Simulation and Highly Variable Environments: A Case Study in a Natural Roofing Slates Manufacturing Plant

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Abstract

High variability is a harmful factor for manufacturing performance that may be originated from multiple sources and whose effect might appear in different temporary levels. The case study analysed in this chapter constitutes a paradigmatic case of a process whose variability cannot be efficiently controlled and reduced. It also displays a complex behaviour in the generation of intermediate buffers. Simulation is employed as a tool for detailed modelling of elements and variability components capable of reproducing the system behaviour. A multilevel modelling approach to variability is validated and compared to a conventional static model in which process parameters are kept constant and only process cycle dependant variations are introduced. Results show the errors incurred by the simpler static approach and the necessity of incorporating a time series model capable of simulating the autocorrelation structure present in data. A new layout is proposed and analysed by means of the simulation model in order to assess its robustness to the present variability. The new layout removes unnecessary process steps and provides a smoother response to changes in the process parameters.

1. Introduction

Variability is an acknowledged driver of inefficiency in manufacturing. Whether it comes in the form of changeable and uncertain demand, product characteristics, resources or processes, it leads to disposing overcapacity, increased work in process and operational risks. State of art process improvement techniques – such as Lean Manufacturing or Just in Time– tackle variability by different mechanisms aimed at reducing it or its impact in production. Manufacturing plants adopt flexible system designs, product and processes standardization, protocols or quality controls among other systems in order to efficiently control and manage variability.

However, there are still sources of variability that cannot be reduced in a profitable way beyond a certain limit. Demand patterns, human resources, machines failures, natural products or the socio economical context are examples of factors whose variability can only be partially controlled.

This chapter deals with a case study of a manufacturing plant which produces natural slate roofing tiles from irregular blocks of rock extracted from a nearby quarry. The variable characteristics of the input material due to the variable geologic nature of the rock introduce a variable behaviour in the plant.

In this chapter, the definition of a highly variable environment will refer to a subjective circumstance of a manufacturing system that reflects the complexity in the analysis of its variability sources and their impact in performance. We are not aiming at introducing a formal definition of highly variable environments but rather an informal one that a process manager or an analyst might employ to define a system with the characteristics given below. Such a system will exhibit the following features:

- There are sources of variability present that cannot be efficiently controlled.
- These sources of variability are key drivers of process inefficiency and thus design of the production system will be oriented to coping with them in an efficient way.
- The interaction between the sources of variability and the elements on the systems responds to a complex pattern which cannot be immediately determined from the particular behaviour of each element.

Discrete events simulation (DES) is a widely employed tool for manufacturing systems analysis due to its inherent capability for modelling variability. By means of a detailed specification of each element logics and related statistical distributions, the DES model is capable of computing the overall performance even if emergent behaviour may arise.

This chapter covers the analysis of a paradigmatic case of a highly variable environment. The modelling and simulation of a natural roofing slates manufacturing plant will be presented covering the discussion of the appropriate modelling approach plus the analysis of a layout improvement proposal taking into account the high level of variability present.

1.1 Sources of variability in manufacturing: A PPR approach.

If we consider a manufacturing process as the transformation of a series of input products into output products through a set of processes and given a set of resources, it would be useful to assign the different components of variation to the different elements involved. Thus a product, process, resource (PPR) approach will provide with a useful way of categorizing the variability sources.

Product variability can be originated either by changes in the characteristics of the process inputs or in the outputs of the system. Changes in the output will usually be linked to changes in demand. For example, changes in the quantity or in the mix of demanded products will cause the system to face changes in the throughput rates and occupancy levels. These changes may be linked to seasonal demand patterns, long term trends or random variations in shorter terms like daily or monthly ones.

Changes in the product specifications or design – like those which are typical in make to order environments or mass customization – make process cycle times to vary and consequently generate intermediate product buffers or performance losses due to blocking and starvation.

A special case in which this sort of product variation is strongly evident happens in natural products processing. The variable characteristics of the natural resources – like those extracted in mining, forestry, fishing or agricultural sectors – cause quality, input utilization rates and process cycle times to vary due to the heterogeneity in the source materials [1], [2].

Process variability might be related to either a lack of standardization in process routines and protocols or to an attempt of active adaptation of the process to the changeable environment. In some manufacturing environments – like small workshops or SME's with low processes standardization – undefined procedures or informal planning and production control schemes lead to a heterogeneous response to similar events and uncertainty. Although this is not necessary a bad feature of a system, since it enhances flexibility, it may often lead to un-optimal responses. Variability in process definition can be intently introduced by management as a means of adapting to different conditions and counteracting the effects of other undesirable forms of variability. Flexible manufacturing is a common approach to improve the robustness of a system to a changeable environment [3]. A flexible capacity dimensioning allows for reallocating resources to where they are most needed. However, difficulties may appear in the practical implementation of these practices. Schultz et al. [4] show in their work how behaviour related issues may harm the expected benefits from a flexible design of work.

Finally, resources driven variability is a frequent circumstance in manufacturing. Machines tend to feature *quasi*-constant cycle times when performing a single task in uniform conditions, but are subject to stochastic failures that reduce their availability. Human resources introduce several components of variability in a system. Within a process cycle scope, two main effects can be noticed. First, workers use to show larger deviations in cycle times than those of automated devices. Second, human beings display state dependant behaviour that further complicates the analysis of labour intensive processes. Humans are capable of adjusting their work pace depending on the system state and workload [5]. The consequence is a form of flexibility in capacity that counteracts some of the drawbacks caused by the larger variability [6]. Evidence from just in time (JIT) manufacturing lines shows that lower connection buffer capacities do not necessary produce the loses in performance that would be expected if considering human factors in a mechanistic way [7]. Human variations in performance may occur in different time horizons or linked to different process execution levels. Authors such as Arakawa *et al*, Aue *et al* or Baines *et al* [8-10] have studied hourly variations of human performance along a shift and across different shifts in a day. Baines *et al* have considered as well longer term variations in performance linked to aging, although they claim that further research and results validation are necessary. Another important source of variation is that related to individual differences [11], [12]These differences may produce balance loses in serial flow lines [13] or more complex effects in parallel arrangements, such as group behaviour and regression to the mean effects when arranged [14].

Finally, characterizing variability is also related to the time horizon in which its effects appear. We might find variability between consecutive process cycles, between different days, between different production batches, etc. Accordingly, a reasonable scope and methodology for modelling variability has to be defined depending on different analysis span (yearly, seasonal, monthly, weekly, daily, shift and hourly variation).

1.1 Statistical modelling of variability

DES models support the high resolution modelling of manufacturing systems via the inclusion of elements' operating logics, sequences of processes and statistical distributions associated to their variability. Common statistical models that are employed span cycle time distributions of machines or workers [15], time between failure and time to repair distributions [16] or demand stochastic processes [17].

Both cycle time and time between failures statistical processes use to be assumed as stationary independent and identically distributed (i.i.d.). Evidence from multiple manufacturing environments justify this assumption [18]. Process cycle execution is commonly regarded as the main driver of variability and therefore of longer term variability calculated from it. For instance, Colledani et al.[19] calculate buffer capacities with a goal on minimizing weekly overall variance in throughput. He *et al* employ Markov processes for calculating production variations originated in the cycle time distributions [20].

However, this assumption is not necessarily valid for all the circumstances. Autocorrelation in stochastic processes and state dependant behaviour are two important deviations from this assumption that could greatly distort simulation results. Autocorrelation patterns are commonly found in demand processes and in the characteristics of natural product inputs [21], [22], although it might be observed as well in other types of highly variable processes such as semiconductors manufacturing [23]. State dependant behaviour also causes important divergences in the simulation results, as noted by Schultz *et al* in the above mentioned work [6]. According to them, the overall performance of a flow line may actually improve along with its length when considering a model in which cycle times are positively correlated with the workload.

2. Case study: The roofing slates manufacturing process

Our case study is based on a Spanish SME 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 paid. 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 [24], [25]. 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.

2.1 Process description

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.

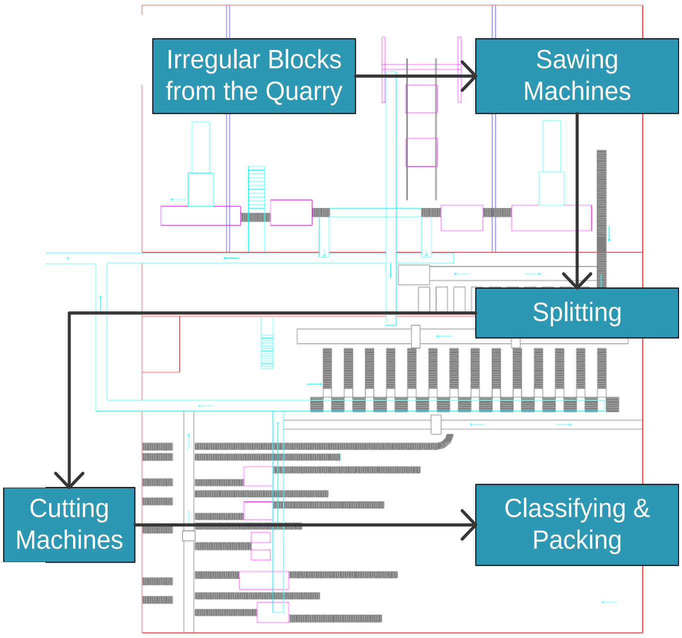

Fig. 1. CAD Layout of the Manufacturing Plant.

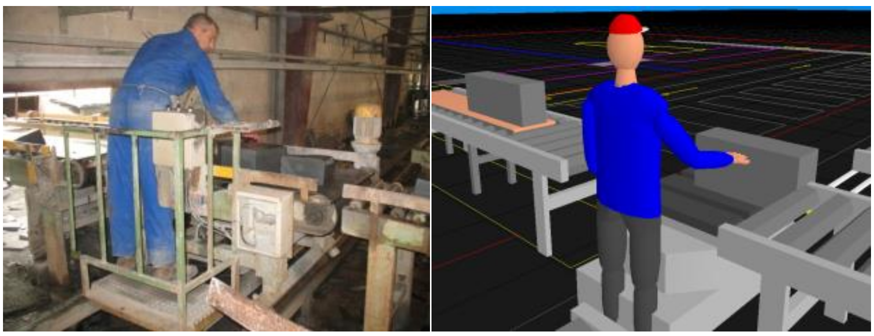

Fig. 2. Slabs Arriving Process from Sawing. Real Process and Simulation Model.

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.

Fig. 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 worker is to stock material in buffers previously located to the machines whenever their 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.

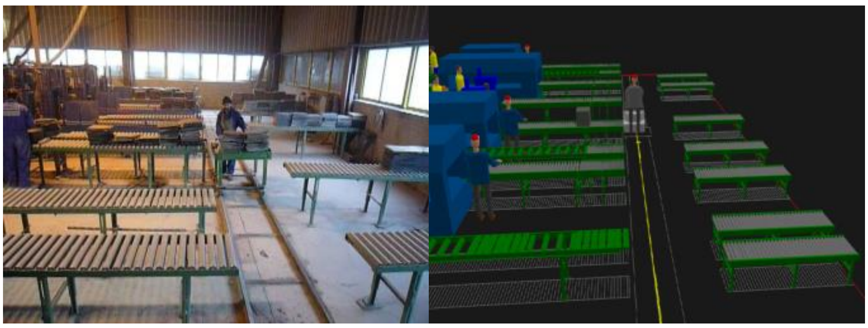

Fig. 4. Distribution of Lots to Cutting Machines.

From the splitting to the packaging 26 transportation and stocking activities take place whilst only 13 value-add operations –mainly transformation and inspection operations- occur. The abundance of these non-value-added operations as well as the presence of feedback lines 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.

2.2 The PPR approach to variability

Natural roofing slate manufacturing is a process perceived by both process managers and workers as highly variable. According to their perception, the system displays the following behaviours:

- The properties of the input slabs to the process are inconstant along time. Some days "good" material enters the process that can be easily split into the target formats and shows good quality in the classification and other days the material is bad and the loss in splitting are large.
- The process bottleneck dynamically moves between the splitters and the classification and packing steps.
- There is a need for large capacity intermediate buffers due to the high variability in products characteristics. Sometimes large work in process accumulates and there is need for space in which to allocate stocks and sometimes queues disappear and material is quickly consumed causing starvation in the last steps of the process. It is this perceived necessity that has configured a layout designed for providing the maximum possible capacity for the connection buffers.

The most relevant source of variability in this process is due to the intrinsic variability of the 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 workers is done according to the state of the system [26].

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. It introduces another relevant component of variability related to the process rules and resources capacity. The foreman dynamically adjusts splitters working hours, adds splitters from a nearby plant and reassigns workers to classification and packing. He may also change the target format specifications or the thickness goal for the splitters. All these decisions are taken according to his long experience in the plant.

The labour intensive nature of this process involves another source of variation. Splitting is a task that requires highly skilled workers among which important differences can be observed in performance. Each splitter has their own technique for splitting the slabs, leading to heterogeneous working paces and material utilization. For instance, some of them are able to split high quality slabs in the target thickness 3.5mm and others not. Classification and packing are another two examples of manual tasks presents in which variety of criteria and working procedures can be found. In despite of the quality standards should provide homogenous criteria for tiles classification, different classifiers adopt more or less conservative criteria and thus their decisions may slightly differ. Packing detailed movements are differently performed by workers and the placement of tiles piles and pallets is variable.

The resulting process is complex, reactive and out of statistical control. Then, the overall system may exhibit emergent behaviours that cannot be produced by any simple subset of components alone, defining a complex system [27]. 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 their characterization and analysis [26].

3. The model

3.1 Conceptual model

As a first step in the model building phase of the project, a conceptual model was developed in order to identify the key process variables and parameters and to suggest hypothesis of their relations. The notation employed in this model will be introduced below.

Subscripts:

- i: Splitter subscript. Its values range from 1 to NS, being NS the number of splitters in the plant. If omitted, the variable represents the sum of all the splitters.
- f: Format subscript. The possible values are 32, 30 and 27 for the respective 32x22cm, 30x20cm and 27x18cm formats. Related to the split process, possible formats are *TF* – which stands for target format, frequently 32x22 – and SF – which stands for secondary format, both 30x22 and 27x18 –. If omitted, the variable represents the sum of all the formats.
- q: Quality subscript. Its values can be F for first quality, T for traditional quality and STD for standard quality. If omitted, the variable represents the sum of all the qualities.
- Th: Thickness subscript. Its values can be 3.5 or 4.5. If omitted, the variable represents the sum of all the thickness values.
- t: Time subscript. If used, the variable contains its average value for the day t.
- c: Cycle subscript. If used, the variable contains its value for the related process cycle execution c.

Product flow rates:

- B: Rate of slabs per unit of time that enter the plant.
- B_i: Rate of slabs per unit of time that are consumed by the splitter i.
- $SL_{f,i}$: Rate of split lots of f format slates per unit of time produced by splitter i.
- CL_f: Rate of cut lots of f format slates per unit of time.
- RL: Rate of recirculated lots of slates per unit of time.
- $PL_{f,q,Th}$: Rate of classified and packed lots of format given by subscript f, quality q and thickness Th slates per unit of time.

Size of slates lots:

- NSL_f: Number of slates in each split lot by format.
- NCL: Number of slates in each cut lot. It is the same for the different formats.
- NPL: Number of slates in each classified lot for packing. It is the same for the different formats.
- NRL: Number of slates in each recirculated lot.

Lots are formed manually by the splitters upon specific goals on their size. Hence all of them are subject to random variations in content but with well-defined mean values.

Product transformation rates:

- NSP: Number of parts generated by each slab in the rough splitting process.
- τ_{SU}: Utilization rate of split blocks. It represents the percentage of the blocks' material that can be transformed into split slates.
- τ_{TF}: Rate of target format slates produced by the splitters
- τ_{rej}: Rejections rate in the classification step.
- τ_{32}: Rate of 32 format slates produced in the factory.
- α_{30}: Relation between the throughput of 30 format slates and 27 format slates.

α_T: Relation between the throughput of traditional quality slates and standard quality slates.
τ_{recirc}: Rate of slates recirculated after the classification process to lower formats.
τ_{thick}: Rate of slates classified as 4.5mm thickness.

Resources parameters:

γ_i: Relation between the individual throughput rate and the average throughput rate for the splitter i.

Figure 5 represents the process flow diagram indicating the flows of intermediate products and the transformation and transportation steps. Acronyms for the resources are inserted at the end of each element's name. As it can be noted, the process type corresponds to a disassembly process in which from a single process input different outputs are obtained.

Product flow balance

The defined product transformation rates link the product flow rates and determine the process performance. Production costs will largely depend on transformation rates since they determine the proportion in which costs of early intermediate products transfer to final products. Within a context in which prices keep constant, economical performance will be subject to variations in process parameters.

Splitting process balance

$$\begin{aligned} SL_{TF} &= \tau_{SU} \cdot \tau_{TF} \cdot B \cdot NSP \cdot \frac{w_p}{w_s} \cdot \frac{1}{NSL_{TF}} \\ SL_{SF} &= \tau_{SU} \cdot (1 - \tau_{TF}) \cdot B \cdot NSP \cdot \frac{w_p}{w_s} \cdot \frac{1}{NSL_{TF}} \end{aligned} \tag{1}$$

Where w_p is the width of a rough split part of a slab and w_s is the width of a slate.

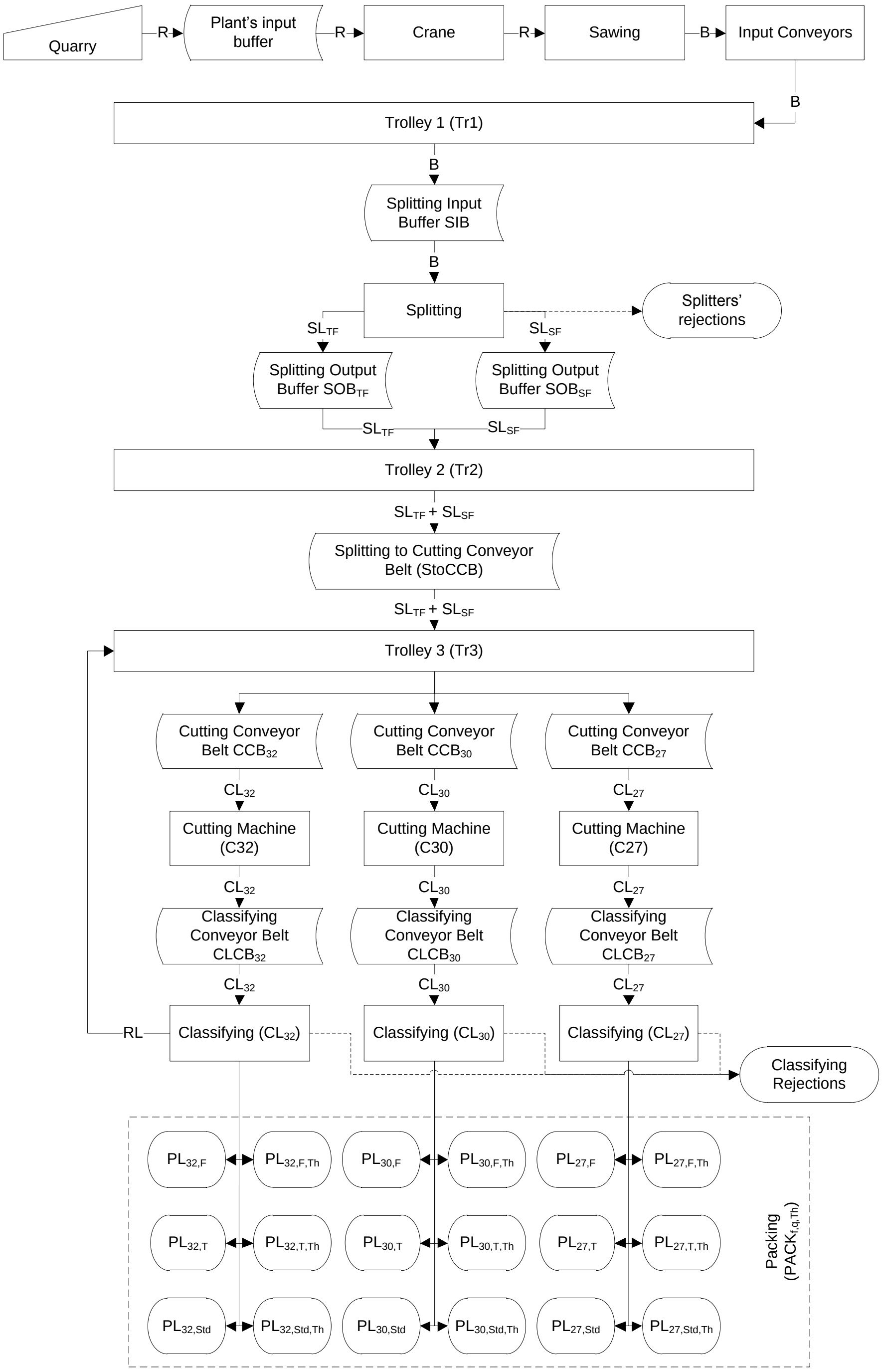

Fig. 5. Process flow diagram

Cutting process balance

$$
\begin{aligned}
CL_{32} &= SL_{TF} \cdot \frac{NSL_{TF}}{NCL} \\
CL_{30} &= \propto_{30} \left(SL_{SF} \cdot \frac{NSL_{SF}}{NCL} + \tau_{recirc} CL_{32} \right) \\
CL_{27} &= (1 - \propto_{30}) \left(SL_{SF} \cdot \frac{NSL_{SF}}{NCL} + \tau_{recirc} CL_{32} \right)
\end{aligned}
\tag{2}
$$

Packing process balance

$$
\begin{aligned}
PL_{f,F,3.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot \tau_F \cdot (1 - \tau_{Thick}) \cdot CL_f \cdot \frac{NCL}{NPL} \\
PL_{f,F,4.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot \tau_F \cdot \tau_{Thick} \cdot CL_f \cdot \frac{NCL}{NPL} \\
PL_{f,T,3.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot (1 - \tau_F) \cdot \alpha_T \cdot (1 - \tau_{Thick}) \cdot CL_f \cdot \frac{NCL}{NPL} \\
PL_{f,T,4.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot (1 - \tau_F) \cdot \alpha_T \cdot \tau_{Thick} \cdot CL_f \cdot \frac{NCL}{NPL} \\
PL_{f,STD,3.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot (1 - \tau_F) \cdot (1 - \alpha_T) \cdot (1 - \tau_{Thick}) \cdot CL_f \cdot \frac{NCL}{NPL} \\
PL_{f,STD,4.5} &= \left(1 - \tau_{rej} - \tau_{recirc}\right) \cdot (1 - \tau_F) \cdot (1 - \alpha_T) \cdot \tau_{Thick} \cdot CL_f \cdot \frac{NCL}{NPL}
\end{aligned}
\tag{3}
$$

3.2 Statistical analysis

Three main sources of information were used for the simulation project: videos, interviews with personnel and production data records. Interviews served us for performing a qualitative analysis of the systems characteristics and behaviours presented before.

Production data analysis

The videos provided with observations of cycle time realizations from which to study the statistical distribution of the diverse elements in the system. Statistical distributions were fitted by means of the software utility Statfit. Regression models for the splitters cycle times were fitted in R [28]. The following items were considered in this analysis:

- Inter-arrival times for the input slabs process. They were fitted to an exponential distribution in which for a single arrival event several slabs may arrive according to the empirical distribution.
- Loading and unloading times as well as speeds of trolleys.
- Splitters cycle times. Data of joint observations of time per slab, number of produced slates and material utilization rate were collected.
- Cycle times of cutting machines. Cutting time per slate was assumed to be constant due to the low coefficient of variation. Variability is introduced in the loading and unloading times plus the number of slates in a pile.
- Cycle times of classifiers. It was fitted to a triangular distribution with a coefficient of variation of 0.3.
- Cycle times of packing tasks. It was fitted to a triangular distribution with a coefficient of variation of 0.3.

The splitters' cycle time was found to be positively correlated with the width of a slab given by the number of rough splitting parts (NSP) in which it is divided and the utilization rate. Slabs in which large fractions are wasted are processed faster. The coefficients of the model and its equation are given below.

$$ST_c = e^{SSP_c} \cdot (NSP_c + 1)^{b_{NP}} \cdot \left(\frac{SSP_c}{NSP_c} + 0.5\right)^{b_{SU}} \cdot e^{\varepsilon_{ST,c}} \tag{4}$$

Where:

ST_c: Splitting time by cycle.
SSP_c: Successful split parts in cycle c.
b_0, b_{NP}, b_{SU}: Model parameters.
$e^{\varepsilon_{ST,c}}$: Random error. It follows a normal distribution with zero mean and standard deviation $\sigma_{ST,c}$.

Table 1. Coefficients of the splitting cycle time model.

Coefficient	Value	Std. Error	p-value
b_0	2.192	0.156	1.74E-15
b_{NP}	1.367	0.089	1.87E-16
b_{SU}	0.620	0.161	0.00054

Fig. **6.** shows the splitters cycle time and throughput depending on the size of the incoming slabs and the utilization rate of the material. Cycle time graphs show a slight concavity. Hence, for both small and big size slabs the throughout rate is lower. This can be explained by taking into account that processing small slabs increases the proportion of auxiliary tasks such as picking them up or cleaning the workstation. Big slabs are harder to handle, thus reducing productivity as well.

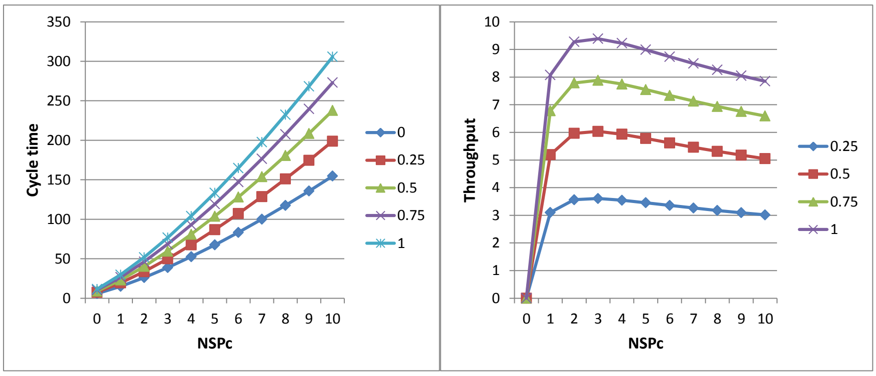

Fig. 6. Cycle Time and Split Lots Throughput Rate as a function of the Number of Parts per Slab (NSP_c) and for various levels of Slab Utilization Rate (SSP_c / NSP_c).

Production data analysis

Production data were gathered from the company's production daily records. A set of 250 days of activity were stored in a relational database implemented in Microsoft Access. Available registries contain the following items:

(Splitters' production records)

- Labour.
- Number of squares lots.
- Number of tips lots.
- Average number of pieces in a squares lot.
- Working hours.

(Packing records)

- Number of pallets by format and quality.
- Number of slates in each pallet.

- Price per slate of each
- Cutting machine in which the pallet had been processed.

Two of the process transformation rates were assumed to be constant due to their less relevant role in the process. They are the percentage of 30cm format over the total of secondary formats and the percentage of traditional quality over the sum of traditional plus standard: α_{30}=0.65 and α_{Trad}=0.473.

Although the data sources do not cover all the relevant process parameters defined before, they allowed us to infer those not explicitly contained. Datasets with parameters values for statistical analysis were derived from these sources. Three variables needed to be inferred from the data: the utilization rate of blocks material, the rejections rate in the classification process and the recirculation rate.

According to information provided by the plant managers, the sawing throughput rates stands roughly constant among different days. Thus, assuming B as a fixed value, and taking into account the variations in the splitting process throughput along time, we can estimate the variations in the utilization rate:

$$\tau_{SU,t} = \frac{8 \cdot NSP \cdot B}{NSL \cdot SL_t} \tag{5}$$

Assuming B as a constant, $\tau_{SU,t}$ will follow a stochastic process that will be directly proportional to $\frac{1}{SL_t}$.

The rejections rate in classification could be obtained by the difference between split and packed slates:

$$\tau_{rej,t} = 1 - \frac{NPL \cdot PL_t}{NSL \cdot SL_t} \tag{6}$$

Finally, the recirculation rate can be obtained assuming that the rejections rate is the same for the different produced formats. Then:

$$\tau_{recirc,t} = 1 - \frac{NPL \cdot PL_{32,t}}{\left(1 - \tau_{rej,t}\right) \cdot NSL \cdot SL_{TF,t}} \tag{7}$$

Table 2. shows the dataset with the seven most relevant process parameters identified before. The statistics summary contains the mean, standard deviation and 1 order autocorrelation of each time series.

Table 2. Most relevant process parameters values.

	τ_{SU}	τ_{TF}	$1-\tau_{rej}$	τ_{32}	τ_F	τ_{recirc}	τ_{thick}
AVG	67.72%	87.46%	78.15%	79.37%	41.47%	7.73%	27.93%
DESV	7.37%	3.66%	10.89%	9.57%	12.06%	5.70%	9.09%
Autocor	0.55	0.64	0.54	0.27	0.35	0.93	0.28

Time series model of process parameters

The first analysis conducted on the process parameters dataset was a principal components analysis (PCA) aimed at identifying the main dimensions of variability present in the data. Data were first standardized and then the PCA analysis performed in R. The first four principal components of variability were selected for further analysis. They account for 80.30% of the total variance. The loadings and standard deviation for each one of these components are given in Table 3. .

Table 3. Loadings and standard deviation of the Principal Components Analysis.

	c_1	c_2	c_3	c_4
τ_{SU}	0.466	-0.254	-	-0.152
τ_{TF}	-	0.566	-0.377	0.236
$1-\tau_{rej}$	-0.537	0.162	0.116	-
τ_{32}	0.451	0.232	0.109	0.151
τ_F	-	-0.343	-0.819	-0.258
τ_{recirc}	-0.492	-	-0.234	-
τ_{thick}	-	-0.397	-0.112	0.897
Standard deviation	1.667	1.344	0.981	0.914

Component 1 is linked to the joint variation in the utilization rate of slabs in splitting, the rate of 32cm format, rejections in classification and oppositely to the recirculation's fractions. Thus component 1 shows a situation in which splitters production is high but there are important losses in classification and the main output is the objective target 32 cm. Component 2 is linked to the joint increase in the target format production in splitting and output, but together with low quality outputs and lower utilization of the slabs. Component 3 is mainly associated to quality, which is a rather independent feature of the output with respect to other process parameters. Component 4 shows the fraction of thick slates to be a fairly independent variable as well. The 1st and 2nd components of variability might interact with process management decisions, since it is possible to alter the priorities with respect to which formats to produce and the incentives in splitting to the different outputs. However, quality and thickness are two variables over which there is no feasible control that can be exerted by the managers. Thus they might be considered as external sources of variation in the process that must be coped with.

Then, the principal components time series were fitted first to a multivariate autoregressive process employing the *vars* package in R [29]. However, this multivariate model only showed significant 1st order autoregressive effects to be relevant. Cross effects were negligible and they only accounted for a small share of the variance.

The models were simplified and fitted again to independent first order autoregressive models for each variable by means of the R *tseries* package [30]. Higher order terms did not improve the accuracy in a significant way so they were rejected. Table 4 summarizes the fitted models.

Table 4. First order autoregressive models

Component	Lag 1 coefficient	p-value	Std. Error	Model equation
c_1	0.71488	<2E-16	1.167	$c_{1,t} = 0.715 \cdot c_{1,t-1} + \varepsilon_{1,t}$ where $\varepsilon_{1,t} \sim N(0,\ 1.167)$
c_2	0.61937	<2E-16	1.048	$c_{2,t} = 0.619 \cdot c_{2,t-1} + \varepsilon_{2,t}$ where $\varepsilon_{2,t} \sim N(0,\ 1.048)$
c_3	0.45178	1.17E-10	0.884	$c_{3,t} = 0.452 \cdot c_{3,t-1} + \varepsilon_{3,t}$ where $\varepsilon_{3,t} \sim N(0,\ 0.884)$
c_4	0.21142	0.00493	0.899	$c_{4,t} = 0.211 \cdot c_{4,t-1} + \varepsilon_{4,t}$ where $\varepsilon_{4,t} \sim N(0,\ 0.899)$

Splitters individual differences analysis

As it has been said in the second section, a remarkable component of variability in the process is given by the splitters individual differences. Differences in skill gender differences in cycle times, utilization rates of material and consequently throughput. Differences in throughput were computed from historical data and summarized in a set of individual effect parameters noted as γ_i.

$$\gamma_i = \frac{SL_i}{SL} \tag{8}$$

Time series of $SL_{i,t}$ values were normalized and the significance of two possible hypothesis tested:

- H1: The daily variation of each individual splitter is associated with the daily variations in the average of the rest of the splitters. This hypothesis would be related with a common cause of variability for all the splitters that would be linked to changes in the quality of the material, associated with changes in the mean values of the slabs utilization.
- H2: The daily variation of each individual splitter is associated with the daily variation of the next splitter lying in his visual field. This effect would be related to behavioural issues consisting of regression to the mean phenomena as considered by Schultz et al [31]. In this case, due to the spatial arrangement of the splitters –linear-, each one can only see his following workmate. Then, behaviour could only be affected by feedback on the next splitter's work-pace.

The model proposed in order to study the significance of these two possible phenomena is the following:

Let

$$r_i = \frac{SL_{i,t} + \mu(SL_i)}{\sigma(SL_i)}$$

be the normalized observation of the splitter *i* throughput at time *t* and

$$r_i^c = \frac{\sum_{j\neq i} \frac{SL_{j,t}}{NS-1} - \mu\left(\sum_{j\neq i} \frac{SL_j}{NS-1}\right)}{\sigma\left(\sum_{j\neq i} \frac{SL_j}{NS-1}\right)}$$

be the normalized observation of the average throughput of all the rest of the splitters but *i*.

$$\begin{aligned} r_{i,t} = {} & \beta_{1,i} r_{i,t}^c + \beta_{2,i} \cdot \left(r_{i+1,t} - cov(r_{i+1}, r_i^c) \cdot r_{i,t}^c\right) + \\ & \varphi_i \cdot \left(r_{i,t-1} - \beta_{1,i} \cdot r_{i,t-1}^c - \beta_{2,i} \cdot \left(r_{i+1,t-1} - cov(r_{i+1}, r_i^c) \cdot r_{i,t-1}^c\right)\right) + \delta_{i,t} \end{aligned} \tag{9}$$

Where $\beta_{1,i}$ and $\beta_{2,i}$ are the coefficients to be estimated by generalized least squares and φ_i a coefficient for considering autocorrelation in the model's residuals following a first order autoregressive process (AR1). $\delta_{i,t} \sim N(0, \varepsilon_i)$ is a white noise error process. The term $r_{i+1,t} - cov(r_{i+1}, r_i^c) \cdot r_{i,t}^c$ represents the daily variation of the next splitter to *i* that is not explained by the first regressor of the model. Thus $\beta_{2,i}$ isolates the effect of possible behavioural phenomena given by the association between the variations of both splitters that are not linked to the variation in the global behaviour of the splitters.

Testing H1 and H2 can be performed by checking the significance of the null hypothesis $\beta_{1,i} = 0$ and $\beta_{2,i} = 0$. Table 5 shows the coefficients, p-values and errors of the fitted models. As it can be noted, only H1 was found to be significant. The p-value of $\beta_{1,i}$ is near zero for all the analyzed splitters, validating the perceived perception of the existence of good and bad input material conditions that affect to the global performance. However, H2 could not be proved significant. The average positive values suggest that larger dataset were available, it might be found significant; but it has a small effect nevertheless.

Table 5. Coefficients, p-values and errors of the splitters models.

	Splitter 1	Splitter 2	Splitter 3	Splitter 4	Splitter 5	Splitter 6	Splitter 7
Avg.	762.85	601.73	752.02	863.18	710.66	643.58	864.28
Std. Deviation	127.46	67.34	88.69	99.80	98.34	71.18	102.98
γ_i	1.03	0.81	1.01	1.16	0.96	0.87	1.16
γ_i	0.824	0.744	0.828	0.750	0.508	0.775	0.501
p-value	0	0	0	0	0	0	‘
$\beta_{2,i}$	-	0.206	0.0139	0.0216	0.0992	0.1066	-0.1245
p-value	-	6e-48	0.8681	0.7049	0.2227	0.1755	0.0788
φ_i	0.095	0.244	0.177	0.062	0.212	0.299	0.337
φ_i confidence interval	(-0.029, 0.216)	(0.120, 0.361)	(0.050, 0.299)	(-0.062, 0.186)	(0.083, 0.334)	(0.175,0.414)	(0.214, 0.449)
Std. Error	0.793	0.756	0.685	0.752	0.865	0.796	0.870

Taking into account the cycle time model given by equation (4), the throughput will be depend on both average cycle time and utilization and thus individual differences might be explained by either differences in work-pace, utilization or a combination of both. At this point, the assumption that individual differences would be only explained by differences in cycle times and global splitting variations by differences in utilization rates was adopted. The reasoning behind it is twofold. First, even though there are differences in the utilization rate of slabs by the different splitters, all of them share the goal of maximizing slabs utilization. And second, differences in skill that make it possible higher rates of material utilization are less important than those related to the different work-paces. Partial collected data together with expert judgement supported this assumption.

Thus the model for the splitters' cycle time remains as:

$$ST_{i,c} = \gamma_i \cdot e^{b_0} \cdot (NSP_c + 1)^{b_{NP}} \cdot \left(\frac{SSP_c}{NSP_c} + 0.5\right)^{b_{SU}} \cdot e^{\varepsilon_{ST,c}} \quad (10)$$

Where the splitting utilization rate can be calculated from the principal components time series as given by equation (11). The rest of the variables in the model are calculated according to their statistical distributions.

$$\tau_{SU,t} = \mu(\tau_{SU}) + \sigma(\tau_{SU}) \cdot (0.466 \cdot c_1 - 0.254 \cdot c_2 - 0.152 \cdot c_4) \quad (11)$$

$$NSP_c \sim Empirical\_distribution \quad (12)$$

$$SSP_c \sim B(NSP_c, \tau_{SU,t}) \quad (13)$$

$$\varepsilon_{ST,c} \sim N(0, \sigma_{ST}) \quad (14)$$

Hence, the proposed model connects the daily variability generated by the principal components time series models with the process cycle variability given by the statistical distributions of the aforementioned variables.

3.3 Model implementation and validation

The executable model was implemented in the simulation software Delmia Quest V5R20. A parameterized model was developed so that the process parameters can be updated on a daily basis and results stored for further analysis by means of a SCL macro. Geometrical and kinematical similarity in the transportation elements could be achieved thanks to the 3D simulation paradigm built in Quest. This feature provided a good means for visually validating the model and accrediting results in front of the plant managers.

Cycle level variation is introduced in the model by means of the statistical distributions of processing times, lots sizes and the splitting model introduced before. Classified slates are randomly assigned to the different categories of classified products according to product transformation rates. For instance, in the classification of 32 format tiles, each one will be randomly rejected, recirculated or transformed into a packed slate with quality and thickness generated according to the product transformation rates values.

Three variability modelling approaches were considered at this point:

1. A static model in which mean values of process parameters are kept constant along the simulation run. Thus only cycle related variability is introduced.
2. A stationary autoregressive model in which process parameters are generated on a daily basis according to the time series models presented before.
3. The 2nd modelling approach incorporating the individual differences.

The experimentation conducted at this step comprised the simulation of 200 days periods in which statistics are collected. The analysed results span:

- Final product production records in the same fashion as they are recorded in the real plant.
- Splitting production records in the same fashion as they are recorded in the real plant.
- Daily averages of resources utilization and occurrence of blocking.
- Daily averages of buffer levels.

The simulated production records provide with a means for validating the simulation model by comparing the time series autocorrelation structure from the real plant with that generated by the model. As it can be seen in the Table 6., the static modelling approach leads to the largest differences with the data from the real plant. Parameters deviations are lower than those present in the plant indicating that variability is being underestimated.

Table 6. Average and Standard deviation parameters for the real and simulated systems

Approach	Statistic	1-tDL	tC	1-tDC	t32	tP	tR	tF
Real	Avg.	0.837	0.875	0.781	0.794	0.415	0.077	0.279
	S.d.	0.091	0.037	0.109	0.096	0.121	0.057	0.091
Model 1	Avg.	0.828	0.874	0.803	0.779	0.412	0.087	0.244
	S.d.	0.021	0.005	0.074	0.042	0.050	0.039	0.053
Model 2	Avg.	0.841	0.876	0.788	0.784	0.424	0.085	0.243
	S.d.	0.079	0.034	0.130	0.061	0.130	0.054	0.093
Model 3	Avg.	0.818	0.869	0.822	0.770	0.423	0.095	0.247
	S.d.	0.069	0.032	0.118	0.057	0.135	0.051	0.095

Table 7. summarizes the principal components loadings for the real and the simulated time series, their variance and the 1st order autoregressive model coefficient and p-value. Principal components loadings display several further dissimilarities and the autocorrelation coefficients are negative. Modelling approaches 2 and 3 provide with a better modelling of the system variability and display a more similar autocorrelation pattern. However, all the autocorrelation coefficients have lower values than those in the generating time series. This result might be explained taking into account that the the cycle level variability generated by the simulation model also affects the daily time series. As model 1 results show, the exclusive consideration of cycle time variability results on negative autocorrelation. Accordingly, the positive

autocorrelation structure generated by the temporary series model is slightly counteracted by the cycle random processes.

Table 7. Principal components loadings for the real and the simulated time series

Parameter		c_1	c_2	c_3	c_4
splitPerformance	System	0.466	-0.254		-0.152
	Model 1			0.564	0.646
	Model 2	0.518	0.239	-0.168	0.226
	Model 3	0.575		0.193	
tauSQ	System		0.566	-0.377	0.236
	Model 1				-0.663
	Model 2	-0.247	-0.472	-0.505	-0.206
	Model 3	-0.452	-0.355		-0.536
tauRej	System	-0.537	0.162	0.116	
	Model 1	-0.149	0.736	-0.135	
	Model 2	-0.536	-0.133	0.234	-0.126
	Model 3	-0.508	0.227	-0.176	0.251
tau32	System	0.451	0.232	0.109	0.151
	Model 1	0.678			
	Model 2	0.229	-0.665	-0.111	
	Model 3		-0.672	-0.167	
tauF	System		-0.343	-0.819	-0.258
	Model 1		0.168	-0.706	0.34
	Model 2	0.121	0.334	-0.58	-0.602
	Model 3	0.31	0.217	-0.349	-0.734
tauRecirc	System	-0.492		-0.234	
	Model 1	-0.686			
	Model 2	-0.502	0.385		
	Model 3	-0.298	0.565		-0.206
tauThick	System		-0.397	-0.112	0.897
	Model 1	0.193	0.642	0.392	-0.145
	Model 2	0.254		0.553	-0.721
	Model 3	0.116		-0.879	0.26
Std. Deviation	System	1.667	1.344	0.981	0.914
	Model 1	1.4654143	1.1581529	1.0732068	1.0105033
	Model 2	1.5718817	1.3638524	0.9884897	0.9638779
	Model 3	1.5440086	1.4516356	1.0101435	0.9127112
AR1 coef.	System	0.71488	0.61937	0.45178	0.21142
	Model 1	-0.53965	-0.4745	-0.41343	0.01391
	Model 2	0.43213	0.28589	0.35404	0.15376
	Model 3	0.548486	0.087541	0.125889	0.224131
AR1 p-value	System	<2e-16	<2e-16	1.17E-10	0.00493
	Model 1	<2e-16	2.44E-14	1.34E-10	0.844
	Model 2	1.88E-09	0.000162	0.00000194	0.049
	Model 3	<2e-16	0.217	0.0735	0.00113

Results from models 2 and 3 do not present relevant differences. This result can be interpreted as that even though the individual differences are clearly present in data; their impact in the global process performance is not relevant. Thus in the rest of the chapter, model 2 will be adopted for simplicity.

The next step in the validation process consisted of an informal validation in which the behaviour of the models was compared to the manufacturing plant behaviour descriptions given by the process managers Table 8.). These features can be summarized as:

- Feature 1. Splitters workload is highly variable. Under some conditions they are near saturation and under some other conditions their workload is lower and they have idle times.
- Feature 2. Slabs utilization rate is subject to large variations. During some periods the slate quality is optimal and the throughput is high. Under some other periods the throughput is high causing idle resources downstream the production line.
- Feature 3. The connection buffers from splitting to cutting are subject to large variations in occupancy levels.

- Feature 4. The process bottleneck dynamically switches between splitting and classification & packing.

Table 8. Presence in the Models of the Experts Percepcion of the System

Feature	Model 1	Model 2
1	Partially present	Present
2	Partially present	Present
3	Not Present	Present
4	Not Present	Present

Comparing the graphs of utilization rates of resources and buffers contents generated by models 1 and 2, the model behaviour features can be checked. As we can see in Fig. **7.** and Fig. **8.**, model 1 displays a much more constant pattern of variability in buffer contents with some random fluctuations around mean values. On the other hand, model 2 shows much larger variations that better match the system's description.

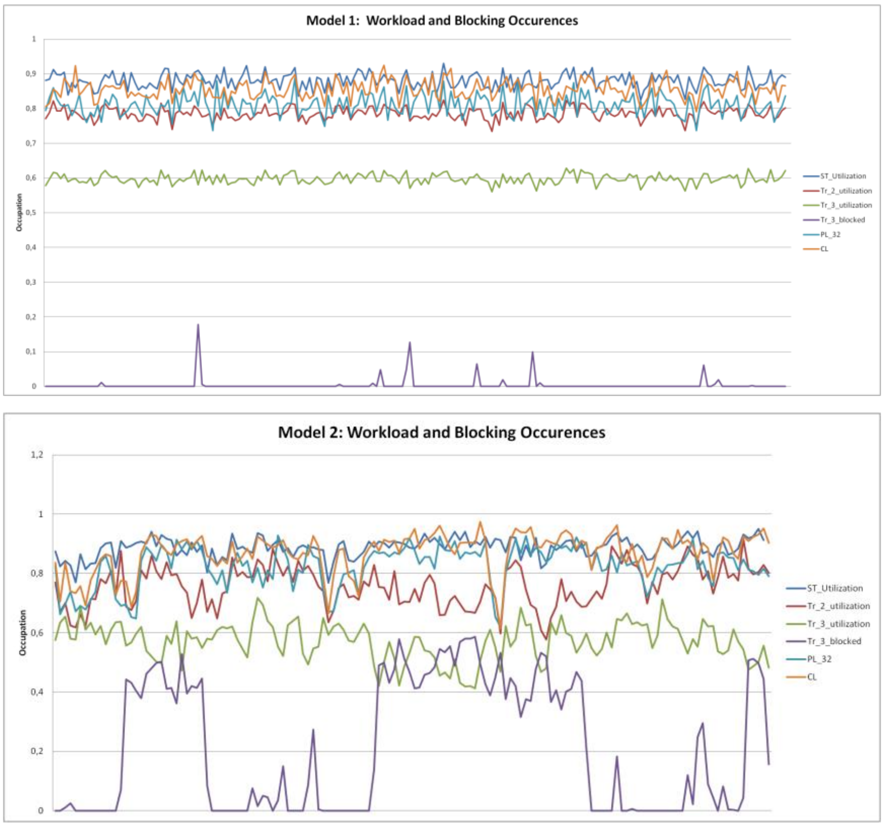

Fig. 7. Workload and Blocking Occurrences in model 1 and model 2

Content of the StoCCB conveyor presents long periods in which it is fully occupied and long periods in which it is almost empty. The emergence of these periods is a feature that matches system's behaviour although it is not immediate to predict from the individual condition of the other elements. On the contrary, due to the lack of variability inherent to its modelling approach, Model 1 is not capable of displaying such behaviour.

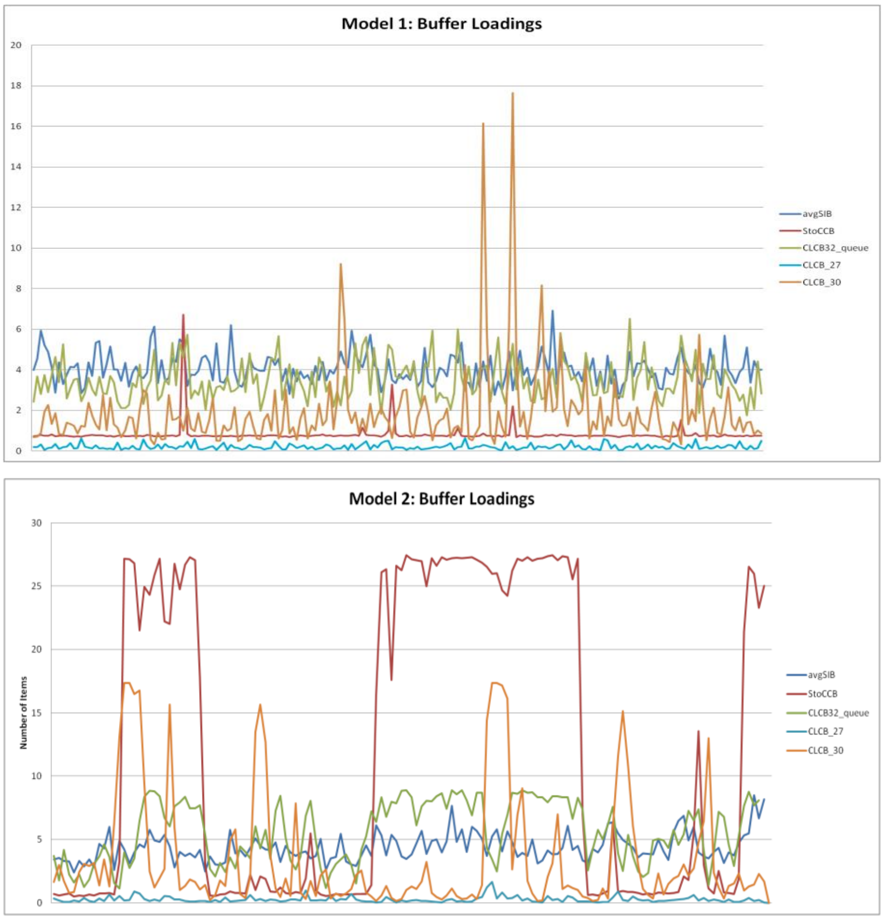

Fig. 8. Buffer Loadings for model 1 and model 2

Table 9. Main Results of Model 1 and Model 2

	Stationary Model				Time Series Model			
	Avg.	S.d.	Max.	Min.	Avg.	S.d.	Max.	Min.
avgSIB	4,0424	0,7306	6,9085	2,5811	4,3692	1,1037	8,4949	2,3910
ST_Utilization	0,8802	0,0216	0,9805	0,8748	0,8879	0,0340	1,0000	0,8184
Tr2_ Utilization	0,7851	0,0175	0,8247	0,7342	0,7573	0,0690	0,9152	0,5765
StoCCB	0,8087	0,4726	6,7110	0,6789	12,0476	12,3275	27,4666	0,5008
Tr3_ Utilization	0,5975	0,0139	0,6284	0,5602	0,5717	0,0644	0,7174	0,4131
Tr3_Block	0,0036	0,0186	0,1785	0,0000	0,2156	0,2224	0,5869	0,0000
CCB_{32_queue}	0,8783	0,6630	4,9862	0,4016	3,2660	2,8620	9,5937	0,3320
CCB_{30}	0,5363	0,6225	7,4219	0,3201	1,5324	2,5546	11,7239	0,1565
CCB_{27}	0,1392	0,0207	0,2169	0,0964	0,2107	0,1416	0,7010	0,0304
CL_{32_queue}	0,8558	0,0380	0,9622	0,7658	0,8696	0,0708	0,9815	0,6136
CL_{30}	0,4001	0,0343	0,5099	0,3077	0,3867	0,0770	0,5489	0,2064
CL_{27}	0,2378	0,0317	0,3369	0,1726	0,2359	0,0514	0,3832	0,1149
$CLCB_{32\_queue}$	3,4739	1,4201	8,3682	1,3766	5,6296	2,6192	8,9343	0,8763
$CLCB_{30}$	1,8763	2,0006	17,6434	0,3215	3,5704	4,8023	17,3718	0,1461
$CLCB_{27}$	0,2063	0,1293	0,6260	0,0403	0,2606	0,2353	1,6384	0,0219
PL_{32}	0,8117	0,0337	0,8992	0,7267	0,8234	0,0704	0,9330	0,6189
PL_{30}	0,7778	0,0484	0,9032	0,6279	0,7575	0,1460	0,9950	0,3506
PL_{27}	0,4506	0,0400	0,5381	0,3483	0,4366	0,0894	0,7252	0,1997

4. Process Improvement

4.1. New layout description

The original process layout was designed aiming at maximizing the intermediate buffers capacity. The StoCCB conveyor and the length of the conveyors in the classification and packing areas are examples of this traditional plant design concept that was common in the sector. A new layout configuration was proposed by the research team based on the idea that more intermediate steps may be actually amplifying process variability. Thus we compared by simulation the original layout with a new more linear one in which trolley 3 and StoCCB conveyor were removed. Fig. **9.** and Figure 10 depict a floor plan of both the old and the new layout.

Two difficulties needed to be overcome with this new layout. First, trolley 2 operation would become more complex. It would have multiple sources and destinations and thus routing logics needed to be defined. A simple nearest pending decision event criterion was adopted as a simple rule for selecting local optimal decisions in the routing process. Second, the arrangement of the pallets on the plant needed to be reconfigured. The decision adopted was to locate the pallets of products with the highest throughput rates in the outer positions so that they can be more easily accessed for retrieval. Pallets of First, traditional and standard qualities were located in such a way that the highest throughput qualities are the nearest to the classification roller belts. The cutting and classification lines were also placed so that trolley 2 movements are minimized. Target format cutting machines are the closest to splitting and secondary formats the farthest. In addition, recirculation roller bets in order to transport recirculated lots from the target format lines to the secondary format ones were connected via trolley 2.

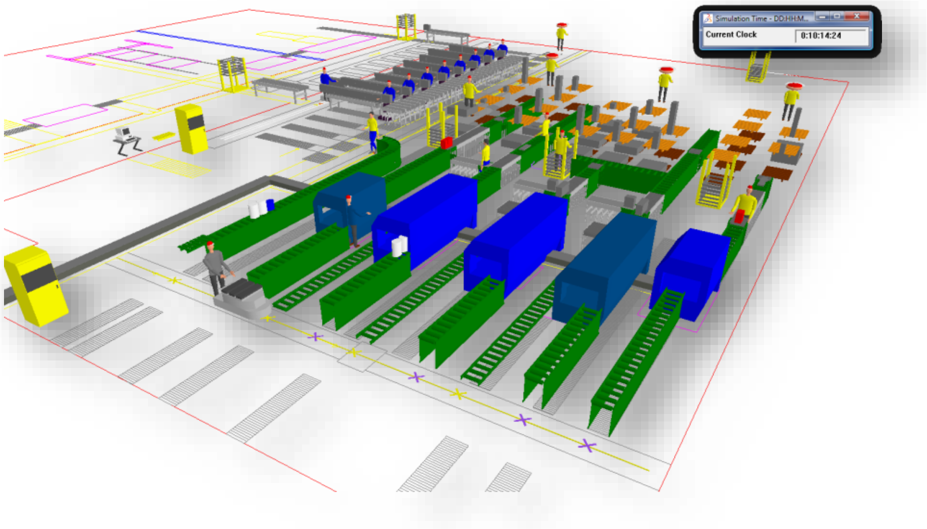

Fig. 9. Model of the Old Layout

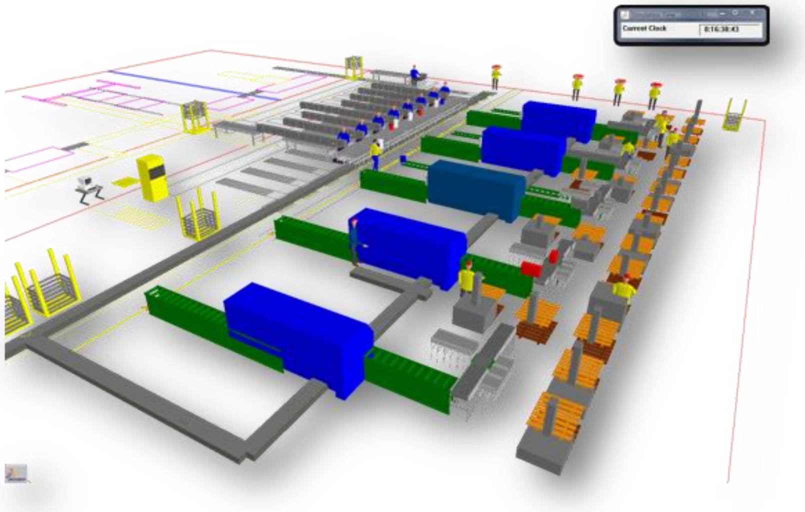

Fig. 10. Model of the Proposed Layout

4.2. New layout simulation

A simulation of 150 working days of the new layout was performed and results compared to those of the original layout. Levels of variability, plant saturation, and buffers occupancy were considered. Table 10. shows the simulation results for the new layout. Fig. **11.** shows the evolution of buffers occupancy and resources utilization.

As it can be noticed, the new layout behaviour is different from that of the original one, providing evidence that the intermediate process steps affect system's behaviour by amplifying variability. Thanks to the appropriate placement of cutting lines along the trolley 2 line, trolley 2 utilization rate is similar to that in the original layout. Buffer occupancies are reduced and the periodic saturation of an element like StoCCB does not occur. In general, the model now behaves in a smoother manner.

Table 10. Simulation Results for the New Layout

	Avg.	S.d.	Max.	Min.
ST$_{_utilization}$	0,8767	0,0470	1,0000	0,7957
Tr2$_{_utilization}$	0,7007	0,0895	0,9284	0,4378
Tr2$_{_blocked}$	0,0188	0,0703	0,4496	0,0000
CCB$_{32_queue}$	0,9372	1,6384	8,9362	0,1046
CCB$_{30}$	0,3407	0,2703	1,9918	0,0346
CCB$_{27}$	0,2280	0,2220	1,7115	0,0365
CL$_{_32}$	0,8514	0,0899	1,0000	0,6186
CL$_{_30}$	0,3396	0,0799	0,5674	0,1361
CL$_{_27}$	0,2838	0,0648	0,4506	0,1383
CLCB$_{32_queue}$	3,0328	2,1494	7,9224	0,5180
CLCB$_{30}$	0,6771	0,7422	4,5029	0,0211
CLCB$_{27}$	0,3093	0,2719	1,4695	0,0251
PL$_{32}$	0,6744	0,0642	0,8325	0,4343
PL$_{30}$	0,5550	0,1474	0,9578	0,2021
PL$_{27}$	0,4614	0,1117	0,7388	0,2042

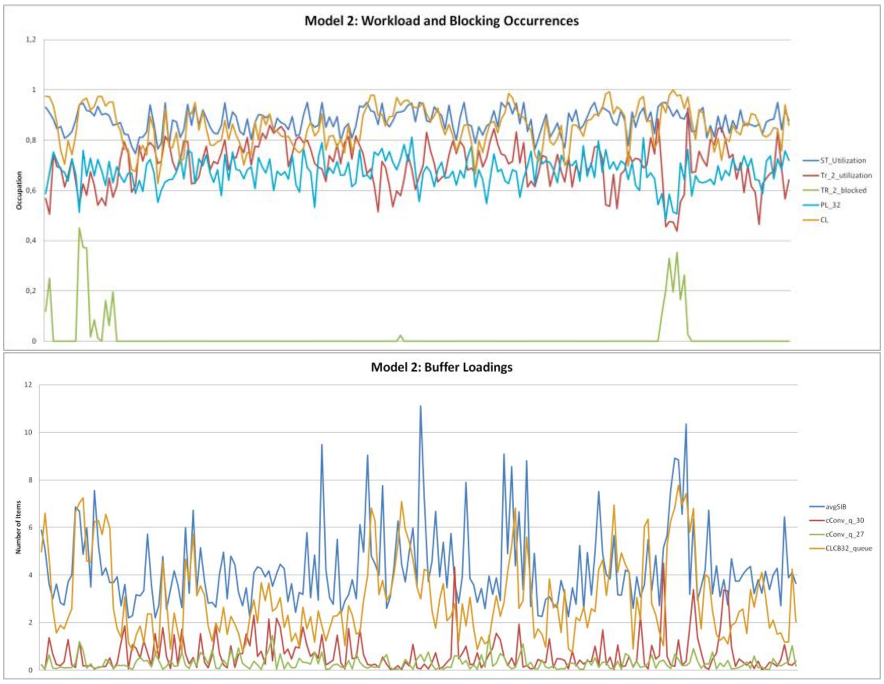

Fig. 11. Workload, Blocking Occurences and Buffer Loadings

5. Discussion and Conclusions

A paradigmatic case of a highly variable environment manufacturing process has been presented. A DES model has allowed a multilevel characterization of variability, so that improvement proposals have been adequately formulated and evaluated. The heterogeneity in input material properties together with the prevalence of manual operations constituted a process with high levels of variability, large work in process and important performance losses.

Data gathered from the manufacturing plant make it possible the construction of a dataset containing daily time series of performance parameters. PCA and AR models were employed in order to identify principal modes of variation and modelling of autocorrelation patterns. These temporary series models provided with a model for the daily variability in the plant. Video recordings provided with data for fitting models of cycle level variability in the system elements.

Models were validated by comparison of simulation results and actual plant's data along with expert criteria. Two modelling approaches were compared: a classical approach in which only cycle related variability is considered and a multilevel one that combines both cycle and daily levels. A third approach considered consisted of introducing individual differences, although it was rejected due to the low impact in results. Only the multilevel approach was capable of exhibiting a sort of process behaviour such as the large variability present in connection buffers. The classic approach lead to an underestimation of the process variations and negative autocorrelation patterns that unmatched real data.

A new layout aimed at increasing the process linearity was proposed and implemented in the simulation model. The new layout removes unnecessary intermediate transportations and connection buffers and standardises and simplifies the location of pallets in the output area. It also reduces buffers average contents and provides a smoother response to the process inherent variability. The time series model of daily variations ensured a robust design of the new layout that leads to a change of paradigm in the design of slates manufacturing processes. Instead of disposing the maximum capacity feasible for connection buffers, an optimized design in which only the minimum necessary buffers capacity is employed becomes possible.

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