



Using discrete event simulation to change from a functional layout to a cellular layout in an auto parts industry

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ABSTRACT. This paper presents a discrete event simulation employed in a Brazilian automotive company. There was a huge waste caused by one family scrap. It was believed one reason was the company functional layout. In this case, changing from current to cellular layout, employee synergy and knowledge about this family would increase. Due to the complexity for dimensioning a new cellular layout, mainly because of batch size and client's demand variation. In this case, discrete event simulation was used, which made possible to introduce those effects improving accuracy in final results. This accuracy will be shown by comparing results obtained with simulation and without it (as company used to do). To conclude, cellular layout was responsible for increasing 15% of productivity, reducing lead-time in 7 days and scrap in 15% for this family.

Keywords: productivity, efficiency, scrap, lead-time.

Utilização da simulação de eventos discretos para alterar o leiaute funcional em celular em uma empresa de auto peças

RESUMO. O presente artigo apresenta um projeto de simulação de eventos discretos realizado em uma empresa do setor automotivo do Brasil. Nela existia uma grande perda em decorrência do índice de refugo elevado de uma família de produtos. Acreditava-se que um dos motivos era a organização funcional do leiaute, pois os funcionários não ficavam especializados em um tipo de produto. Portanto, se o leiaute fosse alterado para o celular, a sinergia dos funcionários e a especialização em um determinado produto seriam maiores. Devido à complexidade no dimensionamento da célula, principalmente pela variação no tamanho do lote de produção e na demanda do cliente, foi utilizada a simulação, possibilitando introduzir essas variações no modelo computacional, tornando o resultado do estudo mais preciso. Por fim, com a criação da célula a empresa aumentou em 15% a produtividade, reduzindo 7 dias do seu tempo de atravessamento e 15% do seu refugo.

Palavras-chave: produtividade, eficiência, refugo, tempo de atravessamento.

Introduction

Computational simulation allows studying a dynamic process and its effects. Different scenarios can be created and its outputs analyzed helping managers in the decision making process. Furthermore, simulation results are more precise and function as an indicator to predict how a system will react when subjected to a specific modification.

An advantage of this operation is that simulations try to repeat the same behavior which real process would have in the same conditions. A simulation model is used, particularly, as a tool to obtain answers to questions like: "what-if..." (BANKS et al., 2010). For example, Choi et al. (2013) used a discrete event simulation to analyze

three different configurations of ship-to-yard vehicles in a container terminal.

The results indicated which scenario performances are dependently connected with the workload requirements and profile. Moreover, layout is another important subject to be studied in order to improve the system. Hasan et al. (2012) identified five most commons layouts: by process, by product, fixed-position, cell and a hybrid cell.

According with Jiang and Nee (2013), choosing the right layout for a specific process may reduce operational costs in 50%. Lu et al. (2011) built a mathematic model to propose a more efficient layout in a Chinese company. The model results prompted this new layout, which would increase machine rate in operation, productivity and reduce

waste with displacement. Wherefore, nothing more natural than using simulation to test different layouts, and then, choosing the most profitable.

Jerbi et al. (2010) claimed that, once a developed model is validated (representing a real system), managers could forecast any kind of combination defined on research scope. In other words, a simulation model may serve as a tool to help choosing the most appropriated layout for the studied object.

Thus, cellular layouts reduce production cost and increase system flexibility for small batches, a current tendency (GHOTBODDINI et al., 2011). The main benefits for this layout are reduction and simplification of the maintenance cost of stock, work in process, setup time and lead-time.

Hence, the aim of this study is to design a cellular layout using discrete event simulation, considering the most adequate distribution for each stochastic data such as client demand, batch size, mean time to repair, mean time between failures, and, finally, generate a scheduling for the first machine to impact its utilization rate. At the end, this paper presents the results achieved through this study.

The Section 2 presents the theoretical foundation and is divided in discrete event simulation and layout. The third part addresses the methodology used. The fourth part presents the results and discussion, and is divided in industry, conception, implementation and analysis. The fifth, and last part, presents the final conclusion.

Material and methods

Discrete event simulation

Simulation is a simplified system representation, made and understood by a specialist, who intends to identify its potentials improvements (TAKO; ROBINSON, 2010).

Simulations allow the evaluation and analysis of a real system from a computational model which can answer question as 'what-if...' rendering itself a powerful tool on the decision making process (BANKS et al., 2010; LAW; KELTON, 2000; LAW, 2007).

Simulation and modeling was increasingly used as a decision-helping tool; its most important feature, which awakes an interest for simulation, is the prospect of working with complexes systems and the possibility of analysis of the dynamics' behavior (BANKS et al., 2010).

According to Sandanayake et al. (2008) discrete event simulation allied with production system analysis, aiming at performance improvement,

became more relevant in the last decades. Together with advancements on computers, discrete event simulation helps specialists in visualizing, analyzing and optimizing complex production processes, in a reasonable period of time and with a reasonable investment.

For example, Hernandez and Librantz (2013) used discrete event simulation to evaluate 12 scenarios' behavior of supply chain process in sugar cane exportation. In the end, they chose the last scenario because it provided a better productivity.

Simulation is a reality imported to a controlled environment, where its behavior may be studied under a sort of condition, without involving physical risks and/or costs (BANKS et al., 2010). Those conditions can be studied aiming at productivity and quality improvement, machine acquisition, changes in layout and process parameters.

Simulation is one of the most used research tools, mainly due to its versatility, flexibility and power of analysis (RYAN; HEAVEY, 2006). So discrete event simulations are a powerful tool, which can be applied to investigate any stochastic system (HILLIER; LIEBERMAN, 2010).

Layout

Accordingly to Slack et al. (2010) layout changes can affect efficiency and operational costs. Thus, nothing more natural than the use of simulations to test different layouts configurations, and choose the one that brings more profits. In this case, a simulation model serves as a tool to help choosing which layout is more appropriated for the company.

Many researches have been done to evaluate and study the best layout for a specific reality, especially when they integrate simulation with a possibility to test a sort of layout configuration and machines positions.

The key indicators used to compare those layouts were time cycle, work in process and machine rate utilization. They concluded that in a scenario without client's demand variation, the classic cell is better than the other two layouts. However, in a scenario with client demand variation (more common in current days), the last cell layout was better than the other two types.

Kurkin and Šimon (2011) used discrete event simulation to propose a new production layout. The study was performed at the Daimler and VW company line. According to both researchers, the main advantage of using a discrete event simulation with layout is the possibility to try a sort of new designs without moving machines in real life. Thus, only when the best configuration is found out it is time to start working.

Modeling and simulation

The object of this study is a modern manufacturing system, so its analysis is complex. Therefore, to help solving this problem, a computational simulation was used. According to Hillier and Lieberman (2010) computational simulations should be used to solve complex problems.

According to Leal et al. (2011) a simulation model development presents three steps: conception or problem formulation, implementation, and, finally, model results analysis.

In the conception phases, the researchers define the simulation's main objective. Then, a conceptual model is built and all required data are collected. IDEF-SIM (PEREIRA et al., 2015) technic was chosen to build the conceptual model. Examples of collected data are: batch size, production frequency for each product, setup time, downtime and time to machine be repaired.

Once the conceptual model is validated, implementation phase can be initiated. In this stage, the conceptual model is transformed in a computational model, and all collected data are used to program it. After that, the computational model must be verified and statistically validated. Sargent (2012) and Leal et al. (2011) proposals were used for computational model verification and validation respectively.

Finally, if the computational model is approved, the analysis phase can begin. Now, any change in computational model represents the same modifications and results in the real system. For this study, the computational layout model was changed to infer some results in real life.

The next section will present the results and discussion as proposed by Leal et al. (2011).

Results and discussion

Industry

The company in question is an auto part industry, and is located in Southeast Brazil. This company presented 38% of scrap for a specific family product.

It was believed that part of the scrap was due to the functional layout presented, since in the functional layout there is no focus on a particular product, as mentioned in the section Layout. Any product can be produced in any idle machine nearby. Thereby, an employee does not become specialized on one product.

One reason for choosing a cellular layout is that the employee becomes more specialized in the product than in the process (D'ANGELO et al., 2000).

The company has more than 6,000 different products to be manufactured. As a characteristic from this company, all machines are manual and completely man dependent. Some dimensional controls are milesymal, so, changing layout to another one that provides more knowledge, restricting other passing by Families, would help to decrease scrap.

Conception

According to Leal et al. (2011), the first step to be worked on is to define the objectives of the study, the construction and validation of the conceptual model and modeling of the data input.

Objectives and definition of the system

First of all, product's flow was mapped. Two different families were identified, with minimal distinction between both. There were 271 products available among both families, responsible for 180 thousand pieces produced each month, about 2 millions in a year. As one Family was responsible for 92% of the volume produced, this study was conducted for this family.

The employment of discrete event simulation was obtaining better results with the possibility of considering batch size and client demand variation as computational model inputs. All cited factors would be tough to consider algebraically, in other words, without simulation.

At the end, an expected result is how many machines will be necessary to reach the client's demand in a new cellular layout.

Construction and validation of the conceptual model

Continuing with the proposed method, the next step corresponds to the creation of a conceptual model. For this, IDEF-SIM mapping technique was used (PEREIRA et al., 2015), in order to map process and resources activities.

The family products arrive at the dock of the company and employees are responsible to make them available in the first machine inventory (Machine 1). This first step does rough-machining operations, so, dimensional control is not strict.

After passing by the first machining, the product goes to an area to be galvanically coated on its surface, which reduces its wear, extending its life. At the end of this stage, the product goes to the second part of mechanical process, which are still thinning operations.

Finally, at the third and final stage, the product undergoes to final operations, finishing processes, and consequently the tolerance measures are smaller than in first stage. Figure 1 represents the mapping of this last stage. It was decided that only a part of IDEF-SIM would be presented, due to the complexity of production flows.

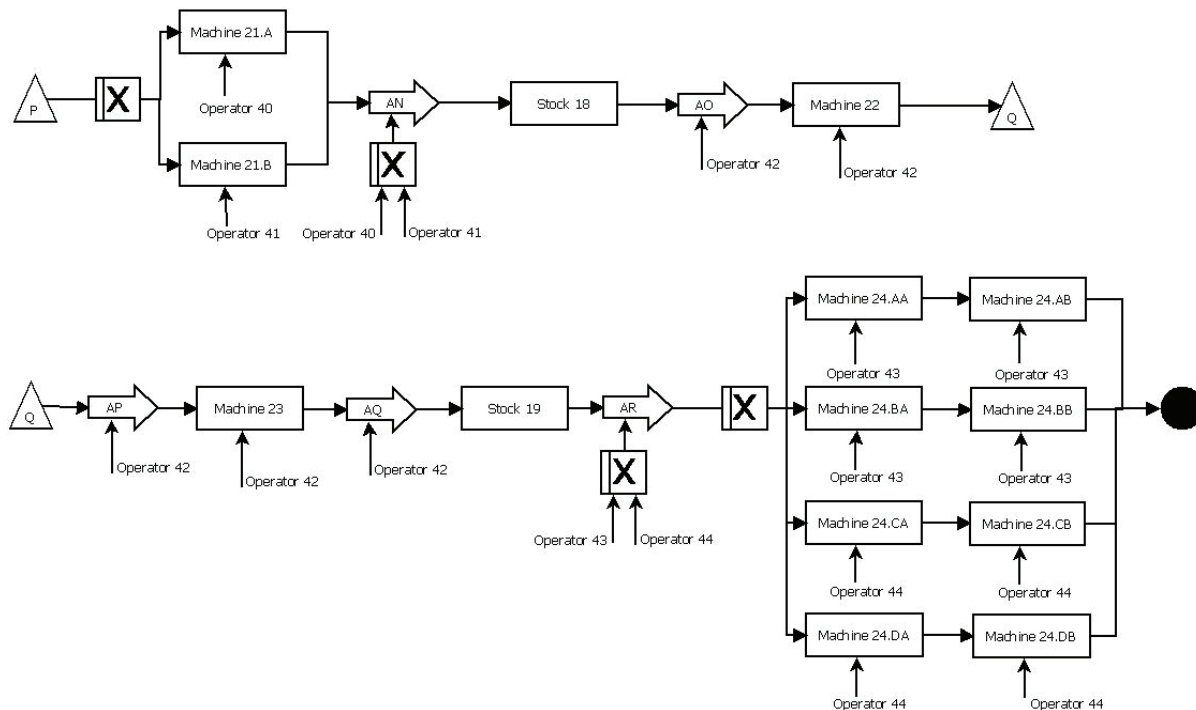


Figure 1. IDEF-SIM from last flow production stage.

It is noteworthy that all mappings performed were validated, using face-to-face validation (SARGENT, 2012), by supervisors and engineers in charge of the area.

Modeling of the input data

The input data used to create the computer model were standard time, plant layout, sales market forecasting, maintenance reports, setup time, batch variation in production and variation in the arrival of the different products of the same family A.

The first survey was conducted with respect to layout, movement and distance between operations, so that the entire computational model was created taking into account the actual distances between operations.

Moving the product is marked on the plant layout in Figure 2 (totaling more than 900 m).

The standard times were based on the database used by the company. These same data are used to feed the ERP (Enterprise Resource Planning) system that calculates the time of production to meet the submission deadline established by the client, as well as its production cost. The machine setup times were also obtained by consulting the default time table of the operation.

Analyzing the various products of which the family consisted, it was concluded that only 9 products accounted for over 80% of its production volume. Therefore, the layout would be adjusted for that product 9.

Once which products would be produced on the new layout were set, a study was carried out to evaluate the size production lot for each of the items and the interval between productions of the same item.

The study consisted of analyzing the outliers from each of the samples of the batch size and production interval. After the analysis of outliers' samples, an analysis was performed to evaluate the dispersion trend in the absence of samples.

Finally, after validating the samples data, a stage of adjustment of their statistical distributions was initiated. According to Banks et al. (2010) the most commonly used distributions are Exponential, Normal, Weibull, Gamma and Johnson.

After obtaining the best-fit results, statistical software Stat::Fit® was used to calculate the appropriate parameters of each distribution to be programmed into the computer model.

At the end of the study to determine the best-fit distributions for the production batch size of the items, the study was initiated to determine the range of production of 9 items, namely to find the best-fit distribution to the arrival frequency of the product for its manufacturing.

Then, we studied the data of machine downtime and maintenance time (mean time to repair and mean time between failures). The same care to adjust the size and frequency of arrival of lots of production was adopted for the fit of stochastic data for MTTR (Mean Time To Repair) and MTBF (Mean Time Between Failures).

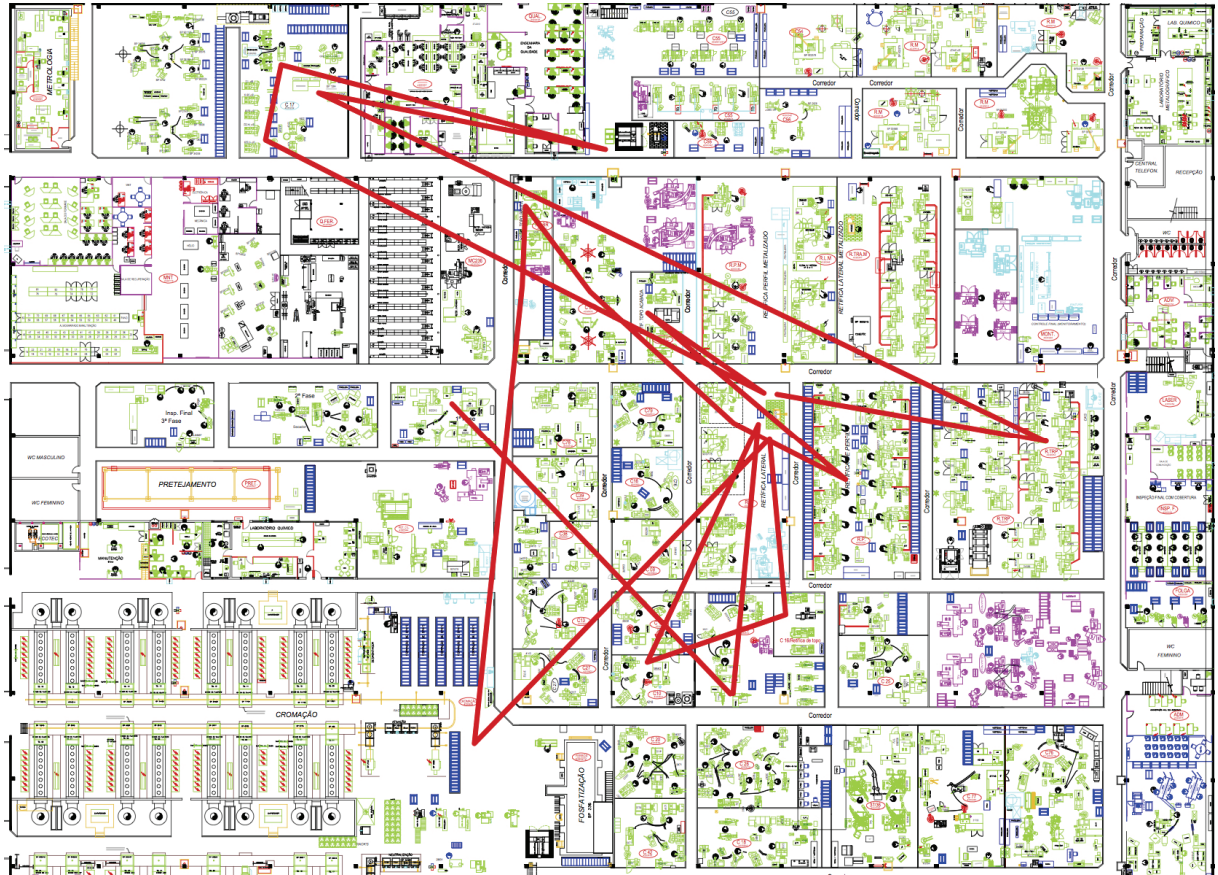


Figure 2. Product flow indicated on the plant layout.

Implementation

According to Banks et al. (2010), the implementation phase is composed of the construction, verification, and finally, the validation of the computational model.

Computational model: construction and verification

In the model's programming phase, ProModel® was used to create a computational model with more than 600 process lines, 87 places, 9 entities with deferent flows and 39 employees.

The model also considered machine breakdown, setup time, displacement and employee availability. Besides that, in this model, the batch size for each entity varies according to the historical logistic log file. The rule for feeding the first operation, when the part leaves the stock, was adopted as random. Otherwise, the rule would be FIFO (First In, First Out), what would not bring up an impact in the operation, because the production sequence would not change during each run.

So, in each replica, there was a variation as consequence of the production mix, as well in the machines' utilization rate. These elements made the model more realistic and helped in its validation, as will be presented below.

The 3D model (Figure 3) was built facilitate stack holder analysis in the company. The project was approved and the new layout configuration is presented in Figure 4.

Validation of the computational model

Computational model validation was performed using two methods: model behavior and statistical comparison between simulation and historical data.

First of all, the computational model was validated using the verification performed by model behavior (SARGENT, 2012). In this process, production engineers and the head of the area can see if model behavior is correct, or else they may suggest any improvements.

After verification, the computational model was set to simulate 20 replicas during 7 months of production period. Besides that, a warm up period of 90 days was implemented in the programming. Warm up periods ensure that simulation data collection had not occurred before the line up had been established.

Replicas results obtained were: mean 1,579,530 pieces and standard deviation of 124,270 pieces. The real data for the same period were: 1,555,753 pieces and standard deviation of 55,790 pieces.

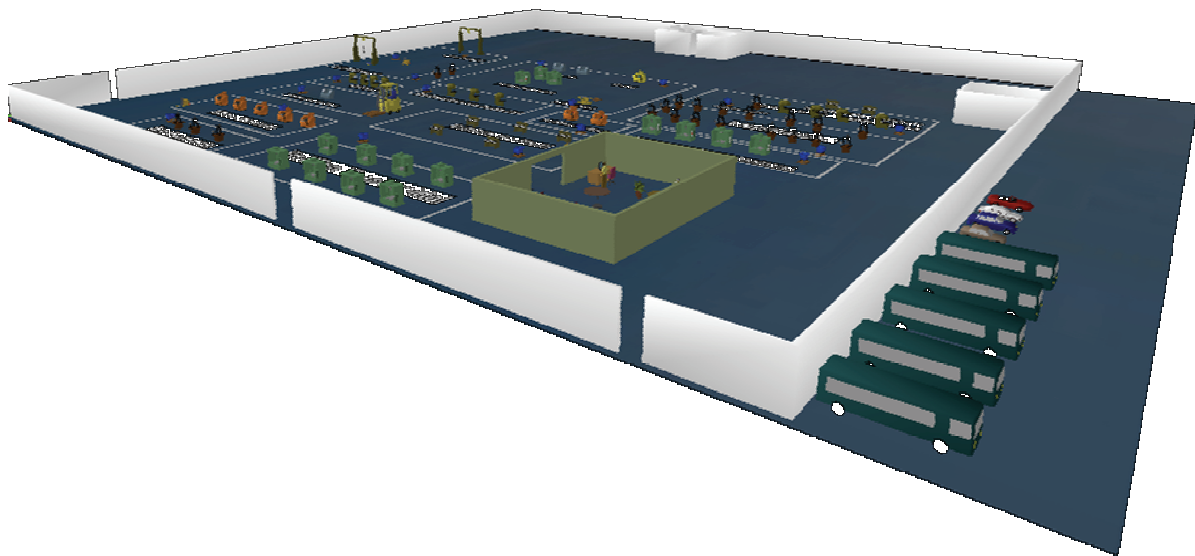


Figure 3. 3D computational model.

Hereafter, statistical validation was made with real and simulation data using the proposal of Leal et al. (2011). In this paper, the authors present all steps required for discrete event simulation statistical validation.

All steps required for validation were followed. In the first step, a normality test was performed (MONTGOMERY; RUNGER, 2010), using the Anderson-Darling's proposal (ANDERSON; DARLING, 1954), with real and simulation data. The result for real data normality test was a p-value of 0.505, and simulation data normality test presented a p-value of 0.951. Both results were higher than 5% (adopted significant level), which proves data's normality.

Then, a variance analysis (MONTGOMERY; RUNGER, 2010) between real and simulation data was conducted using an F test (SNEDECOR; COCHRAN, 1967). The p-value for this test was 0.029, which cannot prove variance similarity. Based on Leal et al. (2011), if the F test failed, it is necessary to use the Smith-Satterthwaite method (SATTERTHWAITE, 1946) before a T test (STUDENT, 1908).

According to the authors, the Smith-Satterthwaite method is used when real and simulation data are normal, but present different variances. This method adjusts liberty of freedom regarding the difference in variances for a critical value.

Finally, a T test using Smith-Satterthwaite method was conducted to prove computational model validation. The result showed a p-value of 0.442, which is higher than the adopted significant level

(5%), so null hypothesis about real and simulation average data is validated and equal.

Thus, using Leal et al. (2011) proposal, computational model is statistically validated for production quantity.

Analysis

According to Leal et al. (2011), this phase will use the operational model, execution of experiments, analysis of the results and conclusions.

Among the results obtained, the most interesting for the present purpose was the use of machines in comparison with the amount of available machines (limit of occupation). The occupancy limit is the amount of machines that are available in the factory and were programmed in the simulation. What means 100% of the occupancy limit represents an operation with only one machine in the system, since an operation with 1,600% of occupancy limit represents an operation with 16 machines in the system.

The operation 1 presented an occupation of 29.3 for a limit of 100%, operation 2 47.4 of 200%, operation 4 59.6 of 300%, the operation 5 32.1 of 300%, operation 14 67.5 of 100%, operation 15 24.8 of 400%, the operation 16 31.3 of 1,600%, operation 17 22.6 of 200%, the operation 18 175.1 of 700%, the operation 19 35.4 of 300%, operation 20 19.8% of 500%, operation 21 66 of 200% operation 22 25.2 of 100%, the operation 24A 97.3 of 400%, the operation 24B 97.3 of 400%.

The difference between the use of the machine and the limit of the operation is the number of machines required for the manufacture of all 9 products. Thus, leaving for the analysis stage of the

simulation and creating scenarios to assist in decision-making, machines that were not required were withdrawn from the computational model: one machine of operation 2, two machines of operation 4, two machines of operation five, three machines of operation 15, fifteen machines of operation 16, one machine of operation 17, five machines of operation 18, two machines of operation 19, four machines of operation 20, one machine of operation 21, three machines of operations 24A and B.

By reducing the number of machines, it can be concluded that the displacement of the product is decreased and the area to be occupied by each cell would be smaller. The results obtained with the simulation, which represents the changes mentioned above, were the same percentage of use of the machines presented previously. That is because only the unnecessary machines were withdrawn from the system, which proved no impact in the delivery end.

The machines that perform operations 24AA 24AB remain in use for about 97.3% of the time, that is, they require little maintenance in order not to compromise the delivery of the products. Due to the high-value of the machines used, it was decided to create the cell with only 2 machines present and if any of them presented problems, the product would have to come out of the cell and perform the operation in one of the other 20 machines present in the company, but they were allocated in other areas.

However, if DES (Discrete Event Simulation) were not applied, Table 1 presents the number of machines that would be required. In Table 1 it is noted that the deterministic model would be necessary to allocate more than one machine in operation 4, more than one machine in operation 18, and two more machines in operation for 24AA and BB, which would result in a loss of over \$1 million in investments in these machines.

Table 1. Comparison between the utilization rates of the machine obtained by the deterministic and the validated models.

Operation	Deterministic Model (% Utilization)	Stochastic Model with inbound rule in OP1 standard (% Utilization)	Validated Model (% Utilization)
Operation 1	45.7	27.1	29.3
Operation 2	84.2	37.1	47.4
Operation 4	110.2	46.3	59.6
Operation 5	46.2	25.1	32.1
Operation 14	90.8	49.1	67.5
Operation 15	39.5	19.8	24.8
Operation 16	51.7	22.9	31.3
Operation 17	31.0	17.2	22.6
Operation 18	273.6	129.7	175.1
Operation 19	50.1	26.6	35.4
Operation 20	34.2	14.7	19.8
Operation 21	99.1	49.0	66.0
Operation 22	52.0	18.4	25.2
Operation 24AA	216.5	74.1	97.3
Operation 24AB	234.4	74.2	97.3

This is because all of the data used were considered in average for the deterministic model, mean time to breakdown and repair of machinery, average frequency of customer demand, medium batch production. Table 1 presents the number of machines that would be required if the randomness of the products into the first operation were not created.

The analysis of Table 1 shows that without creating the input randomness of products in the first operation, the occupation of machines would be smaller. This is due to the fact that for the model with default inbound rule, the sequence produced in the first machine is always the same. However, in real life there is a variation in the sequence to be produced, either by customer demands, either by the providing part of the previous operation. This variation in the sequence generates the occupancy rate of the machine differently, because producing the parts in the order 1-2-3 is different than producing them in the order 2-3-1.

With the use of discrete event simulation, it was easier to make the decision. Managers had more safety and comfort to scale and compare the number of machines needed to meet customer demand.

However, the operations 1, 2A, 4A and 5A together represent 1.1% of the overall waste family. Therefore, we preferred not to move those operations to the new cell, maintaining productivity of the factory. The proposed cell layout is shown in Figure 4.

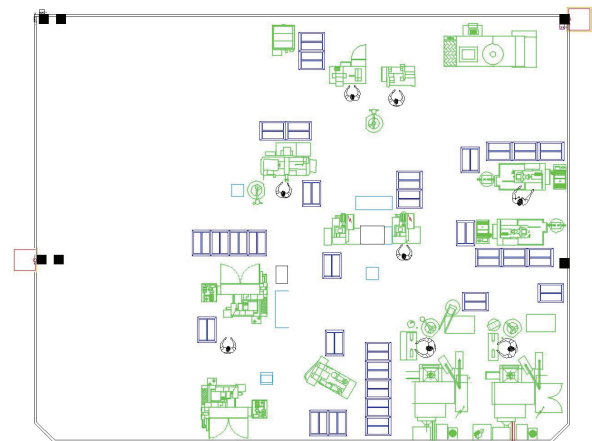


Figure 4. Proposed cellular layout.

The layout has been implemented in the company for one year and has achieved earnings, presented in Table 2.

Table 2. Summary of results.

KPI	Past Layout	New Layout	Earnings	%
Distance (m)	992.1	228.0	764.1	77.0%
Employees/shift	39	37	2	5.1%
Productivity (pieces/men/day)	223.4	227.0	3.6	1.6%
Lead Time (day)	33.2	22.5	10.7	32.2%
Throughput Time / Lead Time	0.0072	0.0087	0.0015	20.8%

Conclusion

The data obtained from the simulation were more accurate than those obtained by the deterministic model, in the way it was used by the company in the change of the project layout. If the company continued to employ the same technique, it would be led to erroneously invest more than US\$ 2 million in buying machines that would be idle.

The company in question has adopted the suggested layout, with the number of machines obtained as the final result of the simulation.

Suggestion for future studies is: dimension employees' utilization rate to balance the activities inside the cell.

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References

- ANDERSON, T. W.; DARLING, D. A. A test of goodness-of-fit. **Journal of The American Statistical Association**, v. 49, n. 268, p. 765-769, 1954.
- BANKS, J.; CARSON II, J. S.; NELSON, B. L.; NICOL, D. M. **Discrete-event simulation**. 5th New Jersey: Prentice-Hall, 2010.
- CHOI, S. H.; WON, S. H.; LEE, C. Comparison of alternative ship-to-yard vehicles with the consideration of the batch process of quay cranes. **International Journal of Industrial Engineering: Theory, Applications and Practice**, v. 20, n. 1-2, p. 84-98, 2013.
- D'ANGELO, A.; GASTALDI, M.; LEVIALDI, N. Production variability and shop configuration: an experimental analysis. **International Journal of Production Economics**, v. 68, n. 1, p. 43-57, 2000.
- GHOTBODDINI, M. M.; RABBANI, M.; RAHIMIAN, H. A comprehensive dynamics cell formation design: Bender's decomposition approach. **Expert Systems with Applications**, v. 38, n. 3, p. 2478-2488, 2011.
- HASAN, M. A.; SARKIS, J.; SHANKAR, R. Agility and production flow layouts: an analytical decision analysis. **Computer and Industrial Engineering**, v. 62, n. 4, p. 898-907, 2012.
- HERNANDEZ, M. A. G.; LIBRANTZ, A. F. H. Improvement of the supply chain for the sugar cane exportation process employing discrete event simulation techniques. **Acta Scientiarum. Technology**, v. 35, n. 4, p. 637-643, 2013.
- HILLIER, F. S.; LIEBERMAN, G. J. **Introduction to operations research**. 9th ed. New York: McGraw-Hill, 2010.
- JERBI, A.; CHTOUROU, H.; MAALEJ, A. Y. Comparing functional and cellular layouts using simulation and Taguchi method. **Journal of Manufacturing Technology Management**, v. 21, n. 5, p. 529-538, 2010.
- JIANG, S.; NEE, A. Y. C. A novel facility layout planning and optimization methodology. **Manufacturing Technology**, v. 62, n. 1, p. 483-486, 2013.
- KURKIN, O.; ŠIMON, M. Optimization of Layout Using Discrete Event Simulation. **IBIMA Business Review Journal**, v. 2011, n. 2, p. 1-10, 2011.
- LAW, A. M. **Simulation modeling and analysis**. 4th ed. New York: McGraw-Hill, 2007.
- LAW, A. M.; KELTON, W. D. **Simulation modeling and analysis**. 3rd ed. New York: McGraw-Hill, 2000.
- LEAL, F.; COSTA, R. F. S.; MONTEVECHI, J. A. B.; ALMEIDA, D. A.; MARINS, F. A. S. A practical guide for operational validation of discrete event simulation models. **Pesquisa Operacional**, v. 31, n. 1, p. 57-77, 2011.
- LU, X.; JIA, Z.; YANG, J.; LIU, H. Design and implementation of Lean Facility Layout System of a Production Line. **International Journal of Industrial Engineering: theory, Applications and Practice**, v. 18, n. 5, p. 260-269, 2011.
- MONTGOMERY, D. C.; RUNGER, G. C. **Applied statistics and probability for engineers**. New York: John Wiley and Sons, 2010.
- PEREIRA, T. F.; MOTEVECHI, J. A. B.; MIRANDA, R. C.; FRIEND, J. D. Integrating soft systems methodology to aid simulation conceptual modeling. **International Transactions in Operational Research**, v. 22, n. 2, p. 265-285, 2015.
- RYAN, J.; HEAVEY, C. Process modeling for simulation. **Computers in Industry**, v. 57, n. 5, p. 437-450, 2006.
- SANDANAYAKE, Y. G.; ODUOZA, C. F.; PROVERBS, D. G. A systematic modeling and simulation approach for JIT performance optimization. **Robotics and Computer-Integrated Manufacturing**, v. 24, n. 6, p. 735-743, 2008.
- SARGENT, R. G. Verification and validation of simulation models. **Journal of Simulation**, v. 7, n. 1, p. 12-24, 2012.
- SATTERTHWAITE, F. E. An approximate distribution of estimates of variance components. **Biometrics**, v. 2, n. 6, p. 110-114, 1946.
- SLACK, N.; CHAMBERS, S.; JOHNSTON, R. **Operations management**. Harlow: Prentice Hall, 2010.
- SNEDECOR, G. W.; COCHRAN, W. G. **Statistical methods**. AMES: Iowa State University Press, 1967.
- STUDENT GOSSET, W. S. The probable error of a mean. **Biometrika**, v. 6, n. 1, p. 1-25, 1908.
- TAKO, A. A.; ROBINSON, S. Model development in discrete-event simulation and system dynamics: an empirical study of experts modellers. **European Journal of Operational Research**, v. 207, n. 2, p. 784-794, 2010.

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