EFFECT OF HUMAN PERFORMANCE VARIABILITY ON DISCRETE EVENT SIMULATION

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ABSTRACT

Simulation models often overestimate the production capacity of manufacturing systems since they do not always consider some key relationships, such as the impact of human performance variability on productivity. The aim of this paper is to investigate the impact of human factors on the work performance variation and, hence, on the computer model's validity. The selected study object was an electronic industry. Four scenarios were created, whose differences rely on the detail level of task times. The time samples showed significant differences throughout the shift, and only one of the four scenarios were validated. The article also points out other factors that may have a significant impact on work rate, such as a pre-established production output target.

KEYWORDS. Discrete-event simulation, Input data modeling, Work rate.

SIM – Simulation

1. Introduction

According to Budgaga *et al.* (2016), it is difficult to predict the behavior of real and complex systems, since they are influenced by a set of internal and external factors, and experiments are often unfeasible. For these situations, the authors recommend the use of simulation. In fact, simulation makes it possible to study different and complex systems in an easier, more flexible and more economical way then experiments [Shen and Wan 2009], and improvement projects can be set with little or even no customization [Sharda and Bury 2011].

Discrete event simulation (DES) is used to model real systems in many different sectors, including manufacturing, healthcare, logistics and services in general [Chwif and Medina 2010]. The same authors state that DES projects should dedicate most of its time to the first stage: the conception, in which the input data is modeled.

In the beginning of the data acquisition process, the researchers must define the types and the amount of data that are necessary to achieve the objectives of the study [Bogon *et al.* 2012]. A model has credibility when its users trust the information generated by the model [Sargent 2015].

When modeling manufacturing systems, input data usually consist of process times, set-up times, tool change times, approval rates, breakdown data, material handling data and production planning data. In most cases, process times take a longer time to be gathered compared to other kinds of input data [Skoogh and Johansson 2009].

Input data modeling in simulation projects often turns into a major problem [Khalek *et al.* 2015]. In one hand, Skoogh and Johansson (2009) observed that the necessary data to the system analysis are normally unavailable or, at least, it takes a long time to collect and prepare them for analysis. Nevertheless, simplifying the model may compromise its credibility. For instance, DES models often overestimate the systems' productivity because they do not consider some key relationships, as the one between the performance of an individual and the factors that influence this performance [Baines *et al.* 2004]. DES projects must remain effective but become more practical with time. In other words, the most significant factors of a system have to be modeled with no excessive input data.

This article aims to investigate this input data modeling problem by simulating a manufacturing line consisted of manual tasks. The research was conducted in an electronic industry. Four scenarios were built differing on input data volume and representation. The shift was divided into periods, in which manual tasks were measured. Besides, since the bottleneck task was identified before the time study, this activity was represented differently than the others in one of the scenarios. Then, three hypotheses were formulated:

(a) there are significant differences of work performance during the shift;
(b) at least the most detailed scenario in terms of process times will be validated;
(c) the model can be validated by representing the bottleneck task times with a higher level of detail and the other tasks in a less detailed way.

Hypotheses (a) and (b) were formulated based on the works of Paiva (2010) and Vilela (2015). Both authors analyzed work performance throughout the shift and observed that the change of performance indeed impacts the model's validation. Hypothesis (c) is related with the theory of constrains (TOC), which establishes that the bottleneck determines the output of the line [Goldratt 2002].

Section 2 provides a background related to this research. The methodology is described in section 3, illustrating the sequence of stages and tasks executed in the simulation project. Section 4 provides information about the object of study and the data collection process. Section 5 details the construction of the scenarios and the set of experiments. Section 6 describes the validation of the scenarios, presenting the results of the statistical tests along with the analysis of the results. Finally, in section 7, the conclusion is presented.

2. Literature review

2.1. Input data modeling of manufacturing systems

The way input data is modeled differs from one project to another. Although, according to Robertson and Perera (2002) there are four main input data methodologies:

(a) Direct and manual data entry: input data is manually gathered and directly supplied in the computational model by the model builders.
(b) External data source manually populated: the input data is manually gathered but stored in an external data source, as a spreadsheet. The data is automatically read by the model, since it is connected to the external data source.
(c) External data source automatically populated: the input data which is available in a corporate business system (CBS) is supplied to an external data source, which is linked to the computer model.
(d) Direct and automated data entry: the model is directly connected to a CBS, and data is automatically supplied to the model.

Most of the simulation projects still use methodologies (a) and (b), and most of the projects still had a low level of input data automation [Skoogh *et al.* 2012]. That implies a long period of time dedicated to the data modeling. However, there are recent works focusing on automated input data systems. For instance, Khalek *et al.* (2015) propose an automated approach for modeling input data using DES to improve construction schedule generation.

Skoogh and Johansson (2009) defined nine input data management activities (Figure 1) and compiled the average percent times spent in each activity of 15 simulation projects analyzed by a survey. A more detailed framework of the activities of their proposed input data methodology is presented in Skoogh and Johansson (2008).

Based on Figure 1, half of the time of the input data process is used in data collection.

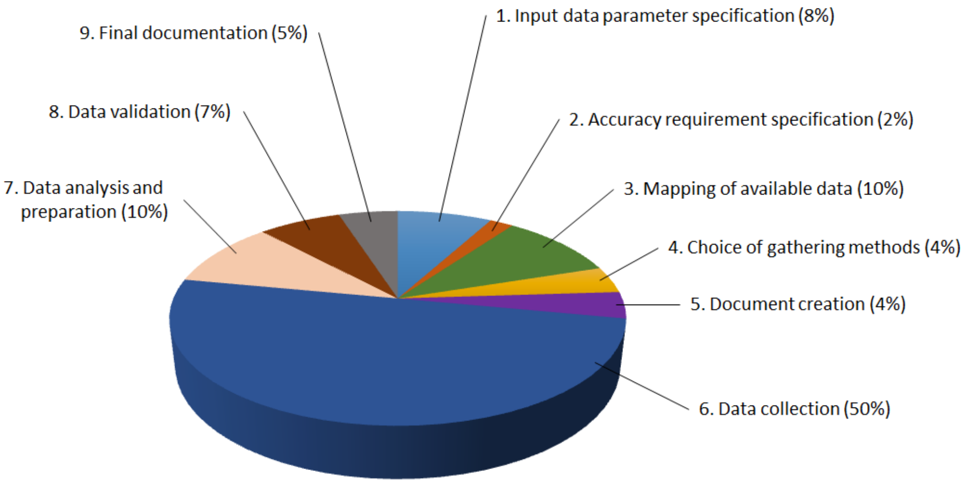

Figure 1 - Time spent in percentages in each input data management activity

Source: adapted from Skoogh and Johansson (2009)

2.2. Human factors in manufacturing simulation

By increasing the level of automation and establishing sequenced steps for input data modeling, simulation projects tend to be executed in less time. Nevertheless, human factors (HF) also play a big role in guaranteeing the credibility of manufacturing systems' models, especially the ones with high level of manual operations.

Digiesi *et al.* (2009) point out several factors that influence the operator's behavior, such as work environment (weather, ergonomic conditions, noise level, personal relationships and group communication), task nature (discrete or continuous, repetitive or dynamics, motor or cognitive) and personal factors (physical and psychological attitude, individual skills, age, sex).

Work performance is related with the circadian rhythm (CR). Spencer (1987) modeled the performance of a task, named the digital symbol substitute task (DSST), predicted for time since sleep (t) and time of day (T), both in hours, as described in Equation (1).

$$\mathrm{DSST}(T,t) = 233.3 + 1.54t - 0.304t^2 + 0.0108t^3 + 4.97\cos(2\pi(T - 17.05)/24) \quad (1)$$

Baines *et* al. (2004) presented Spencer's circadian rhythm model for DSST, in which work start time is 3 hours (t = 3h), as shown in Figure 2.

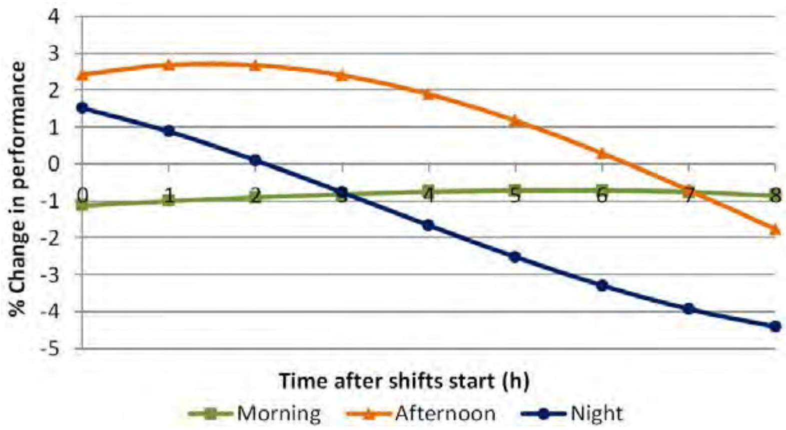

Figure 2 - Spencer's Digital symbol substitute task (DSST) model for t = 3h

Source: adapted from Baines *et al.* (2004)

As observed, work rate varies throughout and among shifts. These variations may be significant in a DES model validation. In fact, there are cases in which the only way to validate a computational model is to consider different probability distributions for each period of the shift and for each day of the week, due the differences on work rate, as in the work of Vilela (2015). Paiva (2010) identified significant differences between the work rate at the beginning of a shift and at the end of it, due to fatigue, monotony and CR.

3. Method

Montevechi *et al.* (2007) propose a methodology for DES projects, as shown in Figure 3. At the beginning of the conception phase, the goals of the study are defined. Then, the conceptual model is built. IDEF-SIM is a business process modeling (BPM) technique that closes the conceptual model language to the computational model, since this technique provides symbols that represent process, entities, resources, logical decision rules and other features. For a more detailed description of IDEF-SIM, see Montevechi *et al.* (2010). Once concluded, the conceptual model is analyzed by the system's specialists. When validated, the last version of the conceptual model is registered. The model builders start to collect data. Input data gathering is the last task of the conception phase. In manufacturing DES projects, process times are usually measured and organized in samples. These samples can be approximated to continuous probability distributions inside some commercial simulators, as *Statfit* in *ProModel®*. As the sample size increases, the sample average distribution closes to a normal distribution [Triola 2005].

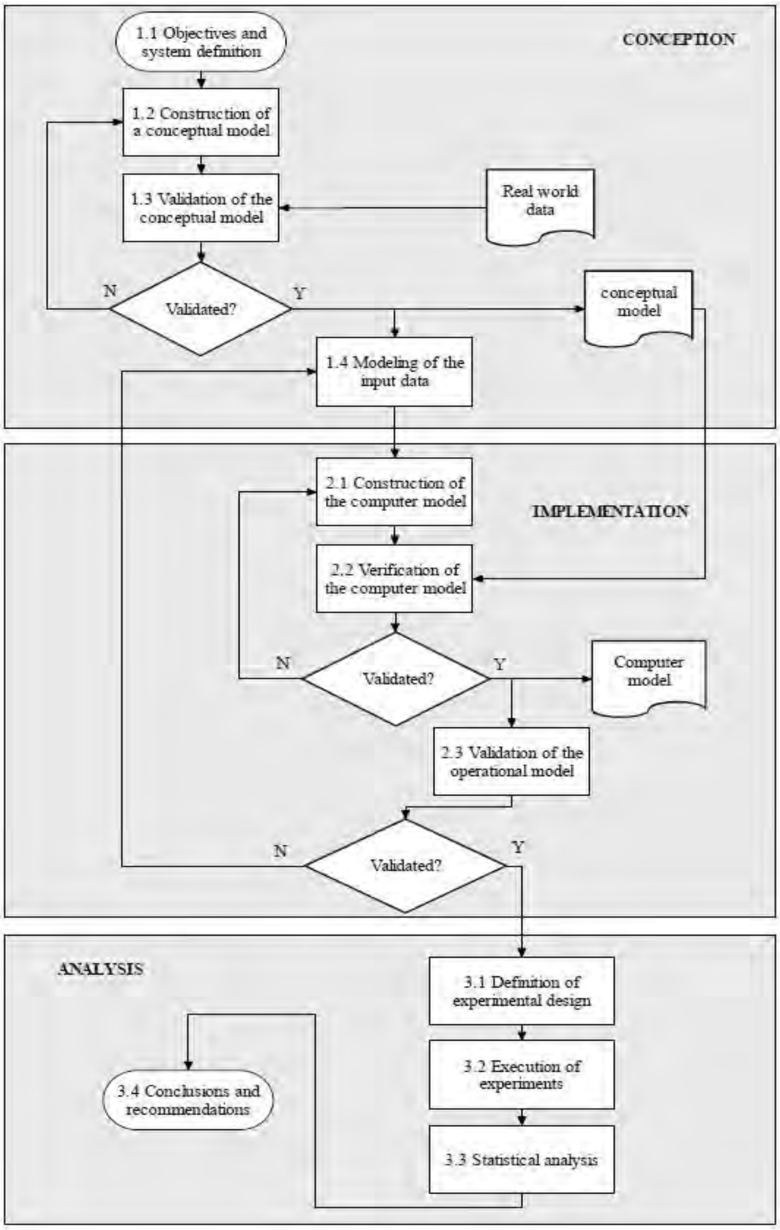

Figure 3 - DES Project methodology

Source: Montevechi *et al*. (2007)

In the implementation phase, the computational model is built. The model is then verified and validated. Verification is the process of guaranteeing that the simulation program and its implementation are correct, while validation consists in certifying that the computational model represents the real system with enough precision and according to the project goals [Sargent 2015]. The same author states that validation can be executed by observing the real system, comparing the present model to others or by statistical comparison procedures using output variables of the model and correspondent real data.

The analysis phase consists of planning, executing and analyzing experiments using the computational model. At this stage, design of experiments (DOE) techniques may be applied, as well as hypothesis tests [Montgomery 2012]. After analyzing the results, the conclusions are presented.

4. Data collection and previous analysis

The research took place in an electronic industry. The selected production line was named line 1. This line had the highest production amount in 2015. Line 1 is dedicated to one product and has two operators.

Operator A is responsible for the assembly station, while operator B works at the kitting station. First, operator A assembles the parts, and at the kitting station, operator B tests the product in an automated machine. After the automatic test, operator B tests the product manually and packs the product. Operator B is also responsible for assembling the boxes of the packages. The product is stored at the end line 1 for sample inspection. The company establishes a daily goal of productivity. During the period of the research, the goal was 123 parts a day.

Table 1 presents the tasks executed by each operator of line 1. The automatic test was not represented as an activity, because the operator can execute other tasks after setting up the test machine.

Table 1 – Tasks by operators in line 1

Operator	Task
A	Assembly
	Testing machine set up
B	Manual test
	Kitting

Source: the authors

A camera was installed behind the work stations in line 1 in order to register all the manual tasks presented in Table 1. Based on the videos, the beginning and the end of each activity's cycle was defined. Then, the cycle times were measured. After eliminating the outliers, 320 times were considered: 80 times for each manual activity presented in Table 1. And for each activity, the times were divided in samples of 20, each of which corresponding to one of the four periods of the shift, named A, B, C and D, as defined in Table 2.

Only five times were collected of the automatic test, since the variance of this process is not significant compared to the variance of the manual tasks.

Table 2 – Line 1 shift and operation periods definition

Period	Start - End	Action
-	08:00 - 08:10	Production preparation
A	08:10 - 10:30	Operation
-	10:30 - 10:45	Coffee break
B	10:45 - 12:30	Operation
-	12:30 - 14:00	Lunch break
C	14:00 - 15:30	Operation
-	15:30 - 15:45	Coffee break
D	15:45 - 17:50	Operation
-	17:50 - 18:00	Workstation organization

Source: the authors

The time samples of the four periods of the assembly tasks were compared by their confidence interval, as shown in Figure 4.

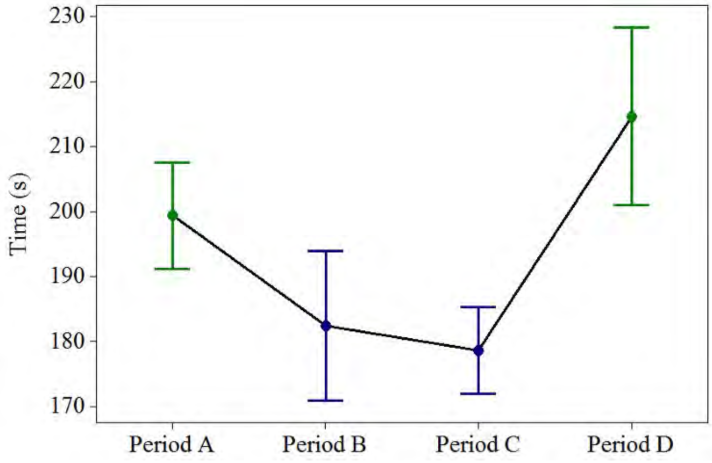

Figure 4 – Confidence intervals of assembly times per period

Source: the authors

In Figure 4, it is possible to observe significant differences among the confidence intervals. The assembly samples' averages were compared by a set of 2-sample t tests. Periods A and D are considered statistically equal (in green), as periods C and D (in blue). The other comparisons presented significant differences. Hence, a significant work rate variation was in fact observed, which confirms hypothesis (a).

In order to investigate the causes of the work rate variation, the operators were interviewed. They reported that they accelerated their performance during the morning, so that they could slow it down in the afternoon, aiming to produce not less, but not many more than 123 parts a day. Thus, there is an intentional change in the work performance during the shift due to this predefined production goal. This change in work rate is modeled with the use of probability distributions in different periods of the shift, as described in section 5.

5. Scenarios

Figure 5 presents the computational model layout of line 1 on *ProModel®* software. Software *Statfit* was used to identify the best continuous probability distribution fit for each sample of the manual tasks. The cycle times of the less frequent tasks were represented by deterministic values in the model.

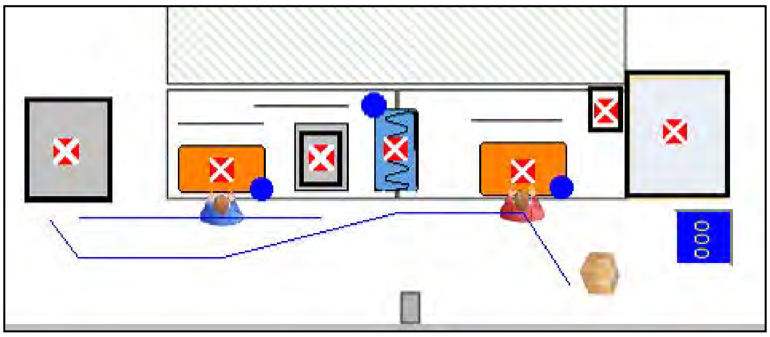

Figure 5 – Computational model layout of line 11 on *ProModel®* software

Source: the authors

In order to test hypotheses (b) and (c), four scenarios were created and organized from the simplest to the most detailed one, and they are described as follows:

- Scenario 1: for each manual task, one sample was randomly selected from the total of 80 cycle times available on the data base, as if only 20 times were collected in the first place. This way, each task time was modeled by only one probability distribution throughout the shift.
- Scenario 2: the shift was divided into morning and afternoon, and 20 cycle times were randomly selected from the 40 morning cycle times and for each manual activity. The same procedure was executed for the afternoon cycle times. Thus, the work rate was modeled by two different probability distributions.
- Scenario 3: for the cycle times of the bottleneck task (assembly), all data available were used. So the assembly task was modeled by four probability distributions, one for each period of the shift (A, B, C and D) defined in Table 2. The other tasks' times were represented by their means, which were calculated from a random sample of 20 cycle times of the database. The specific goal of this scenario was to test hypothesis (c).
- Scenario 4: all data collected were used. In other words, each task was modeled by four probability distributions, one for each period of the shift (A, B, C and D).

Table 3 illustrates the differences among the scenarios regarding input data. On Table 3, the letter "*X*" represents a sample mean. The green gaussian represents the continuous probability distribution identified as the best fit, but not necessarily the normal distribution.

Table 3 – Input data modeling by scenario throughout the shift

Scenarios	**Tasks**	**Input data modeling**			
		Period A	**Period B**	**Period C**	**Period D**
Scenario 1	Assembly				
	Other tasks				
Scenario 2	Assembly				
	Other tasks				
Scenario 3	Assembly				
	Other tasks	$\bar{X}$			
Scenario 4	Assembly				
	Other tasks				

Source: the authors

6. Validation

The output variable considered in the model validation was the daily production. Historical data were collected to compare the real system and the model outputs. During the research period, line 1 ran for approximately one month. After eliminating the outliers, 18 days were considered.

The execution of each scenario was replicated 18 times, and the output samples were compared by hypothesis tests. Table 4 presents the means, standard deviations and the Anderson-Darling p-values of the output samples.

Assuming a confidence level of 95%, the output samples of scenarios 1, 2 and 3 are considered normally distributed, since their Anderson-Darling p-values are higher than 0,05. The same can not be inferred about scenario 4 and the real system outputs. Therefore, the output samples can not be compared by 2-sample t tests. For these situations, Montgomery and Runger (2012) reccomend Mann-Whitney tests. Table 5 shows the results of the Mann-Whitney tests used in the comparison between each scenario's outputs and the real system's.

Table 4 – Statistical parameters and results of the scenarios' outputs and the real system's outputs

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Real system
Mean	123,6	121,8	118,9	119,1	121,1
Standard dev.	1,9	2,8	2,8	4,1	4,5
Anderson-Darling p-value	0,393	0,319	0,068	<0,005	< 0,005

Source: the authors

Table 5 – results of the Mann-Whitney tests

Test statistic	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Mann-Whitney p-value	0,038	0,912	0,003	0,009

Source: the authors

Based on the results presented in Table 5, and assuming a confidence level of 95%, only scenario 2 was validated, since p-value > 0,05 in both cases. Therefore, hypothesis (b) was rejected. Differently from what we expected, scenario 4, the most detailed one, was not validated, while the simpler scenarios were. Hypothesis (c) was also rejected because scenario 3 was not validated.

Both scenarios 3 and 4 model the assembly task times in the most detailed way: with four probability distributions, one for each period of the shift. Nevertheless, the computational model does not predict these intentional changes in the task cycle times. That may be the cause of the differences between the results achieved and the predefined hypotheses. Hence, an established production goal may have a significant impact on the performance of manual tasks.

7. Discussion

This article presented a study on input data modeling and work rate variation. First, task times were measured in different periods of the shift and then compared. The work measurement revealed significant changes in work rate throughout shift, as shown in Figure 4. Hence, hypothesis (a) was confirmed.

Then, different scenarios regarding the amount and representation of the task times were created and compared. The task times were approximated to continuous probability distributions in the computational model. The model's daily production outputs of each scenario were compared to the real system's in the validation process.

Only scenario 2 was validated, which is an intermediate scenario regarding the level of detail of task times. Unlike the initial hypothesis, scenario 4, the most detailed one, was not validated. Moreover, scenario 3 did not appear to be effective, since representing only the bottleneck in a detailed way was not enough to validate the model. Thus, hypotheses (b) and (c) were rejected.

In fact, the results obtained in this work are restricted to the object of study and its current circumstances. However, the results also pointed out other potential factors that may have an impact on work rate variation. Beyond the circadian rhythm, a predefined production goal may also influence the work rate. It was revealed that operators tend to change their performance based on how close they are from an established goal. Measuring task times in different periods of the shift to represent these intentional changes in performance by may not be the best strategy. For future work, the researchers aim to study other approaches to represent work rate variation, considering not only physiological factors, but also psychological ones, as a predefined production goal.

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