MODELLING AND SIMULATION OF A NATURAL ROOFING SLATES MANUFACTURING PLANT

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ABSTRACT

Producing natural roofing slates is a highly wasteful activity. Depending on commercial formats, only a 3% of material extracted from quarry becomes final product. Processing a block of slate weighing several tons into a tile of slate only a few millimetres thick requires great energy consumption as well as the use of an important level of resources, both human and material. The whole process is subject to the intrinsic variability of natural products which determines its reactive nature. In this paper, we present our work for the global improvement of a natural roofing slates manufacturing plant. To do so, a Modelling and Simulation approach has been adopted. Developing a Discrete Event Simulation (DES) model of such a highly dynamic, variable and labour-intensive process has been proposed as a systematic way for its characterization and analysis.

Keywords: process simulation, flexible manufacturing systems, natural roofing slates.

1. INTRODUCTION

Europizarras S.L. is a Spanish company that produces natural roofing slate for institutional and residential buildings. More than 80% of its production is exported to other countries in Europe, especially France, where their slates have been awarded with the NF mark which sets the highest quality requirements in the industry.

The company is mainly devoted to the production of the highest value added roofing slates, that is to say, the thinnest commercial tiles. The thinner the tile is the harder and more wasteful the manufacturing process becomes. On the other hand, there is a quite constant demand of 3.5 mm thick tiles from France which provides a stable market.

In spite of the Spanish slates are the most employed in the world, the sector has scarcely benefited from technological transference from other industries. The level of automation is low as well as the application of lean manufacturing principles. The most arguably reason is perhaps the relative geographic isolation of slate production areas, mainly located in the northwest mountain region of Spain. Besides or as a result, it is labour-intensive and workers are exposed to very hard conditions both environmental and ergonomic. It is indeed difficult to find skilled workers or even convince youngsters to start this career so high salaries have to be offered. Accordingly, labour and operating expenses account for one third each of the total company costs set up.

In this context, the company has started a global improvement project comprising actions in the fields of production, quality, health and safety and environment. The purpose is to achieve a more efficient process in terms of productivity and the first step is to gain knowledge about the operations involved aiming at reducing uncertainty, defining capacities, and identifying both opportunities and limiting factors for a subsequent process optimization. These first steps are presented in this work.

2. THE PROCESS

For the extraction of slate from quarry light explosives are employed. The results are irregular and heavy blocks that are then loaded onto dumpers and transported to the manufacturing plant, located a few kilometres away. These blocks are then introduced in the Sawing Plant and stocked, so an adequate level of input is always assured. In this plant blocks are first cut into strips by means of circular saws and then a second group of saws cuts the strips into slabs which are then carried to the splitters on an automated conveyor belt.

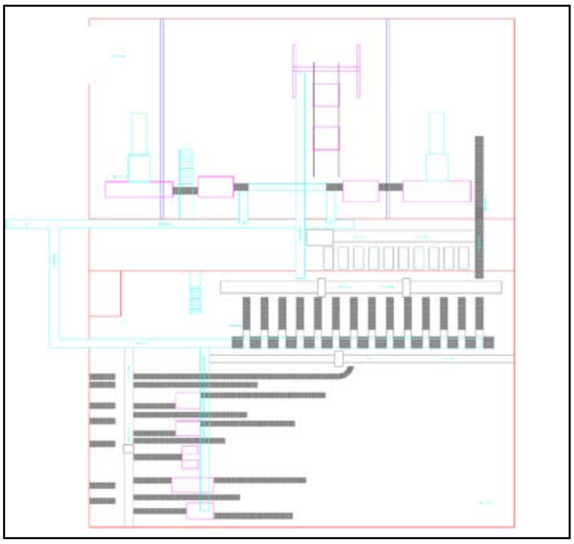

Figure 1: The CAD layout of the Manufacturing Plant

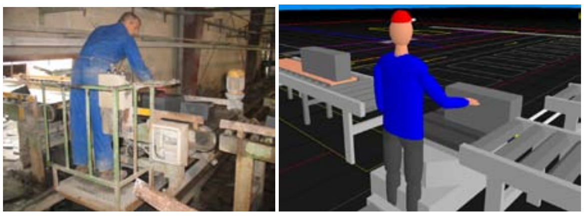

Figure 2: Slabs Arriving Process From Sawing. Real Process and QUEST Model

An operator on an electric rail mounted vehicle receives and distributes slabs among the splitters according to the specified format and their stock level (Figure 2).

Slabs are taken by the splitters one by one and cut in several pieces by means of a special type of chisel so they can handle them better and also determine its quality. Then, they change to a smaller chisel for cutting these parts into plates The chisel, placed in position against the edge of the block, is lightly tapped with a mallet; a crack appears in the direction of cleavage, and slight leverage with the chisel serves to split the block into two pieces with smooth and even surfaces. This is repeated until the original block is converted into a variable number of pieces. The resulting number of slates of different formats is variable, depending mostly on the quality of the slate rock from quarry as well as the splitters experience and skill.

Figure 3: A Splitter (left) and the Resulting Output: The Target Formats (regular lots in the left) and Secondary Less Quality Output Formats (the two series in the right).

A second operator collects the slates lots produced by the splitters on a second electric trolley and takes them to a third one who carries and distributes them amongst the cutting machines. Split stone is then mechanically cut according to the shape and size required. This operation is done both by manual and fully automated cutting machines.

Finally, slate presented is inspected one by one by classifiers with a trained eye prior to being placed in crate pallets. Slate that does not meet with quality requirements is set aside and recycled to be cut again into another shape until it complies with company standards. In case this is not possible, it is rejected. Slate pieces are packed until they are ready for final use. Slates are available under different sizes and grades. Quality is assessed in terms of roughness, colour homogeneity, thickness and presence and position of imperfections – mainly quartzite lines and waving-. Accordingly, the company offers three grades for every commercial size: Superior, First and Standard

Alternatively, the latter operator takes the recycled plates and transports them to their corresponding machines. A third task assigned to this labour is to stock material in buffers previously located to the machines' inputs whenever machines' utilization is full. So a triple flow is shared by one transportation system connecting a push system (lots coming from splitters) and a pull system (lots required by cutting machines). And even more, the assignation rules that the operator follow depend on his criterion, so it is easily comprehensible the complexity of modelling this system.

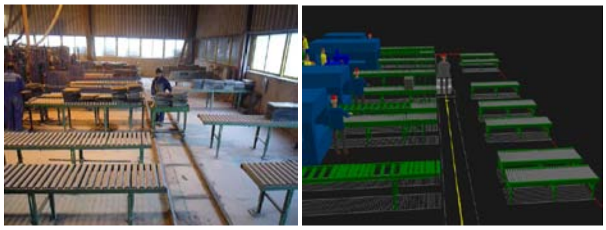

Figure 4: Distribution of Lots to Cutting machines.

A general process diagram is represented in Figure 5. Arrows in grey and triangles in red represent transportation and stocking operations respectively. These operations do not add value to the product whereas green circles and squares represent value-added operations, mainly transformations and/or inspections.

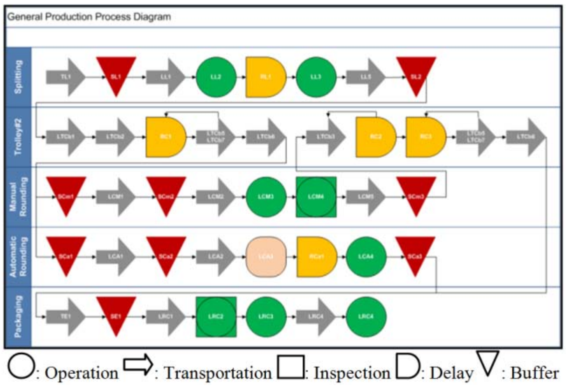

Figure 5: Complete Process Diagram.

The General Process Diagram offers at first glance a quick assessment of the abundance of these operations as well as the presence of feedback lines which also diminish the overall process performance. It becomes clear the necessity of reducing non value-added activities and rearranging the whole process in terms of layout design.

This process characterization has been employed in the definition of elements, processes and flows (both logical and physical) for the simulation model.

3. THE PROBLEM: VARIABILITY

Natural roofing slate manufacturing processes are subject to the intrinsic variability of natural slate. This variability corresponds with the possibility of variations both in mineral composition and morphology so that undesirable visual and structural effects in the final product may appear. It is the geological nature of the specific zone in the quarry that is eventually being exploited which determines this circumstance. Although there is certain knowledge about the quality of rock that is expected to extract in the quarry according to previous experience and/or mineral exploration operations, it is not possible to determine the real continuous mineral profile at a microscopic or visual level.

This uncertainty about the final quality has traditionally configured the whole manufacturing process resulting in a reactive system, that is, a system where there is no previously determined schedule and the assignment of operations to machines or labours is done according to the state of the system (Alfaro and Sepulveda 2005).

In our case, a foreman dynamically decides the formats to be cut as well as the number and identity of splitters, classifiers and machines assigned to each format according to his perception of process performance. Eventually, the functions performed and messages sent are allowed to adapt such that feedback paths in the process occur. Then, the overall system may exhibit emergent behaviours that cannot be produced by any simple subset of components alone, defining a complex system (Clymer 2009).

When proposing modifications in these systems special care has to be taken since even small changes in deterministic rules (SPT, FIFO, etc.) may result in a chaotic behaviour. Developing DES models of such processes has been proposed as a systematic way for its characterization and analysis (Alfaro and Sepulveda 2005). However, DES projects rely heavily on high input data quality (Leemis 2000). Accordingly, the input data phase constitutes on average one third of the total time of simulation projects (Skoogh and Johansson 2008). What it plays a negative role in the acceptation of simulation methods as a tool for improvement as long as it leads to unacceptable lead-times when dealing with well defined processes (Skoogh and Johansson 2007) can be turned into an advantage when facing a process in an early stage of statistical control.

In our plant, there is not such a thing as an organized and structured information system but heterogeneous and incomplete sources of data from which our input data management process may start. Only two data collection points had been implemented and they did not properly connect inputs and outputs between different operations, so traceability of products was not available. But above all, the dynamic nature of output formats according to a changing commercial strategy made really difficult to rely on a stable basis of data from which building useful information for an eventual simulation validation phase.

Adopting a Modelling and Simulation approach (M&S) for the slates process characterization provides an efficient and systematic procedure for this purpose as well as the necessary time for carrying out the definition of a data management system.

Thus, the modelling process has been employed as a means for determining and defining such sources of data and has finally lead to the proposal of a Data Acquisition System (Figure 6) consisting in the definition of control points and procedures by means of which subsequent stages of the classical MS methodology can be developed. The system involves the assignation of responsibilities, the implementation of control procedures and the computer management of data.

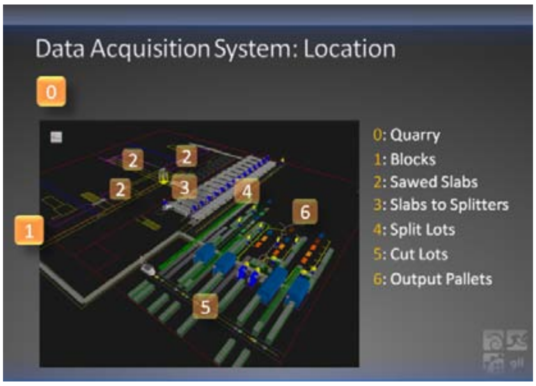

Figure 6: Location Points for Data Acquisition.

This constitutes a first attempt to distinguish between the two types of process variation (Deming 1986), i.e., Common Cause variation, which is intrinsic to the process and will be always present, and Special Cause variation, which stems from external sources and indicates that the process is out of statistical control.

In consonance with this purpose, we suggest the Product, Process and Resources (PPR) concept as an integrating approach to variability aiming at carrying out a complementary and parallel process of modelling and analysis. It is the Dassault Systèmes' integrated model that interlinks representations of the Product, the manufacturing Resources (tooling, factory, operators, etc.) and the production Process (DS 2009). In Figure 7 the identity and flow between sources of variability is depicted.

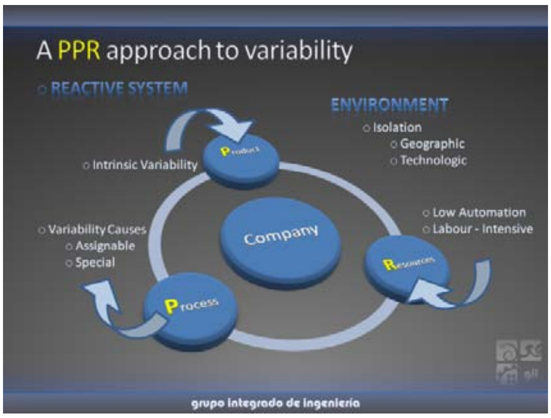

Figure 7: A PPR Approach to Variability

As it has already been explained, the product introduces its natural variability in the process, which is on its part affected by the environment. The utilization of human resources in physical and decision making processes relative to the product also involves a new source of variation. The resulting process is complex, reactive and out of statistical control.

Achieving statistical control will lead to improved levels of productivity and allow a proactive commercial management. An initial control system should permit the assessment of changes in transportation systems, layout design and other operational parameters. A final stage involves the implementation of a QC system by means of Artificial Vision Techniques for a more robust and powerful statistical control process. In the next diagram the proposed milestones in order of complexity and financial effort are resumed.

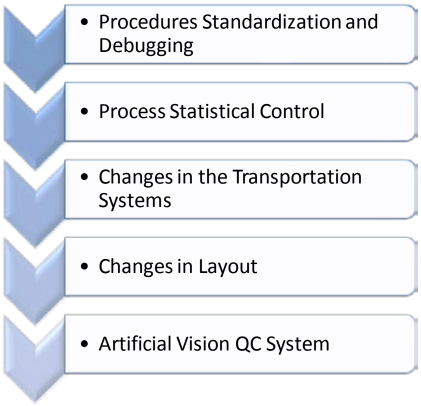

Figure 8: The Global Improvement Project: a Growing Set of Goals.

4. STATISTICAL ANALYSIS

Once processes had been identified it was possible to start a data analysis phase. Data have been collected from two main sources. The first has been the analysis of recorded videos and other measurements performed during periodical visits to the plant. The second set of data was obtained from historical records provided by the company. Statistical tests of independence, distribution fit and goodness of fit of the available real data have been conducted. We have employed the MLE method for model's variables distribution fitting using the statistical software StatFit and R (R 2005). Distribution verification and selection is done according to the p-values obtained in the Kolmogorov-Smirnov test and by graphical inspection of the QQ and PP graphs of a wide range of typical distributions in the simulation field.

The process' core is the splitting operation. It is the task where product, resources and process circumstances converges in a less controllable way from a variability point of view. A piece of evidence is shown in Figure 9, where data collected during a period of three months of the number of lots produced per splitter is depicted. The presence of different splitting patterns corresponds with personal performance and the variability within a single pattern is an evidence of product variability.

Besides, this process is a constant in all slate manufacturing plants regardless process configurations so methodology and results are extensible.

A splitting process model has been made in order to assess upstream and downstream impacts on transportation processes and stock levels. To do so, we focused on its inputs and outputs, i.e. slabs arriving from Sawing and piles leaving from Splitting.

After an ABC classification of the number of slates produced, we could divide into two groups all the different formats that are produced in the plant for the sake of simplicity. One is the target format of tiles of 32x22x3.5 mm –the 80% of the total, that we named L32 (Slates Lots of 32) – and the other one gathers all other formats in a category named LN32 (Lots of Not 32). In addition, this two outputs model is in line with the assessing of changes in the simulation models focused on increasing levels of target format output whilst reducing levels of the rest of outputs.

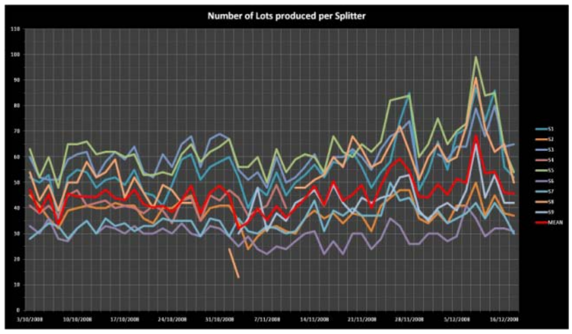

Figure 9: Evolution of Splitters' Production (three months of historical data)

We have modelled the generation of lot sizes and splitting times per slab by means of three random variables: the Splitting time per slab, the Deviation in the number of plates, and the Proportion of target plates.

These three variables are related. A higher splitting time can be associated with the processing of bigger slabs resulting in a higher number of plates. However, a perfect association between the splitting time and the number of plates is not acceptable since it is a common situation a bigger slab –and consequently a higher time– being partly dismissed due to its low quality and giving fewer plates than a smaller one but with better quality. The most suitable way to model this variability is generating such variables from its estimated joint probability distribution. Independence hypothesis was not accepted nor the perfect association one as we would be losing the relationship between slabs splitting rate and the number of plates produced or not considering that source of variability, respectively.

As simulation aims at providing information about the influence of changes in both sides of the splitting process it is necessary to build a model in which arriving slabs become slates lots in a realistic way.

An analysis of correlation between these variables was then made leading to a model for randomly generating processing times per slab and their corresponding lot sizes. As we had more data of processing slab times than of lot sizes, the random generation is done by obtaining first a splitting time from which a depending number of plates is generated together with the corresponding fraction of L32 plates according to the fitted distributions. Distribution fitting results for the splitting time, the estimation of total number of plates and distribution of residuals are summarized in the following figures. We could not find a good fit for the marginal distribution of L32 fraction so we use an empirical table from collected data.

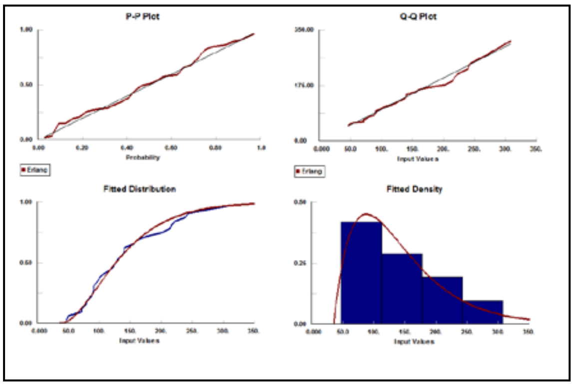

Figure 10: Erlang Distribution Fit of Splitting Time (k=2, min = 35s, beta = 53.18)

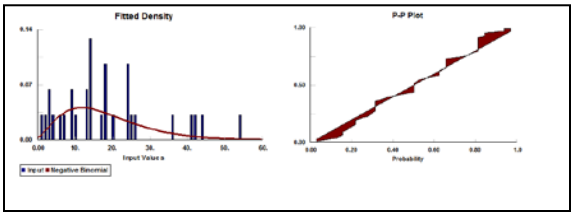

Figure 11: Negative Binomial Distribution Fit of Total Number of plates (k=3, p=0.141)

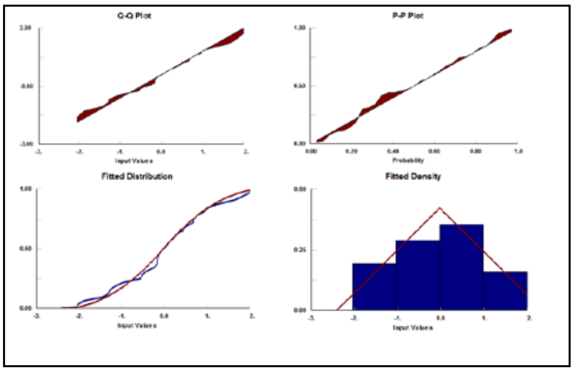

Figure 12 Triangular Distribution Fit of Residuals in Total Number of Plates Estimation (minimum =-2.41771, maximum = 2.37337, mode =-2.62736e-002)

At this point, the question about the quality of our input data and the worthiness of continuing data collection activities arises. One way to tackle with this uncertainty is by means of simulation. As explained in the next chapter, a splitting sensitivity analysis model was proposed and results lead to an interesting and simplifying conclusion.

5. SIMULATION MODEL

We have built a simulation model of the manufacturing plant in DELMIA QUEST. DELMIA stands for Digital Enterprise Lean Manufacturing Interactive Application and it is the Dassault Systèmes' solution for engineering lean manufacturing processes. QUEST is a powerful three dimensional simulation environment by means of which a model can be comprehensively defined and assessed.

The classic model's definition paradigm establishes that a model that describes a system as network of system components and focuses on the physical details is called architectural. A model that describes a system as a network of functions and focuses on the behavioural details is called functional flow. The functional flow model is used during the conceptual system design phase of a system design project whereas the architectural model, after functions have been allocated to the system components or subsystems, is used during the system design phase (Clymer 2009).

Unlike this classic model's definition paradigm, the model's building process in QUEST is accomplished by an integrated development environment combining both the functional and architectural definition. The PPR approach is utilized as a way for the definition of model's elements, i.e., products (different types of parts, in QUEST terminology, representing different stages of slate transformation), resources (labours, transportation systems, and machines) and the process logical set up (controllers and logic recipients). This allows the progression of model building when data sources are variable or not well established and a direct implementation of the previous process depicting work.

In fact, since operational similarity is obtained by assuring geometric and kinematic similarity, model verification and assessment of changes in layout design can easily and quickly be noticed.

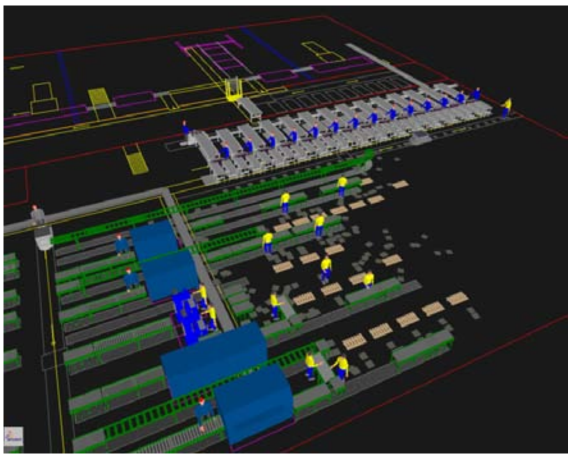

Figure 13: The QUEST Simulation Model of the Manufacturing Process.

Initial experimentation has included the assessment of the three different types of classifying arrangements that were actually being employed in the plant (Figure 15 and Figure 16). Every machine has two dedicated labours assigned for the quality inspection, classification, recirculation and packaging. Depending on their location, labours adopt a different position and split tasks in a different manner. There is not a certain reason why different operational modes are adopted.

The first mode consists of a confined labour performing classification tasks and the other one only performing packaging operations. The term confined refers to the fact that the labour is totally surrounded by rolling conveyors so he is not able to support his team mate whenever he is idle. In the second schema the classifier is not confined and thus can assist to his packer mate when idle. Finally, the third type is the one in which the two labours carry out both classification and packaging operations independently. The packaging process is made up by the loading, unloading, and transportation and return tasks.

These logical behaviours have been coded in SCL language and implemented in the model. Positions of labours and pallets as well as paths followed during their movements have been identically proposed as the real ones so a geometric assessment may be carried out. In Table 1 results obtained from a set of 50 simulations for every operational mode are summarized. Specifically, the number of lots processed, the time of tasks' completion, the total distance and the utilization ratio depending on mode of operation are presented.

Table 1: Time in hours and Distance in meters for every Task depending on Operational Mode

	Mode 1		Mode 2		Mode 3	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
	Packer				Packer & Classifier	
Lots	363.4	2.82%	61.2	41.84%	181.308	3.94%
Load	0.304	3.75%	0.186	152.81%	0.174	3.15%
Unload	1.034	4.86%	2.552	3.50%	1.642	2.56%
Transport.	0.768	2.97%	0.08	42.39%	0.312	4.18%
Return.	0.672	3.39%	0.096	40.75%	0.648	3.68%
Distance	3049	2.75%	638.6	40.15%	2043	3.73%
Util.(%)	100	0.00%	100	0.00%	100	0.00%
	Classifier					
Lots			337.2	11.54%		
Load			0.284	11.30%		
Unload			1.102	13.03%		
Transport.			0.718	8.89%		
Return.			0.674	7.68%		
Distance			2943.8	8.04%		
Util.(%)	83.2	2.74%	100	0.00%		

In Figure 14, the distribution of the time spent in the packaging's tasks is depicted. It comes out that transportation and return tasks consume on average half of the working time spent by the labours performing this job. Once again, these are non value-added operations and will have to be minimized by a convenient layout redesign.

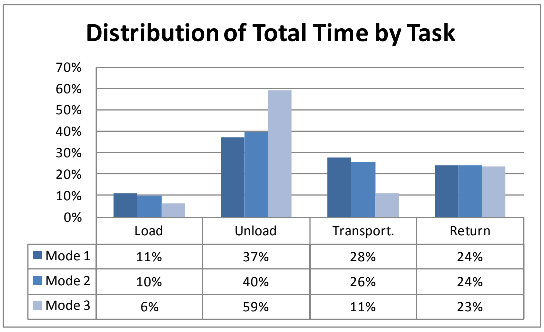

Figure 14: Time Distribution between Tasks depending on Operational Mode

Table 2: Results of the Assessing Classifying Modes Simulations

Mode	1	2	3
Production Rate (tiles/h)	1439.06	1577.66	1435.96
Standard Deviation	2.82%	3.37%	1.97%
Distance per working hour (km)	1.10	1.29	1.47

The results shown in Table 2 concluded that the best option is the intermediate one, that is to say, a classifier that may support packing tasks when idle. It implies an almost 10% improvement in productivity respect to the other two schemas and only requires a cheap and quick rearrangement of rolling conveyors at the machines' output area. This result is of special relevance since this final process stage actually becomes the bottleneck in those days when the slate coming from the quarry is good.

Figure 15: The Different Modes of Classifying Operation

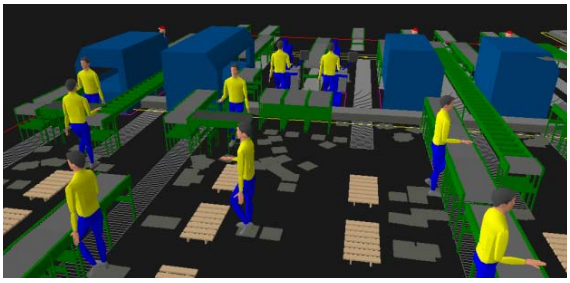

Figure 16: The Classifying Operation. The Three Different Arrangements Have Been Simulated

Another set of simulations was performed as a means of determining the worthiness of deepening in the statistical process analysis. This way, simulation has been employed to assess the influence of the assumption of splitting variable's independence versus different levels of correlation on queues and second transportation system utilization (splitters output).

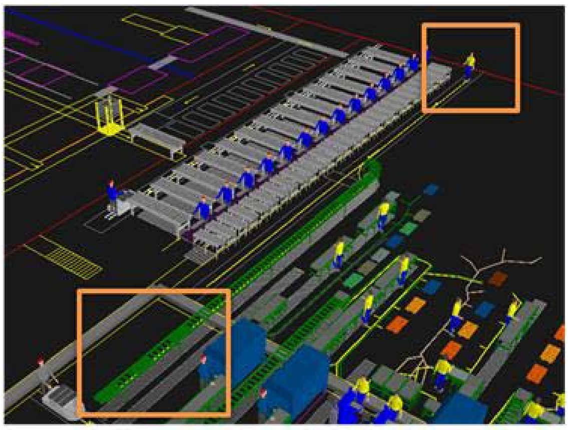

Figure 17: The Splitting Simulation Model. The Squared Areas Are the Points of Interest Where Assessing Results

Three different scenarios have been then proposed: the splitting linear model previously described resulting on a correlation of r=0.806, the absence of correlation (r=0) and a perfect correlation situation (r=1).

Conducted experiment consisted of the simulation of a typical shift of 5 hours. Initial conditions are full buffer levels of blocks from sawing that the trolley has delivered after the end of the last turn. At the end of each simulation, average buffer level before cutting machines and splitters' pick up trolley utilization are measured. For each level 230 replications are made. To check differences on buffer level distribution, Wilkoxon difference's test has been applied due to lack of normality, unlike the trolley utilization, on which the F-test could be applied.

The results do not show any significant difference between the independence assumption and the developed correlation model proposed as it is shown in the following box plots.

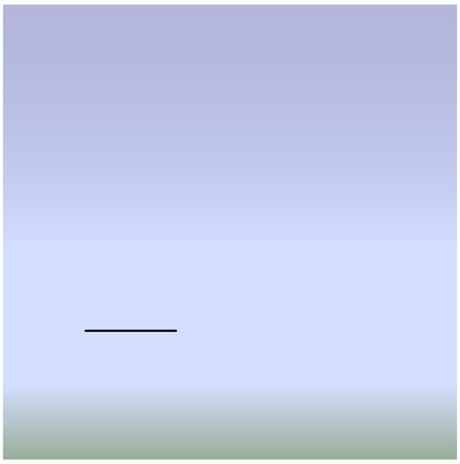

Figure 18: Average Queue Length and Trolley Utilization versus Degree of Correlation

Only in the case of perfect correlation differences are met. An arguably explanation might be that the first two models imply a higher variability on model's behaviour, and thus queues generated are bigger. The conclusion of this result is that it is unnecessary to include the correlation model when attending to study the effect of splitter's behaviour on the downstream steps of the process. It would be enough to accept the independence hypothesis and so employ the marginal distributions. This result is then considered in our statistical analysis so further effort in data analysis was discarded.

CONCLUSIONS

An M&S approach has been proposed as a means to characterize a poor structured and highly variable system. The model's building process allows a better understanding of real processes as well as the definition of following stages in the own simulation project. In the case of the natural roofing slates sector, this is a total innovative initiative that is being accomplished.

A splitting statistical model has been developed and by a combined use of early simulation experimentation the extent of statistical analysis has been limited so the model verification and validation can reliably go on. Besides, as a result of simulation, a simple and cheap recommendation regarding classification policies has been proposed leading to increased productivity in the final process stage.

Finally, further research is necessary in order to complete the whole systems' characterization and once a database is built, to define experimentation for a validating simulation environment for process optimization, both operational and morphological.

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