SC_{LL}) \qquad (1)$$

$$t_F = \mathcal{N}(\mu t_F, \sigma t_F) \qquad (2)$$

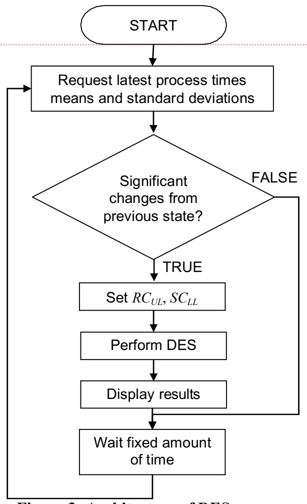

Figure 3: Architecture of DES program

3 – Results

The values of Table 1 represent the baseline values to run the testing of the simulation. The values of the means and standard deviations were obtained from the internet request to the remote server.

Each time the DES runs, it simulates a day of work (8 hours). The values of the baseline were altered in the web app to test two different scenarios:

1) The operator has higher variability: The standard deviation was increased 3 times.
2) The operator is slower: The means were increased 150%. The results of these scenarios are shown in Figure 4. The

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results for the time per item and level of storage chamber concerning the nominal capacity, are shown only for the first hour of operation. The results for level of recovery chamber to upper limit capacity are shown for the first 4 hours. While the baseline and scenario 1 produced 531 and 532 items per day, respectively, scenario 3 produced only 346 per day.

Table 1 Baseline values for the DES simulation

Parameter	Value	Unit
μt_F	20	s
μt_s	10	s
μt_{ON}	1	s
μt_P	25	s
μt_{OFF}	1	s
μt_R	15	s
μt_E	10	s
μt_F	2	s
σt_s	2	s
σt_{ON}	1	s
σt_P	2	s
σt_{OFF}	1	s
σt_R	2	s
σt_E	1	s
RC_{UL}	90	%
SC_{LL}	20	%

4 – Conclusions and future work

In this work, the concept of combining the present capabilities of industrial IoT with DES was presented. A brief literature review of the current state of DES and its contribution to new technologies was developed. The main advantage of the proposed concept is that the information obtained from the DES is going to be based on the latest data generated in the smart factory. A study case in which a generic process of manufacturing an item was proposed and simulated. Parameters of this process were accessible through a web request allowing the DES, which was coded using Python and executed locally, to incorporate the last data. The results display the type of process indicators that can be obtained including time per item, the number of parts a day and the number of times that the chamber needs to be refilled per hour. Variation of the input parameters performed through three different scenarios, provided insight into the change of the indicators. Future work includes to incorporate real data generated with sensors and produce a DT of the physical objects including the machine. Also, the simulation allows the future testing of scenarios and run optimizations in parameters that control the process.

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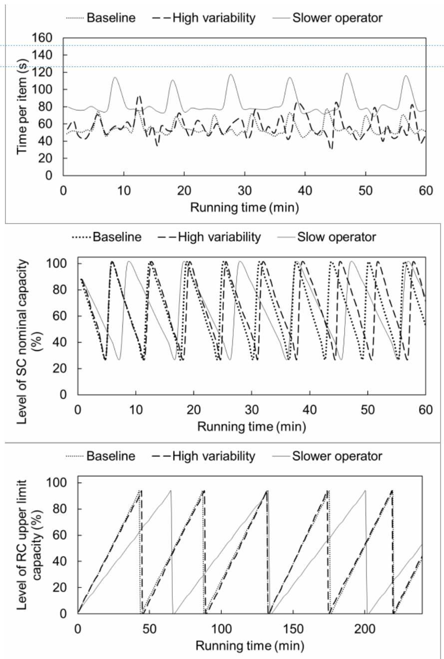

Figure 4: Results of the DES for time per item (up), level of the SC to nominal capacity (middle) and level of the RC to the upper limit (bottom)

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