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FORUM

Submitted 27.07.2017. Approved 02.11.2017.

Evaluated by double blind review process.

Scientific Editors: Cristiane Biazzin, Elyn L. Solano Charris, and Jairo Alberto Jarrín Quintero.

DOI: <http://dx.doi/10.12660/joscmv10n2p06-17>

SIMULATION ANALYSIS OF A FABRICATION PROCESS OF A TANNERY: CASE STUDY OF A LATIN AMERICAN COMPANY

ABSTRACT

A large number of real-life optimization problems in economics and business are complex and difficult to solve. Among the solutions techniques available in the Management Science, Discrete-Event computer Simulation (DES) can be considered as one of the most preferred by practitioners. DES has been used as an analysis tool to evaluate new production system concepts, and has also been used in the operation and planning of manufacturing facilities. In this paper, we propose to apply DES for the analysis of a leather manufacturing facility. The objective is to analyze the current performance of the production system in order to propose alternatives for improvement, as well as optimum parameters for production. Results obtained showed the advantages of using such a quantitative decision-aid technique by capturing most of the complex characteristics of the production process.

KEYWORDS | Leather fabrication, simulation, process improvement, case study, Colombia.

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INTRODUCTION

As explained in detail by Blanco and Paiva (2014), Latin American countries have a booming middle class increasingly demanding more sophisticated products and services. Global companies are investing in new plants in Latin American countries in order to decrease logistics costs. Some local multinational companies (“multi-latinas”) are strong global players in diverse industries (e.g., airplanes, food, oil, cement, beverages, banking and telecommunications, leather, etc.). As a consequence, research works inspired in real-life cases have enriched the fields of operations, logistics and supply chain management.

The purpose of the current paper is to study a real-life decision-making problem related to the operation of the fabrication process of a tannery in Colombia. As most real-life optimization problems in economics and business, this manufacturing process is complex and difficult to solve. The Operations Research community has developed efficient and effective solution techniques since its first applications in industry in the 1940’s (Hillier and Lieberman 2005). Traditional solution approaches include mathematical programming (linear, integer and even nonlinear modeling), dynamic programming and exact algorithms like branch-and-bound techniques. Because of the current interest by researchers on considering more and more constraints during the modeling process, problems in business under study nowadays cannot be solved in an exact manner within a reasonable amount of time (Talbi 2009). Among the solutions techniques available in Operations Research and the Management Sciences, discrete-event computer simulation (DES) has proven to be very useful for practitioners in real-life decision-making (Banks et al. 2009). In today’s globalized environment, industries are calling for immediate action to develop computational and simulation-based methods that will lead to faster transactions, reduced operating costs, and improved performance and customer service. DES has been used as an analysis tool to evaluate new production system concepts, and has also been used in the operation and planning of manufacturing facilities. For several years, simulation has been used in the long-term planning, design and analysis of manufacturing systems (Solano-Charris & Paternina-Arboleda, 2013). These models have been termed as “throw away models” because they are seldom used after the initial plans or when designs are finalized (Son and Wysk 2001, Smith and Brett 1996, Harmonosky 1995). Over the past de-

cade, however, researchers and practitioners have taken advantage of the power of simulation technology to develop models that can be fully integrated into complex manufacturing systems and run in real-time. The ability to automatically generate simulation models for certain applications has also been achieved (Son and Wysk 2001). Recent attempts to use simulation modeling in the control and analysis of production logistics and manufacturing systems may be found in the works of (Mullarkey et al. 2000, Rabbath et al. 2000, Lee et al. 2002, Dangelmaier et al. 2006, Barra Montevechi et al. 2009, Zülch et al. 2009, Sharda and Bury 2010, Pawlewski and Fertsch 2010, Montoya-Torres 2010, Montoya-Torres et al. 2012) just to mention a few. Note however that most, not to say all, of these works have been performed in developed countries, and very little applications and successful case studies are presented in the scientific literature for small and medium enterprises in emerging economies. The focus of this paper is hence to contribute to the formal analysis of production processes in emerging countries, and in particular in the tanning industry, towards the use of computer simulation models in order to improve daily decision-making processes. As stated before, simulation modeling methodology is used on a real-life case study from a medium enterprise located at the north of Bogota, Colombia.

Whereas simulation has already been used for many years as a tool for planning and controlling production processes, very little attention has been given to the improvement of production processes of a tannery, to the best of our knowledge. The inexistent use of simulation into the tanning industry may be attributed to the complex and changing character of both the product and the production process. In this paper, we propose to apply discrete-event computer simulation for the analysis of leather manufacturing. The objective is to analyze the current behavior of the production system in order to propose alternatives for improvement, as well as optimum parameters for production. The work presented in this paper is an extension of the results presented in Pirachicán-Mayorga et al. (2010). In comparison with that paper, we present here more detailed results obtained from simulation runs and also extend the analysis of the optimization approach.

This paper is organized as follows. The current manufacturing process is first described. Afterwards, the proposed simulation model and the analysis of results for the current situation are presented, followed by

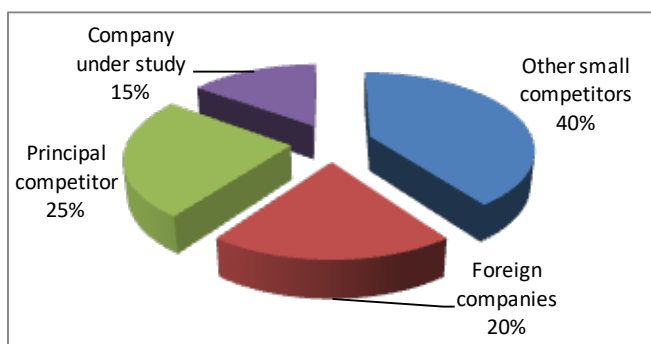
the analysis of some improvements and their managerial implications. These scenarios are further analyzed by using a simulation-optimization technique. This paper ends by presenting some concluding remarks.

MANUFACTURING PROCESS AND PROBLEM SETTING

Overview of the Manufacturing Process

The case study considered in this paper corresponds to a medium company within the tanning industry, whose name is kept confidential, dedicated to manufacture leather for furniture and cars. The company currently has 15% of the market share, while its principal competitor has 25% (see figure 1). The other 60% of the market is divided among many small enterprises (40%) and foreign companies (20%).

Figure 1. Distribution of the marketplace



The production process we are describing next is based on the product named “Carioca black leather”. We choose this product because it can provide sufficient characteristics and complexities to understand well the global manufacturing process. In addition, its demand is the highest among the total production of the market supplied by the company. The process of leather preparation is quite wasteful and time consuming. Figure 2 shows a diagram of the process. The process begins with the arrival of the skin to the factory. When the skin-pieces are not entering the process immediately, sodium chloride is added to them for dehydrate (salting process), and then they pass to soaking (a pre-wash process with water and wet), in order to afterwards remove hair from the skin. The skin goes to fleshing, fixing and split, where the tissue is separated in order to made leather (dermis).

Transformation of the skin into leather is done by a chemical process called tanning. The skin is cut in order to reduce its thickness to an appropriate standard.

This process requires a large quantity of water and it is hence necessary to drain it. Defects in the raw material have to be then corrected or mitigated. This is one of the most important steps of the operation since it affects the processes of greasing, staining, painting and finishing that define the final features of the leather. So the leather is conditioned in order to moisten for an efficient implementation of those steps. Finally, the leather is softened to break the adhesion between the fibers and provide flexibility and softness.

Problem Description

At the moment of starting this simulation project, the company presented various problems that all together unfavorably interfere with the production process, generating over cost and quality decrease. By implementing a computer simulation model, we represent the current production situation; carry out a diagnosis of potential problems in the productive process and are able to quantify their impact on the overall performance of the system. In particular, the majority of problems identified concerns the low quality of raw material received from suppliers, which is difficult to identify at an early stage (i.e: when received) since skin has to be chemically treated: such defects are detected when the product has advanced nearly 40% of the stages. Table 1 shows the categories of raw material selection according to their acceptance level.

Figure 3 classifies in a Pareto chart the different types of defects found in the product along the process. It is important to clarify that such defects do not necessary imply product non-conformities. That is, defects in leather are inherent to the nature of raw material. The fact of finding them only implies that a series of additional steps are required throughout the production process in order to obtain the final quality level for the finished product. Another issue to be addressed is the quantity of raw material to be negotiated with suppliers. The problem here is that the company under study does not have an accurate procedure for demand forecasting and planning. Hence, the enterprise’s managers are not able to negotiate in advance with suppliers in order to obtain better quality of raw material. We argue that the better the knowledge of the marketplace the better the possibilities to establish long term relationships with suppliers and therefore the better the quality of raw material. At the end, this will lead to a decrease of production costs, since, depending on the features of the purchased leather (skin), the production pro-

cess and the quality will be affected, increasing or decreasing its value. Figure 4 presents three types of raw material received by the enterprise under study. However, from the management standpoint, we do believe that first the impact of having to pro-

cess the current raw material must be quantified to afterwards propose an eventually different purchasing policy to negotiate with suppliers. The proposed simulation study will give us some insights about this concern.

Figure 2. Process flow diagram

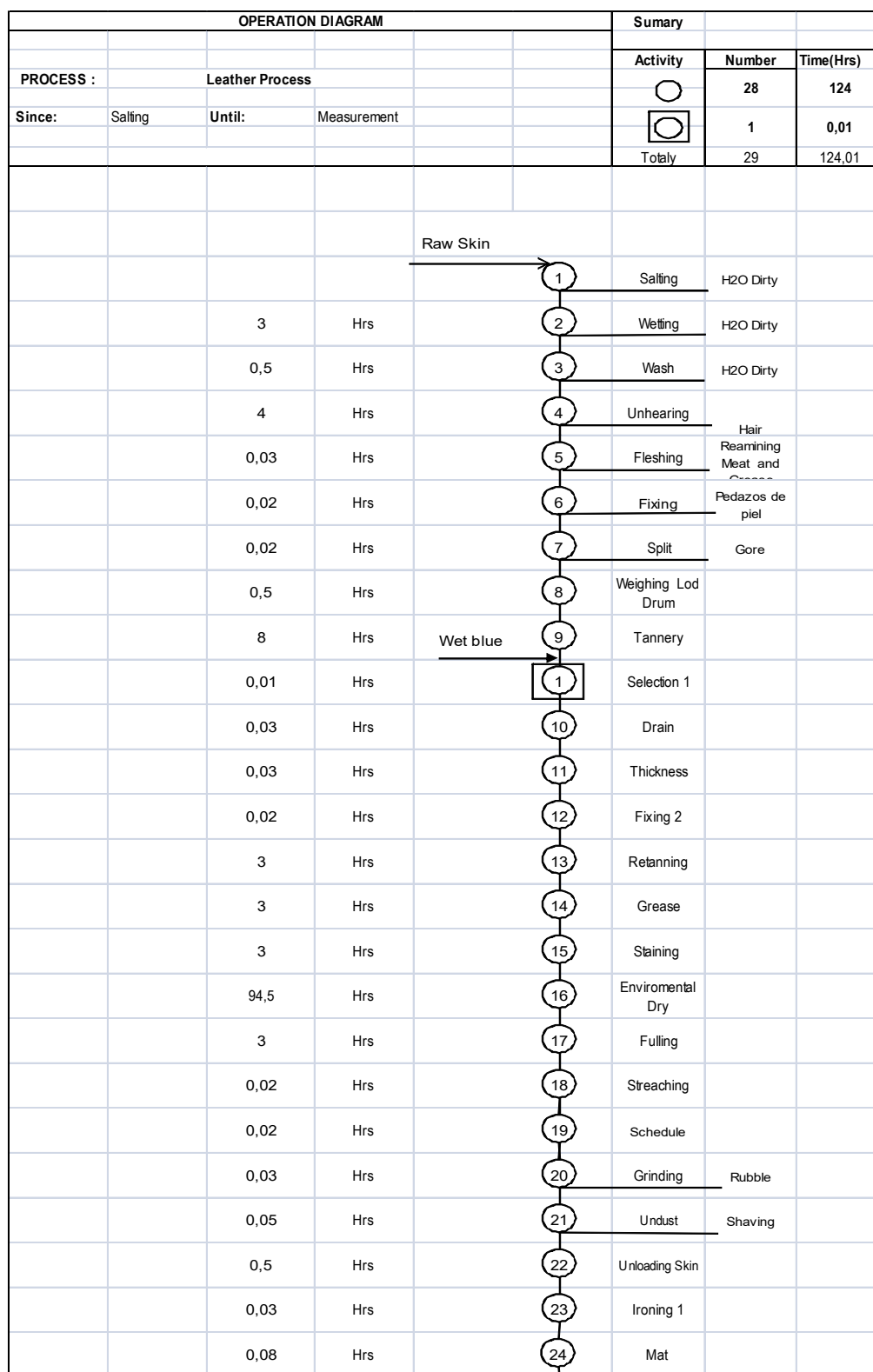


Table 1. Raw material selection categories

| Selection category | Accepted quality features |
|--------------------------------|---|
| First selection (type 1A skin) | Few scratches (patched in site) located in the center of the skin |
| Second selection | Little holes of insects and low fixed scratches |
| Third selection | Notorious insects holes and evident scratches |
| Fourth selection | Any defect that could be ground |
| Fifth selection | Any defect that could be ground and holes |

Figure 3. Pareto chart of raw material

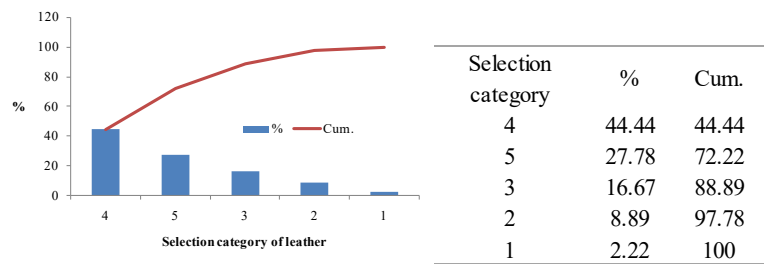


Figure4. Types of raw material entering the production process



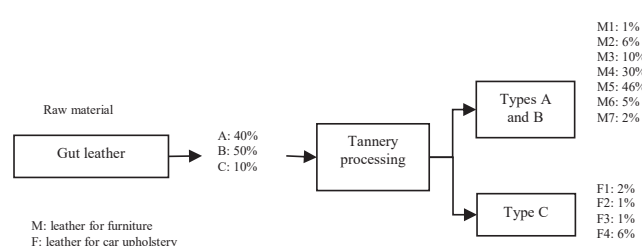
As explained before, raw material is received from suppliers at different stages of processing. Figure 4 presents the three types of raw material received by the enterprise under study. Depending on the previous state of processing, the quality of leather entering the process will strongly affect the global cost of manufacturing. For instance, for the case of raw leather, since hair is still present not all defect are visible and hence a processing is required in order to remove it. About 45% of this type of raw material does not accomplish quality specifications after some processing. However, the decision-makers do prefer buying leather with skin because it is possible to control the defects during manufacturing. According to managers' experience, the enterprise estimates the following percentages of defects: 5%,

10% and 10% having, respectively one, two or three holes at the lower part, 40% having more than three perforations at the lower part and some in the center and some scratches, 3% having more than three holes located at the center of the leather, and 2% corresponds to leather with multiple defects and not possible to be repaired. These defects are only detected once the product becomes gut leather, that is, after eliminating the hair from the raw material. Note that according to quality requirements by customers, only leather fitting within the first three categories can continue processing: 55% of the total raw material. The other 45% of material is considered waste and does not generate any value-added processing for the enterprise. However, 22% of this waste product could be sold at a lower price than bought by the enterprise.

For the case of gut leather, defects are clearly visible at the time of purchasing. The range of selection is not as big as when raw leather is purchased; it is assumed that this leather has already been preselected. There are three types of selection for the gut: Type A is used for high quality furniture, type B is used for manufacturing standard quality furniture, and Type C is devoted to make cars upholstery. When the raw material is purchased as gut leather, the tanning process allows it to become wet blue leather (or simply wet blue) and it is ready for actual production. Another specific selection can be made. From a lot of 100 pieces, the distribution of leather is shown in figure 5, ordered

by decreasing quality level. Finally, wet blue leather is bought in order to satisfy picks of demand when there is not enough time to process the raw material since the beginning of the production process. Even if this supply strategy allows flexibility and agility to satisfy demand, buying wet blue leather implies high cost and hard difficulties to repair quality defects. Two categories of product are defined: first-class leather dedicated to furniture (by decreasing order of quality: M1: 15%, M2: 40%, M3: 35% and M4: 5% of pieces), and second-class (low quality) leather, which is devoted to car upholstery (F1: 2% and F2: 3% of pieces).

Figure 5. Quality distribution of gut leather purchases



Note that the purchase of raw material has been the most significant problem for the company. The inherent defects of the skin where at some time a key problem to be solved. However, researchers working for the enterprise have generated very good chemical processes that are the most valuable knowledge they have developed. The challenge now is to understand both economic and productive implications of continuing processing leather with those quality conditions. The proposed simulation model is developed in order to attain such objective.

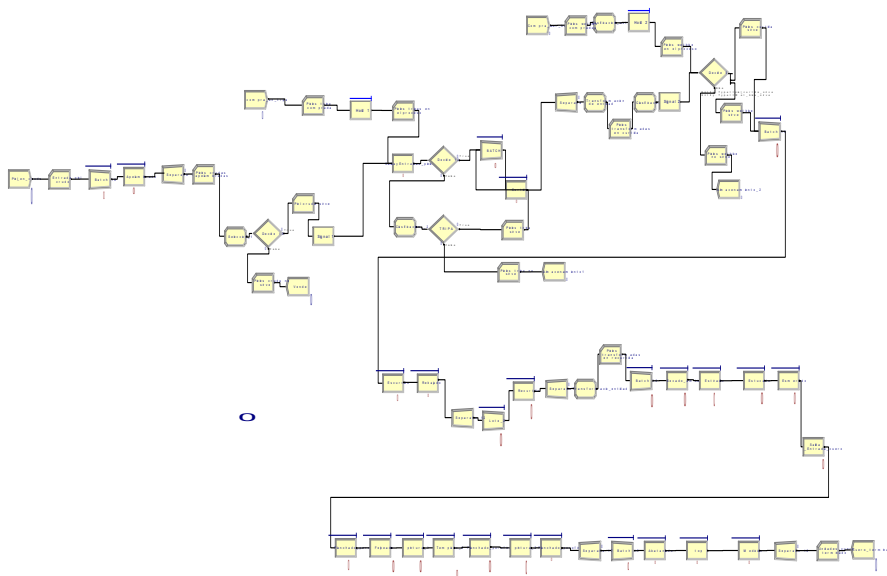
SIMULATION MODEL

As explained previously, discrete-event simulation (DES) was used to analyze the behavior and global performance of the leather manufacturing system. The model was built using Arena® software, which is a generic simulation package able to simulate a large variety of systems (Fábregas et al. 2003). The model allows presenting the current production situation and modeling different production scenarios seeking the improvement of key performance metrics. The model was built to simulate the operation flows of the Carioca black leather, the most representative product manufactured by the company. It began with the entry of the raw leather and later other

types of purchase where introduced, gut leather and wet blue. The process flow, described in Section 2 (see figure 2), was represented using logical blocks provided by the software. Some complex operations had to be modeled using several blocks.

Input data concerning the information about processing times and time between arrivals was obtained from two sources: historical data provided by the company and data obtained after carrying out a time study. Tests of fitness were carried out in order to obtain the best probability distributions that characterize those data. Since most of available data about arrival and processing times were obtained from small samples (30 or less), a Kolmogorov-Smirnov test of fitness was chosen for all the processes (Montoya-Torres 2006). For some processes, uniform and constant distributions were considered to be the most appropriate due to lack of data or because carrying out on-field sampling was too long lasting and wasteful. In particular, this last was the case of the tanning process: processing duration is typically between 48.5 and 51.3 hours. Other input information was taken from the enterprise database, such as costs. Other operating conditions like number of resources, input processes, assignment of operators to machines, etc., were modeled exactly as currently existing at the enterprise. The length of simulation was set to be one year of production and a total of 10 replications were performed. The whole model is presented in figure 6. A warm-up period was considered and statistics collected during this period were discarded in order to eliminate initialization bias. Model's operational validation and verification was done by using two independent and complementary techniques presented in Banks et al. 2005, Sargent 2001, as employed in many simulation case studies (see for example the work of Montoya-Torres et al 2009). The first technique is the classical statistical validation. The appropriate statistical test is a *t*-test. The average total simulated processing time was compared with the theoretical processing time (i.e. the sum of processing times on all machines). The obtained probability of no reject the null hypothesis was 0.97 and hence this test provides no evidence of model inadequacy. The second technique consisted of a Turing test, for which the knowledge of experienced engineers about the system behavior is used to operationally validate the simulation model.

Figure 6. Structure of the simulation model



ANALYSIS OF RESULTS: CURRENT SITUATION

This section presents a summary of results obtained from the simulation of the current situation at the factory. The objective here is to identify the global system bottleneck resource(s) and to identify possible scenarios for improvement, as well. Key performance metrics were defined to be the average waiting time of an entity in a queue (time an entity has to wait before being processed by a resource), the average number of entities in a given queue, and the average resource utilization rate.

Values obtained for the first metric are presented in figure 7. We can observe that the processes with the longest average waiting time of entities in queue are unhairing and re-tanning (re-tannery). This is explained by the fact that the number of arriving entities is higher than at the other parts of the process, and because these two operations require a large amount of time when compared to the rest of the process. This situation is verified by the results obtained for the two other key indicators: average number of entities in queue (figure 8) and average resource utilization (figure 9). It has to be noted that resources in this last figure are ordered alphabetically. Hence, the reader must remark that resource named “Drum_3” is the resource that corresponds to re-tanning operation.

Figure 7. Average waiting time in queue: all process stages

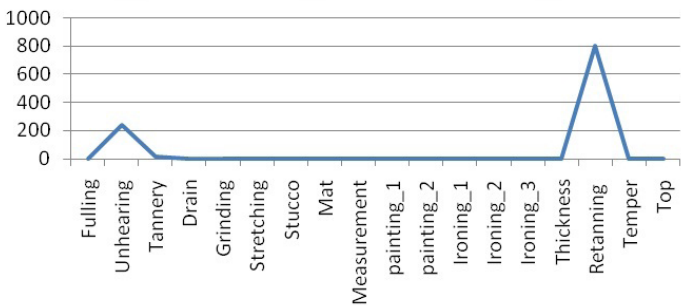
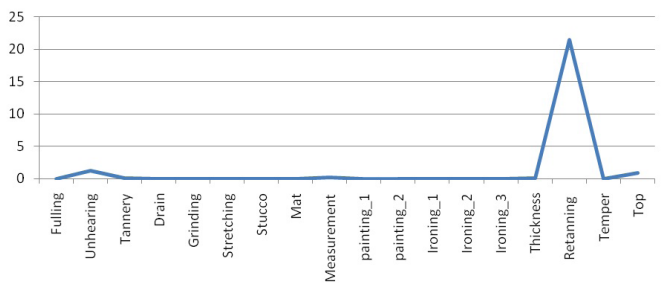


Figure 8. Average number of entities in queue



Another interesting analysis to be carried out concerns the study of costs related to the production process. Figure 10 is a comparative chart of utilization costs of each resource (machines and operators). The most expensive operator for the company is the person performing the operations of thickening and grinding (“Employ_4” in the figure), who is paid per hour and per finished piece. On the other hand, the

most expensive machine is the “Press” which is used three times during production.

Figure 9. Average resource utilization

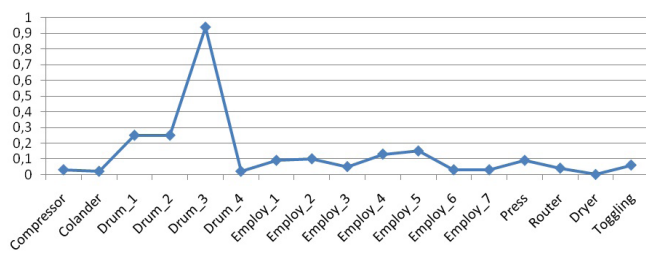
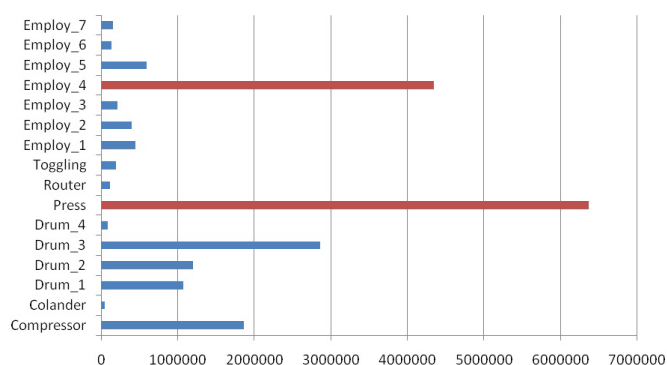


Figure10. Comparison of operational costs per resource



ANALYSIS OF SCENARIOS

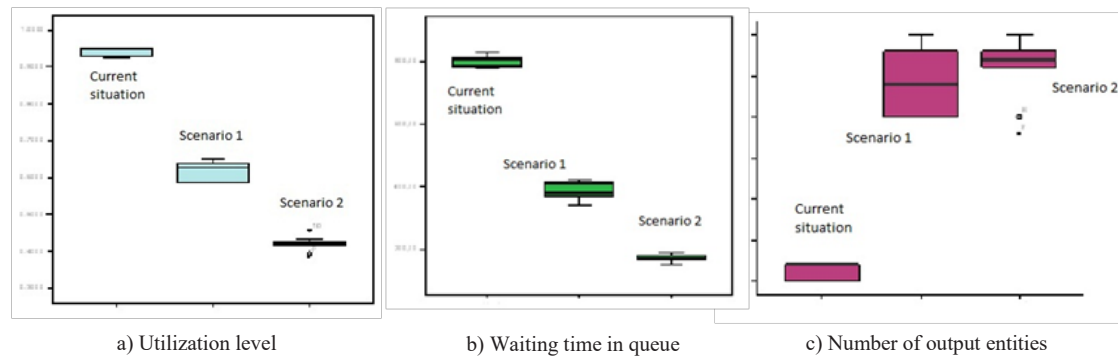
Once we have analyzed the current behavior of the production system, we proceeded to explore several alternatives in order to improve key performance metrics. Different manufacturing scenarios were studied and comparison between them was carried out using statistical methods. As we could observe in the simulation results, two critical resources are present in the production line: the “drum” of tan-

nery process and the operator in charge of coat, flush and measurement processes. Hence, considering this situation, a first analysis was performed by adding one or two drums to re-tanning processing. Results for the first set of experiments are shown in table 2 and figure 11, for key performance metric named resource utilization, number of entities processed at this stage of the production process (i.e. entities completely processed by the resource) and waiting time in resource’s queue. Then, a second analysis was carried out by adding one or two operators. Results of this second analysis are presented in table 3.

As we can observe in table 2, there is a difference between average values of resource utilization, which is explained by the fact that having more resources to perform the re-tanning process, arriving entities will be distributed among them. Hence, waiting times in queue will diminish, and the number of entities that are actually completely processed will increase. By observing box-and-whistles diagrams in figure 11, generated using SPSS software, we can observe that the values of both metrics resource utilization and waiting times in queues are statistically different when compared to the current situation and the two new scenarios. However, this is not the case of the number of entities finishing processing at this stage of manufacturing. We can observe that box-and-whistles diagram of the two proposed scenarios overlap. Hence, there is no statistical difference in having three drums in comparison with the performance with two drums. The huge investment required for buying, installing and operating this third drum will not be reflected in the number of finished products. It is to note that similar results will then be obtained later in Section 6 when performing the optimization of the simulation model.

Table 2. Description of scenarios

| Scenario properties | | | Responses (average values) | | |
|---------------------|---|---|----------------------------|----------------------|-------------------------------------|
| Name | Control variable (number of resources) | | Resource utilization | No. entities exiting | Waiting time in resource’s queue |
| Current situation | Re - tanning process | 1 | 95.1% | 36 | 780.93 |
| Scenario 1 | Re - tanning process | 2 | 60.7% | 46 | 357.26 |
| Scenario 2 | Re - tanning process | 3 | 42.6% | 49 | 173.49 |

Figure 11. Comparison of scenarios

For the case of the operator in charge of coating, flushing and measurement processes, experiments were also carried out by adding one or two more operators to help the execution of these tasks. Results of the comparison of scenarios, average values, are presented in table 3. A local analysis of this production step will not give any interesting output by adding one or two more operators because waiting times in queues are zero and hence the number of entities actually finished at this step remains the same

whatever the scenario. We can observe that resource utilization rate decreases by adding more operators, which is logic. The interest of performing these simulations is to analyze the impact that the decision of speeding this process step will have on the final stages of the production process. By adding one operator at this stage, entities are finished faster and an increase of the utilization level was observed at the subsequent resources. This will be observed in detail in the next section when performing optimization.

Table 3. Description of scenarios

| Scenario properties | | | Responses (average values) | | |
|---------------------|---|---|----------------------------|----------------------|----------------------------------|
| Name | Control variable (number of resources) | | Resource utilization | No. entities exiting | Waiting time in resource's queue |
| Current situation | Operator | 1 | 15,5% | 29 | 0 |
| Scenario 1 | Operator | 2 | 7,8% | 29 | 0 |
| Scenario 2 | Operator | 3 | 5,2% | 29 | 0 |

OPTIMIZATION USING SIMULATION

The problem of determining the best combination of variables to use as input for a simulation model often arises in practice (Paternina-Arboleda et al. 2008). Typically, the input values have to be chosen such that the cost function is optimized, where the latter is computed from the output variables of the model. This problem has to be addressed in application domains where the modeling of the system is not possible by using a mathematical approach. In the area of manufacturing systems, for instance, simulation-optimization has been applied to optimize several practical objective functions such as productive machine hours, the cost of automated transport/storage systems, the idle time of assem-

bly systems, or to tune the parameters of scheduling heuristics or to configure Kanban systems (Kleijnen 1993, Rosenblatt et al. 1993, Mebarki 1995, Paris et al. 1996, Paternina-Arboleda et al. 2008). A simulation-optimization problem is an optimization problem where the objective function is a response evaluated by simulation (Andradottir 1998, Boesel et al. 2001). It may be formulated as , where Z is the criterion (or the vector of criteria) evaluated from simulation, x is the vector of variables and each variable x_i takes its values in a domain D_i .

Several studies have been carried out on simulation-optimization. These approaches can be categorized in four major classes: gradient-based search methods, stochastic approximation methods, response

surface methodologies, and heuristic methods (Andradottir 1998, Fu 1994, April et al. 2003, 2004, Kim 2006). Basically, the aim of each of these approaches is to propose a strategy to explore the solution space D with a limited number of simulation experiments (Pflug 1984). Two types of strategies exist. The first consists in collecting a sample of interesting points (e.g. using experimental design) and exploiting these points in a second step (e.g. using a response surface). The second strategy consists in searching iteratively the domain D , which requires a connection between the optimization algorithm and the simulation model (Haddock and Mittenthal 1992).

One of the optimization tools available in commercial simulation packages is OptQuest®. This tool favors the optimization procedure of the simulation model by employing meta-heuristics optimization procedures: the meta-heuristic optimizers chooses a set of values for the input parameters and uses the responses generated by the simulation model to make decisions. The meta-heuristics procedures employed by OptQuest® are Scatter Search in conjunction with the memory-based approach Tabu Search (April et al. 2006). OptQuest® finds the optimal solutions for the simulation model through the generation of entries (admissible values for the control variables) starting on the recursive evaluation of the responses (April et al. 2001). The control variables and minimum, suggested and maximum values considered in the simulation-optimization model are defined to be: the drum with values 1, 2 and 3, respectively, and the number of operators performing the processes of coating, flushing and measurement with values 1, 2 and 2, respectively. Responses (optimization objectives) were defined to be the minimization of the total cost per entity, the value added cost per entity and the total accumulative cost of the process. Figure 12 presents the evolution of the objective function of the three cost metrics. Results recommended by OptQuest® for the control variables according to the optimization of costs functions are present in table 4. After running the optimization, we observed that when the accumu-

lative total cost per process is taken into account, the investment in an additional operator is not interesting for the global performance of the manufacturing system. This result was very surprising for managers of the company since they believed that increasing the speed of the processes of coating, flushing and measurement will influence positively the global system performance. On the other hand, from the point of view of the entities, there is an increase in the amount of outgoing entities from the resource called “drum”: those entities are sharing the global cost and hence it would be worth to invest in an additional resource of this type. It is to note that the company currently has one resource “drum” for the re-tanning process and hence 1450 skins are processed during the production period (one year). If another “drum” is purchased, then 2100 pieces could be processed. Obviously, an investment is required and there will be an increase in fixed costs. However, this cost will be absorbed by the additional amount of finished products exiting the system during the production period. Hence, a positive profit is obtained by about 44.62% of increase. This profit can be computed by considering the number of finished products sold versus the cost incurred when installing the additional resources.

Figure 12. Converge of optimizations according to the objective function

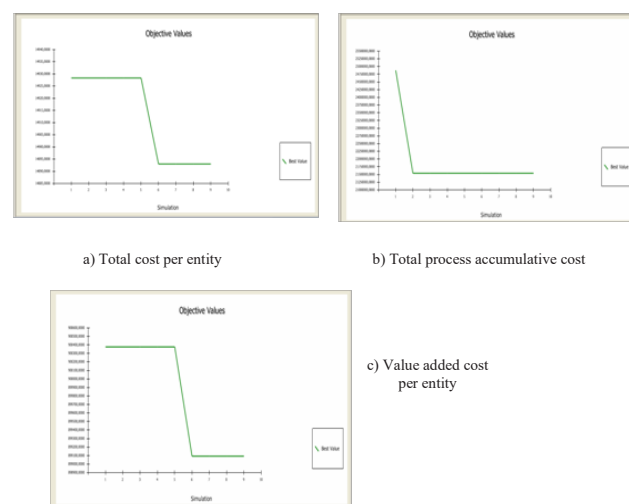


Table 4. Results recommended after optimization for the control variables

| Configuration | Value added cost / entity | Total cost / entity | Output enti- ties (1_Drum) | Output entities (2_Drums) | Total cost of out- put entities | Total process ac- cumulative cost |
|-----------------|------------------------------|------------------------|-------------------------------|---------------------------------|------------------------------------|--------------------------------------|
| Sc. 1 (2 drums) | \$889,094 | \$14,893,00 | - | 2100 | \$1,,888,,097,,400 | \$31,275,300 |
| Sc. 0 (1 drum) | \$919,419 | \$15,232,33 | 1450 | - | \$1,,333,,157,,550 | \$22,066,086,5 |
| Gap | | | | | \$554,939,850 | \$9,188,421,5 |
| Gap (%) | | | | | 40% | 42% |

CONCLUDING REMARKS

This paper considered a complex manufacturing process found in a tannery production. We proposed a simulation model in order to analyze the current production process and to propose alternatives for improvement. The model achieved good performance in terms of confidence with respect to the real situation in which the company operates. The simulation found that the bottleneck resource is in the process of re-tanning because of the lack of capacity of the “drum” to process the amount of entities that arrive. Among the nonphysical resources, operator dedicated to the processes of coating, plushing and measurement showed to restraint the global production capacity.

An optimization routine, based on the standard OptQuest® tool for Arena®, was also developed and optimum parameters of the simulation model were found. It was found that investing on a “drum” allows the company to increase production by 44.83%. But, to hire an additional operator to help the processes of coating, flushing and measurement is statistically indifferent.

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