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Human factors in an automotive discrete event simulation model

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ABSTRACT. Human beings have naturally different variations in performance which may lead towards significant differences between the results forecasted by simulation models and those actually obtained. Current research studies the effects of human factors such as circadian rhythms and variations in workday shifts on operators´ performance. It also proposes a method for collecting time data in assembly lines, which takes into consideration different time periods for each work shift to apprehend the variability of human performance at different points throughout the day. The new method was applied in an industrial process with a high rate of manual labor and its production results on the shifts were compared. Results reveal that human factors have a significant impact on the simulation model, providing results closer to reality, which, in turn, lead to more accurate production forecasts.

Keywords: simulation, human factor, circadian rhythm, shift work.

Fator humano em um modelo de simulação a eventos discretos do setor automotivo

RESUMO. O ser humano pode apresentar variações naturais em seu desempenho, o que pode levar a diferenças significativas entre os resultados previstos por modelos de simulação e os obtidos no sistema real. Este trabalho tem como objetivo estudar os efeitos dos fatores humanos, tais como o ritmo circadiano e o trabalho em turnos no desempenho do operador. Este trabalho também propõe um método para a coleta de dados de tempo em uma linha de montagem. Este método leva em consideração os diferentes períodos de tempo para cada turno de trabalho para capturar a variabilidade do desempenho humano em diferentes pontos ao longo do dia. Com este novo método, um processo industrial que possuía um elevado percentual de trabalho manual foi modelado e os resultados de produção durante os turnos foram comparados. Pode-se concluir que a consideração dos fatores humanos mencionados tiveram impacto significativo no modelo de simulação, proporcionando resultados mais próximos da realidade, o que, por sua vez, conduziram a previsões de produção mais precisas.

Palavras-chave: simulação, fator humano, ritmo circadiano, trabalho em turnos.

Introduction

According to Rutberg, Wenczel, Devaney, Goldlust, and Day (2015), discrete event simulation is a tool for computational modeling that represents complex systems, allowing for possible interventions to be studied without compromising the real world with changes, where it is impossible to know the likely effects. In fact, discrete event simulation has often and increasingly been employed to aid decision-making (Pereira, Montevechi, Miranda, & Friend, 2015).

Through modeling, analysis and system design, the impact of input parameter variations on the performance of output parameters may be characterized (Banks, Carson II, Nelson, & Nicol, 2010, Garza-Reyes, Eldridge, Barber, & Soriano-Meier, 2010, Sargent, 2013).

However, when a system is forwarded with many manual activities, largely dependent on the work of operators, simulation cannot faithfully apprehend all the system´s details and, thus, simulation results may not reflect true results (Baines, Mason, Siebers, & Ladbrook, 2004). The above may be attributed to the human element represented in most of the simulation models (Siebers, 2006). Deterministic performance rates are often considered for their activities, which result from studies of time and methods. According to Baines et al. (2004), people must be represented realistically with their actual behavior and subsequent performance so that simulation accuracy may be improved.

According to Siebers (2006), specialized literature clearly indicates that workers' performance varies throughout the execution of tasks. This may occur between different workers performing the same task or when the same worker repeats a task. Similarly, the literature has also shown that workers' performance also varies as a result of their reliance on past events and on the current state of the system.

It is important to consider the human factor early since in the design process this is easier and cheaper than making changes to products and systems (Miles & Swift, 1998, Perez & Neumann, 2015). Studying the human factor focuses on how behavioral and non-behavioral variables affect task accomplishment (Meister, 1989) and human-centered design requires integration between the human, machine(s) and work environment (Mallam, Lundh, & MacKinnon, 2015).

According to Maguire (2001), thoughtful human-centered design should increase productivity, decrease errors, reduce training and support, improve user´s trust and enhance system reputation. In addition, taking into consideration the human factor may facilitate overall system design outcomes, improve project management resources and enhance lifecycle cost-savings (Hendrick, 2008).

The incorporation of human factors into computer simulation models has been considered a 'missing link' (Baines et al., 2004), with scanty progress in this matter. Most simulation software represents total machine behavior but treats workers as mere resources (Chen, Huang, Shih, & Chang, 2016, He, Qiu, Fan, & Liu, 2016, Ergai et al., 2016).

However, changes are taking place on this subject and the incorporation of human factors has become a major discussion among professionals from different areas of modeling and simulation, as reported by Cummings and Guerlain (2007), Bruzzone, Briano, Bocca, and Massei (2007), Hannah and Neal (2014) and Chen, et al. (2016).

In this context, current paper will explore and illustrate the influence of human factors on operators' performance and how these factors may alter the results predicted by simulation models. Thus, our initial aim is to discover how to insert human factors into a simulation model; afterwards we assess whether the incorporation of such factors has changed the expected results.

To this end, a simulation study was conducted on a highly manual assembly line, in which two human factors were incorporated into the simulation model that would influence the operator´s performance: circadian rhythm and shift work. These factors were added to the model by performing a time analysis in four periods during each work shift. This analysis ended up changing the standard time stipulated by the engineering team.

Current paper is divided into four sections. The first section contextualizes the research problem and its objectives. The second section presents the research method, whilst the third section discusses the application of the research method, followed by an analysis of the results. The final section comprises the conclusions.

It is important to consider HF as early in the design process as possible because its effectiveness is constrained by time; the longer it takes to apply HF in design the harder and more expensive it is to make changes to products and systems, since the window of opportunity contracts over time (Miles & Swift, 1998).

Material and methods

The simulation computational model was constructed using the method proposed by Leal, Costa, Montevechi, Almeida, and Marins (2011). The method presents the phases of a simulation project in which three models must be developed: (1) conceptual model at the conception phase; (2) computer model at the implementation phase; and (3) operational model at the analysis phase.

Due to the peculiarity of this research, namely, the inclusion of human factors in a simulation model, the steps presented by Baines et al. (2004) for selecting the human performance model were followed. They were based on three aspects:

- The models must be valid in the context from which they were originally derived.
- The literature should sufficiently indicate that the human factor represented by the model is present in the industrial context.
- The inputs required for the models should be easy to obtain.

Hence, current study will use the methods by Leal et al. (2011) and Baines et al. (2004) to conduct the simulation project associated with the insertion of human factors. As indicated earlier, usually humans are considered 'machines' in simulation models with default behaviors during the simulation time, with no distinctions in human behavior between the different scenarios.

Application of the method

Current research was applied in a production line of cable harnesses (electrical system components of electronic injection vehicles) with a high proportion of manual work and 12 operators. Although three types of cable harnesses are produced in this line, only one of the products was analyzed since it comprised 91.6% of the production mix. In the case of this particular product, the line studied has an expected output of 189 pieces per shift.

Following the aspects presented, some human performance models in the literature were identified but they had been applied in contexts which were different from the object of current investigation. The context of current study involves a highly manual assembly line and, consequently, human resources in the system are a key factor for performance success. This main feature supports the incorporation of human factors in a discrete event simulation model, which is the main goal of current research.

Due to the scarcity of literature on the identification of human performance models that may be applied in any context, we decided to first identify by a theoretical review which human factors might affect the operators' performance during shift work. We chose to assess the influence of two factors: circadian rhythm and shift work. Further, the above factors were chosen due to the feasibility of measuring the operators' performance variability through changes in processing time.

Hence, the processing time of activities in the assembly line was analyzed, with four periods over two shifts and then variation in total production was assessed. The work shifts were divided into four periods due to the feasibility of collecting the data during the periods. The First Shift was divided up as follows:

- First Period (6:00 to 08:00 a.m.): this period was chosen to assess the operators' performance at the beginning of the shift, when the operators were starting their activities;
- Second Period (08:00 to 10:00 a.m.): this period was chosen to assess the operators' performance before lunchtime;
- Third Period (10:00 to 12:00 p.m.): this period was chosen to assess the operators' performance after lunch to verify whether performance was affected by their returning from the lunch break;
- Fourth Period (12:00 to 03:00 p.m.): this period was chosen to assess operators' performance during the last period of the shift to verify whether the operators' performance was affected by fatigue, monotony and variations related to biorhythm.
- Four periods were similarly determined for the second shift.

After defining the human factor to be analyzed and determining how to insert it into the simulation model, we were able to develop the model within the method proposed by Leal et al. (2011).

In the conception phase, the Idef-SIM mapping technique was used to prepare the conceptual model. This technique was chosen because it allowed a graphical representation of human resources (operators) to be inserted in the process flow or in the state and object transition network (Maurício, Montevechi, Leal, Miranda, & Lombardi, 2015), which was important for the context of the study.

The conceptual model was developed and validated by the face-to-face technique through which experts of the system assessed whether the model accurately represented the real thing. After this phase, the model was documented (Figure 1).

For the development of the conceptual model, it was necessary to establish the following elements in the graphical library of the simulation model: Hanger (parts positioner), Test Hanger (place for storing the products to be tested in the test bench), Cell and Station (place where the pre-assembly and assembly activities are carried out), Basket (place to store the finished products), Retention (bench used to perform quality and dimensional inspection of whips), Labor Error (place to check the product and perform the electrical test), Shuttle (tool for gravitational connection), and Test (bench used to perform the final electrical test of the harnesses). This nomenclature, common to the company, was maintained in current paper due to the familiarity with these terms by the people involved in the simulation project within the company (Figure 1).

The next step was the modeling of the input data. The activity was developed by conducting a detailed time analysis of the activities to assess the influence of 'circadian rhythm' and 'shift work' on operators' performance.

During the first phase of data collection, information was collected in loco by direct observations and from interviews with the 12 operators. The second phase comprised the collection of the following data: product processing times, trading volume and production mix. In the third phase, the 'Times and Methods', considered in current study as the standard engineering times, were collected. These times were used by the company to calculate the daily production of the assembly line.

In the fourth and final phase, a time analysis in all 12 work stations was conducted. It was established that the times had to be collected in 4 periods defined during a normal working day of the production line, in the first and second shifts, as mentioned earlier and shown in Table 1.

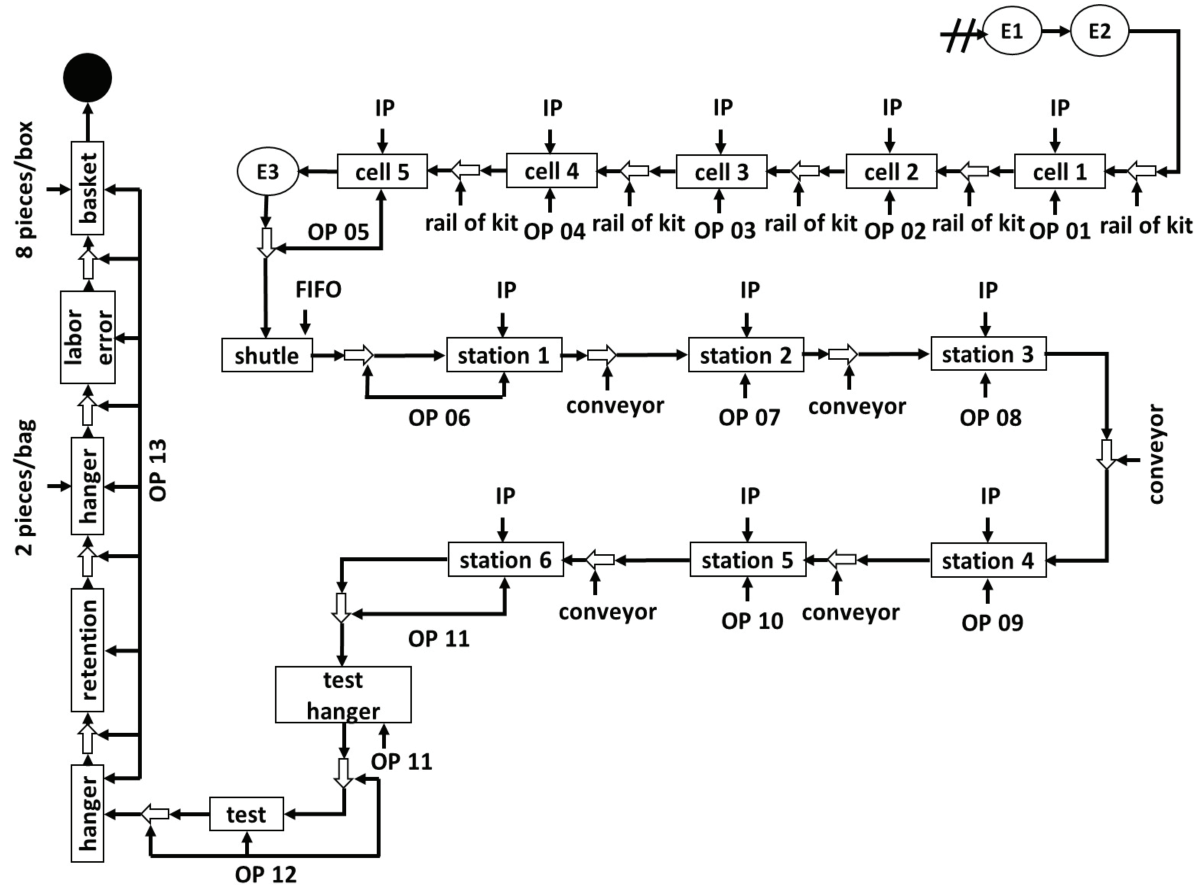

Figure 1. Conceptual model through the Idef-SIM technique.

Table 1. Periods of data collection.

Shift	Period			
	First	Second	Third	Fourth
First	6:00 - 7:00 a.m.	9:45 - 10:45 a.m.	12:45 - 1:45 p.m.	2:45 - 3:45 p.m.
Second	4:40 - 6:00 p.m.	7:00 - 8:00 p.m.	9:00 - 10:00 p.m.	12:00 - 1:40 a.m

Probability distributions for each data set were identified from the data collected in each period, and were inserted into ProModel® by using a software feature for reading external files in Excel®. So that the model could 'understand' which distribution should be used in each period, the Macro feature of Promodel® was used. A logic using each of the distributions at different periods was defined for the model. Hence, every two hours the model used the distribution associated with the respective period. Probability distributions were identified for all processing times collected during the four periods in the first and second shifts.

The conceptual model in the implementation phase was converted into a computational model by the ProModel® software. At this point, verification of the computational model was first performed by means of debuggers in software to verify possible programming errors. When verification was done, the validation process was initiated.

Techniques proposed by Sargent (2013), comprising validation by model animation, validation by comparison of the simulated model with other analytical models, face-to-face validation, and validation by comparison of the production records of the real model in relation to the simulated model (statistical validation) were used for model validation.

In the case of statistical validation, the chosen variable was the total number of parts produced per hour. Although the processing times collected by engineering were initially used, it was not possible to validate the computer model by using these times due to outdated engineering times which no longer reflected real production line.

Therefore, processing times collected through time analysis to validate the model were employed. Validation was made by comparing parts produced per hour using time analysis data to parts produced per hour for the same period during the real system.

Statistical validation was conducted with the method proposed by Leal et al. (2011). First, a normality test to simulated and observed data was applied. Then, Anderson-Darling's test was applied to prove that the real-world data (p-value = 0.226) and the simulated data (p-value = 0.726) could be approximated by a normal distribution at a 95% confidence level.

Further, the F test tested the hypothesis that both sets of data (real and simulated) have equal variances. In fact, both sets of data (real and simulated) did not have equal variances, at p-value < 0.05.

According to Leal et al. (2011), when variances are different, it is necessary to use the Smith-Satterthwaite's method before the application of the T-test. Smith-Satterthwaite's method adjusts the degrees of freedom in relation to samples´ variance difference. T-test was applied using the Smith-Satterthwaite's method and the equality of real and simulated average rates was proved (p-value = 0.467). Results in Table 2 indicate that the model may be considered statistically validated for the output variable 'total number of pieces produced'. Therefore, the computer model is called an operational model because it provides the real system too.

Table 2. Statistical tests.

Test	P-value	Results
Normality Test of Real Data	0.226	Accepts H_0 = Real data are normal
Normality Test of Simulated Data	0.726	Accepts H_0 = Simulated data are normal
F-test	< 0.05	Reject H_0 = Variances are equal
Two Sample T-Test	0.467	Accepts H_0 = Validated Model

Thirty replications were initially performed during one working day for each of the seven scenarios in the two shifts. The initial number of replications was calculated according to Kleijnen (1995) to ensure an error of less than 1 piece produced, considered satisfactory by the company's management.

After validation, it was possible to use the model for the last step of the method by Leal et al. (2011), or rather, analysis. Seven scenarios were developed for the first and second shift, presented in Table 3.

The first experiment involved the deterministic processing times provided by engineering, named Scenario 1 in current study. Since time was deterministic, it was not necessary to perform replications. In Scenario 1, total production amounted to 184 pieces per day.

The remaining experiments performed at this stage took into consideration stochastic processing times and were divided into different scenarios, as presented in Table 2.

Since times were stochastic, the simulator was programmed to perform 30 replications of the model according to the probability distributions previously inserted in the software. Consequently, the number of pieces produced per day was generated at random.

Table 3. Description of Scenarios.

First shift	Second shift	Description
Scenario 1-T1: Model using deterministic engineering times.	Scenario 1-T2: Model using deterministic engineering times.	For the whole shift, the times collected by engineering, taking into account the average standard time of five samples collected, regardless of the time of day, in the first shift.
Scenario 2-T1: Model using stochastic engineering times.	Scenario 2-T2: Model using stochastic engineering times.	For the whole shift, the times collected by engineering, taking into account the average standard time of five samples, the standard deviation, and its distribution, collected, regardless of the time of day, in the first shift.
Scenario 3-T1: Model using the times collected in the first period.	Scenario 3-T2: Model using the times collected in the first period.	The distribution in the first period was used during the whole shift.
Scenario 4-T1: Model using the times collected in the second period.	Scenario 4-T2: Model using the times collected in the second period.	The distribution in the second period was used during the whole shift.
Scenario 5-T1: Model using the times collected in the third period.	Scenario 5-T2: Model using the times collected in the third period.	The distribution in the third period was used during the whole shift.
Scenario 6-T1: Model using the times collected in the fourth period.	Scenario 6-T2: Model using the times collected in the fourth period.	The distribution in the fourth period was used during the whole shift.
Scenario 7-T1: Model using the times collected in all periods.	Scenario 7-T2: Model using the times collected in all periods.	For each period of the day the corresponding distribution.

Table 4 and 5 provide a summary of the results obtained from the initial seven replications of Scenarios 2, 3, 4, 5, 6 and 7, respectively for the first and second shifts. Data exemplify the results achieved during the first simulated week, but data analysis was performed taking into consideration all 30 replications.

Table 4. Results of experiments generated for the first week by Promodel® - First Shift.

Replication	Total of pieces produced					
	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
1	185	185	182	184	176	182
2	185	186	182	185	175	183
3	185	185	183	184	174	183
4	184	184	183	185	174	183
5	184	185	182	185	177	182
6	185	185	182	185	175	181
7	184	183	182	183	177	182

Table 5. Results of experiments generated for the first week by Promodel® - Second Shift.

Replication	Total of pieces produced					
	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
1	185	184	187	184	180	184
2	185	185	183	186	180	187
3	185	182	184	183	178	186
4	184	185	185	184	179	184
5	184	186	185	182	179	188
6	185	186	187	186	177	182
7	184	186	185	185	182	185

Results and discussion

A statistical test was initially performed for the two shifts to verify the normality of the total number of pieces produced. The statistical normality test rate (p-value) for each scenario was smaller than the significance level (0.05), signifying that all sets of data could not be approximated by a normal distribution.

The first experiment investigated whether there was any difference between the deterministic and stochastic engineering times among the total produced.

A One-Sample Sign test was performed to compare the mean rate of the total number produced in Scenario 1 (deterministic engineering times) with the total number produced under Scenario 2 (stochastic engineering times). Since the test resulted in a p-value of 0.00, the null hypothesis that production is equal between the scenarios was rejected. Consequently, the total number of pieces produced in Scenario 1 was significantly different from the total number produced under Scenario 2.

The second experiment verified whether there existed a difference in total production between default time used by the company (Scenario 2) and the times collected in the assembly line (Scenarios 3, 4, 5, 6, 7). In this case, the Mann-Whitney test was performed to assess median equality of non-normal samples, as shown in Table 6 and 7, for the first and second shifts, respectively. To utilize the Mann-Whitney test, the equality of variances of the data for each scenario was initially warranted by Levene's test and tested samples were ensured to follow the same distribution.

Table 6. Results of the hypothesis test of the first shift.

Hypothesis tests		P–value
Mann-Whitney/One–sample sign		Total produced
Scenario 1	Scenario 2	0.00
Scenario 2	Scenario 3	0.00
Scenario 2	Scenario 4	0.00
Scenario 2	Scenario 5	0.03
Scenario 2	Scenario 6	0.00
Scenario 2	Scenario 7	0.00

Table 7. Results of hypothesis test of the second shift.

Hypothesis test		P–value
Mann-Whitney		Total produced
Scenario 2	Scenario 3	0.00
Scenario 2	Scenario 4	0.00
Scenario 2	Scenario 5	0.00
Scenario 2	Scenario 6	0.00
Scenario 2	Scenario 7	0.00

When Scenario 2 was compared with Scenarios 3, 4, 5, 6, 7 of the first shift, the Mann-Whitney test resulted in a p-value that was less than 0.05 for all cases, i.e., the hypothesis of samples being equal was rejected. As a result, the total amount of pieces produced by Scenario 2 was different from total produced in the other five scenarios. Interpretation of results revealed that production obtained by using data collected in a laboratory was different from the production actually obtained by the assembly line.

The Scenarios of the second shift were successively analyzed. At this stage, it was not necessary to assess the difference between numbers produced in Scenario 1 and Scenario 2 of the second shift, since both scenarios would result in a total production that was statistically equal to the total produced in Scenarios 1 and 2 of the first shift.

The same conclusions from the data analysis carried out earlier could be reproduced for the second shift, i.e., the total number of pieces produced under Scenario 2 would be different from the total produced in the other five scenarios. These results enhanced the difference between the laboratory simulations under these two scenarios and assembly line conditions.

The third experiment examined whether there was a significant difference in production between the times collected in the assembly line according to the shifts. Results may be seen in Table 8. The Mann-Whitney test demonstrated that only the totals produced by Scenarios 3 and 5 could be considered statistically equal.

Table 8. Results of hypothesis test of the first and second shifts.

Hypothesis test		P–value
Mann-Whitney		Total produced
Scenario 3 – T1	Scenario 3 – T2	0.44
Scenario 4 – T1	Scenario 4 – T2	0.00
Scenario 5 – T1	Scenario 5 – T2	0.07
Scenario 6 – T1	Scenario 6 – T2	0.00
Scenario 7 – T1	Scenario 7 – T2	0.00

In the case of Scenario 3, the result may be explained by the fact that the processing time of the first period of each shift was applied to all shifts. Since operators usually start their shift in good conditions, free from any symptoms of fatigue or hunger, it is expected that they probably have similar performance at the beginning of each shift. Moreover, the processing times of Scenario 5 have been collected just after lunch and dinner, when employees are going to restart their work and probably have the same conditions.

For the other scenarios, the Mann-Whitney test´s statistics was smaller than the significance level. Consequently, totals produced were statistically different.

The difference for Scenario 4, which uses the time frame of the second period of each shift, is probably caused by reduced worker performance. At this time of the day, workers have already been working for two hours and they are also getting closer to lunch or dinner hour.

In Scenario 6, the difference between totals produced by both shifts may have been caused by the processing times being collected at the last period of each shift, and, hence, workers were affected by fatigue, monotony and variations related to biorhythm.

Finally, when Scenario 7 of the first shift was compared to Scenario 7 of the second shift, the Mann-Whitney test resulted in a p-value of 0.00, or rather, the hypothesis that samples were equal had to be rejected. Therefore, it follows that the total number of pieces produced during the first shift was different from that of the second shift.

Based on the results of the hypothesis test, it may be concluded that there was a significant difference between the times provided by engineering (considering standard conditions in a laboratory) and the times collected in the assembly line.

Finally, so that the differences between the totals produced during each period of the day and the difference between the totals produced by shift could be assessed, Mood's median test was performed to verify the equality of medians of non-normal samples. Figure 2 shows the average results in Mood's median test for both shifts at 95% confidence level.

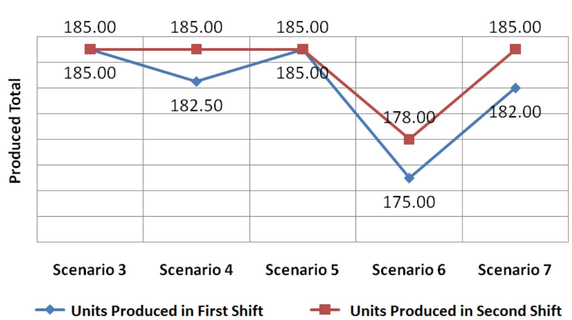

Figure 2. Comparison of production per scenario and per shift.

Figure 2 reveals that the difference between the totals produced in the first shift was greater than the difference between the totals produced in the second shift.

In the first shift, the number of pieces produced in Scenarios 3 and 5 is equal, whereas it is different in Scenarios 4 and 6. The greatest variability in this case occurred in Scenario 6, explained by the accumulation of fatigue, monotony and variations related to biorhythm.

On the other hand, in the second shift there was no difference between the production in Scenarios 3, 4, and 5. However, the number of pieces produced under Scenario 6 is different from that in the other scenarios. Similar to the first shift, the greatest variability occurred in Scenario 6, explained similarly as that for the first shift. Further, Scenario 6 of the second shift displays the last two hours of the workday, a period when the human body is preparing for sleep through a reduction in body temperature and increasing melatonin (sleep hormone) production.

When the productions of Scenario 7 of the first shift was compared with Scenario 7 of the second shift, the difference between the shifts was significant, in spite of the difference between the periods of the second shift was smaller when the four periods were taken into account in the same model.

Conclusion

Current research studied the effect of circadian rhythm and shift work on the performance of operators, through time analysis performed in the assembly line. Results showed that the circadian rhythm and shift work required models to take into account variations in production throughout the entire work shift. For the increase in accuracy and quality, it is important to take human factors into account when developing simulation models. We consider the inclusion of human factors in simulation models is a challenge that has yet to be overcome and further research is required for such purpose.

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References

Baines, T., Mason, S., Siebers, P. O., & Ladbrook, J. (2004). Humans: the missing link in manufacturing simulation? *Simulation Modelling Practice and Theory, 12*(7), 515-526.

Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, D. M. (2010). *Discrete-event simulation*. Upper Saddle River, NJ: Prentice-Hall.

Bruzzone, A. G., Briano, E., Bocca, E., & Massei, M. (2007). Evaluation of the impact of different human factor models on industrial and business processes. *Simulation Modelling Practice and Theory, 15*(2), 199-218.

Chen, S. Y., Huang, P. R., Shih, Y. C., & Chang, L. P. (2016). Investigation of multiple human factors in personalized learning. *Interactive Learning Environments, 24*(1), 119-141.

Cummings, M. L., & Guerlain, S. (2007). Developing operator capacity estimates for supervisory control of autonomous vehicles. *Human Factors, 49*(1), 1-15.

Ergai, A., Cohen, T., Sharp, J., Wiegmann, D., Gramopadhye, A., & Shappell, S. (2016). Assessment of the human factors analysis and classification system (HFACS): Intra-rater and inter-rater reliability. *Safety science, 82*(2), 393-398.

Garza-Reyes, A. J., Eldridge, S., Barber, K. D., & Soriano-Meier, H. (2010). Overall equipment effectiveness (OEE) and process capability (PC) measures: a relationship analysis. *International Journal of Quality & Reliability Management, 27*(1), 48-62.

Hannah, S. D., & Neal, A. (2014). On-the-fly scheduling as a manifestation of partial-order planning and dynamic task values. *Human Factors, 56*(6), 1093-1112.

He, Q., Qiu, S., Fan, X., & Liu, K. (2016). An interactive virtual lighting maintenance environment for human factors evaluation. *Assembly Automation, 36*(1), 1-11.

Hendrick, H. W. (2008). Applying ergonomics to systems: some documented "lessons learned". *Applied Ergonomics, 39*(4), 418-426.

Kleijnen, J. P. (1995). Verification and validation of simulation models. *European Journal of Operational Research, 82*(1), 145-162.

Leal, F., Costa, R. F. D. S., Montevechi, J. A. B., Almeida, D. A., & Marins, F. A. S. (2011). A practical guide for operational validation of discrete simulation models. *Pesquisa Operacional, 31*(1), 57-77.

Maguire, M. (2001). Methods to support human-centred design. *International Journal of Human-Computer Studies, 55*(4), 587-634.

Mallam, S. C., Lundh, M., & MacKinnon, S. N. (2015). Integrating Human Factors & Ergonomics in large-scale engineering projects: Investigating a practical approach for ship design. *International Journal of Industrial Ergonomics, 50*(11), 62-72.

Maurício, T. B., Montevechi, J. A. B., Leal, F., Miranda, R. C., & Lombardi, F. (2015). Using discrete event simulation to change from a functional layout to a cellular layout in an auto parts industry. *Acta Scientiarum. Technology, 37*(3), 371-378.

Meister, D. (1989). *Conceptual aspects of human factors*. Baltimore, MD: Johns Hopkins University Press.

Miles, B. L., & Swift, K. (1998). Design for manufacturing and assembly. *Manufacturing, 77*(5), 221-224.

Pereira, T. F., Montevechi, J. A. B., Miranda, R. C., & Friend, J. D. (2015). Integrating soft systems methodology to aid simulation conceptual modeling. *International Transactions in Operational Research, 22*(2), 265-285.

Perez, J., & Neumann, W. P. (2015). Ergonomists' and engineers' views on the utility of virtual human factors tools. *Human Factors and Ergonomics in Manufacturing & Service Industries, 25*(3), 279-293.

Rutberg, M. H., Wenczel, S., Devaney, J., Goldlust, E. J., & Day, T. E. (2015). Incorporating discrete event simulation into quality improvement efforts in health care systems. *American Journal of Medical Quality, 30*(1), 31-35.

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation, 7*(1), 12-24.

Siebers, P. O. (2006). Worker performance modeling in manufacturing systems simulation: proposal for an agent-based approach. In J. P. Rennard (Ed.), *Handbook of Research on Nature Inspired Computing for Economics and Management* (p. 661-678). Hershey, PA: IGI Global.

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