# A STOCHASTIC APPROACH TO IMPROVE PERFORMANCE OF PRODUCTION LINES

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**ABSTRACT**
In our increasingly competitive world, today companies are implementing improvement strategies in every department and, in particular, in their manufacturing systems. This paper discusses the use of a global method based on a knowledge-based approach for the development of a software tool for modelling and analysis of production flows. This method is based on data processing and data mining techniques and will help the acquisition of the meta-knowledge needed for the searching of correlations among different events in the production line. Different kind of techniques will be used: graphic representation of the production, identification of specific behaviour and research of correlations among events on the production line. Most of these techniques are based on statistical and probabilistic analyses. To carry on high level analyses, a stochastic approach will be used to identify specific behaviour with the aim of defining, for example, action plans.

Keywords: Knowledge-based systems, Modeling and simulation of production systems, Discrete event abstraction, Stochastic approach.

## 1. INTRODUCTION

The search for productivity sources makes the improvement of the contemporary production systems necessary. The production actors are, in a systematic and permanent way, engaged in three stages: the audit, the diagnosis and the search for solutions to improve their production systems.

For the audit of production systems, recent Internet and Intranet technologies allow measuring and storing the state of the different production resources in real time.

From these data, and during the stage of analysis of production flows, the production personnel and the staff in charge must be able to find and formalize the problems inducing a faulty operation of the manufacturing system. Solutions must be imagined in order to increase the productivity at a given cost.

The stages of diagnosis and solution search are, nowadays, primarily instrumented by little formalized expert knowledge. This lack of formalism generates heavy development costs, does not guarantee reproducibility and does not support the necessary knowledge capitalization for the improvement of the production system within the same company. To solve these problems, a solution consists in formalizing the necessary knowledge to set and solve the problems related to that lack of productivity from the data collected during the audit stage. This formalization has to give birth to software tools for assisting the involved actors in a permanent and proactive way.

Several works have been carried out on the performance evaluation of unreliable production lines (Tempelbeier and Burger 2001; Van Bracht 1995; Xie 1993). However, research on the simultaneous consideration of maintenance policies, production planning and quality improvement from an industrial point of view has still to be done.

Confronted with these industrial problems, there are two research lines. On the one hand, there is a great number of scientific works on the detailed modelling of production resources and activities. On the other hand, a much less developed research line is interested in the modelling of problem solving in production systems design. From these two categories, our research group is interested in the understanding and modelling of the field experts reasoning during the stages of production flow analysis and solution searching. We are also interested in automating this reasoning in order to bring proactive software assistance.

This article presents our approach for performance analysis of production flows. The approach is based on statistical and probabilistic methods and will be a new case of application of the stochastic approach (Le Goc, Bouché, Giambiasi 2006). Section 2 presents the industrial context and describes the project. Section 3 presents the data graphical representation before setting the definition of phenomena in Section 4. Section 5 effectively presents the stochastic approch and finally, Section 6 states our conclusions and perspectives of future work.

## 2. THE INDUSTRIAL CONTEXT

As we have presented in previous communications (Zanni, Barth, Drouard 2007; Bouché, Zanni 2008; Zanni, Bouché 2008), our group is interested in the developing of a software tool for allowing the decision makers companies to have an analysis of their production line flows. This analysis will consist in a general and by-workstation productivity evaluation, the main objective being the maximization of this productivity in terms of the number of produced parts in a given time window.

This diagnosis will be followed by an action plan for the improvement of the line, according to three criteria (quality, maintenance and yield) and a valorisation of the losses which could have been avoided if the action plan was executed. The general idea is to maximize the productivity by improving the production cycle time and by reducing the workstations breakdowns / outages and the number of rejected parts.

We are using a data acquisition system that, after having placed sensors in strategic places of the production line, allows the measuring of different indicators.

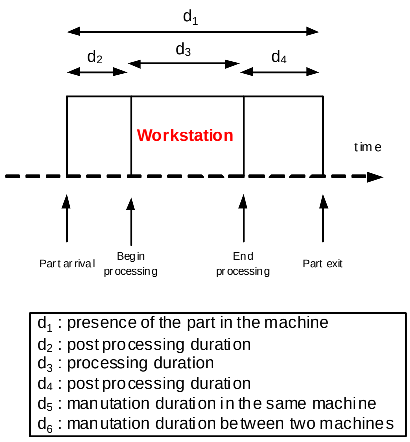


Figure 1: Indicators to be measured during production

During the production stage, we are able to detect if the part is good or bad (and, eventually, the associated fault code) and the times of (Figure 1):

- The arrival of the part to the workstation,
- The beginning of processing of the part in the workstation
- The end of processing of the part in the workstation, and
- The exit of the part from the workstation.

They aim at defining a set of durations linked with the different stages of the work on the piece on the workstation (Figure 1).

In the case of failure of a workstation, the indicators we measure are:

- The failure beginning time,
- The failure end time,
- The identification code of the failure.

The data acquisition system will also provide other necessary information, in particular, the control parameters of the workstations, i.e. some workstation characteristics which will be specific for each process plan. It will also provide maintenance data, information on production modifications, and other relevant information.

We study production lines such as the one described in Figure 2:

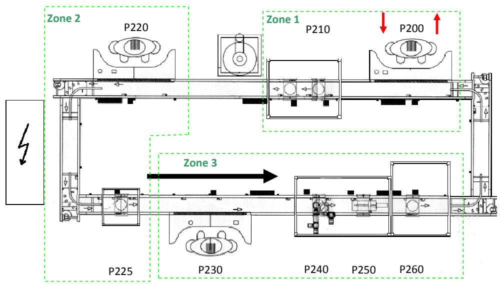


Figure 2: Example of a production line

This is a closed loop, where we have a set of workstations which can be automatic or manual. In Figure 2, workstation P200, for example, is the point where pieces are injected in the line and where they go out. There is also a finite set of pallets that turn around in the loop for transporting the pieces form a workstation to the next one.

This organisation makes necessary to take into account a last set of parameters which are:

- The instance of the production plan,
- The working team.

To take these parameters into account, data are separated by production type and/or by working team; the idea is to guarantee that time periods for analysis are uniform.

## 3. DATA GRAPHICAL REPRESENTATION

These data can be analyzed with frequencies and sequential methods.

First we can proceed to a Poisson analysis. A Poisson process is a process of enumeration which describes the evolution of a “quantity” in time (Figure 3). In our study, it will be a question of tracing the evolution in time of durations ($d_1$, $d_2$,…). In the case of a perfect process, the Poisson curve is a line characterized by its slope λ (λ is a ratio number parts/time).

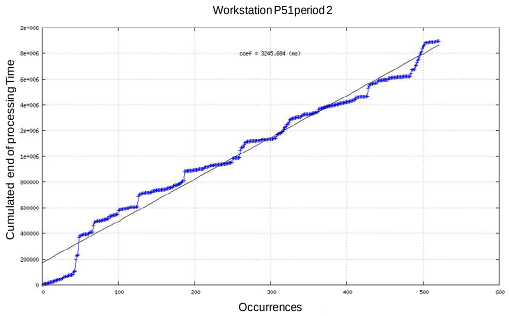


Figure 3 : Poisson process of evacuation times of a workstation

In real processes, we will observe various slopes which will make possible, for example, to determine the moments when the production is “faster”, if there are intervals of drif in the workstation, and to define ranges where the behaviour of the station requires a more thorough analysis.

Second, we can study the evolution of the working time with a model inspirated on control charts which are used in Statistical Process Control (Ishikawa, 1982). We trace the different durations of the tasks according to time (Figure 4).

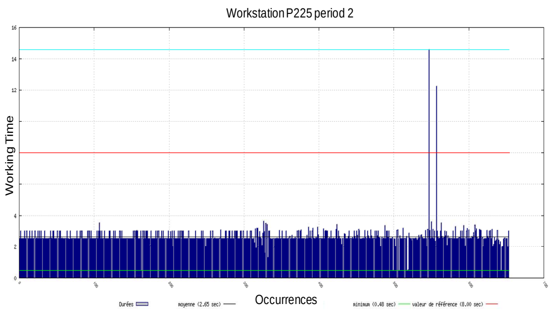


Figure 4: "Control chart" of processing times of a workstation

That will make possible to study possible drifts of the workstation to check that the process is “under control”, to identify the places where improvements could be made, to identify changes of rate/rhythm, or perturbations.

Finally we can analyse properties of the distribution of duration (Figure 5). We trace the frequency of the durations to study the setting under statistical laws of the station to consider.

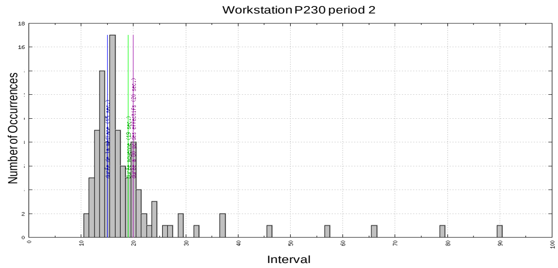


Figure 5: distribution of processing times of a workstation

From these curves, a certain number of analysis may be carried out, such as the analysis of dispersions, of aberrant values, or others.

Other graphical representation could be imagined, such as synthesis representations. But the three types of presented representations are, for us, the base of the analysis. This is a first method to have a better view of reality, and to identify specific zones of bad behaviour or specific phenomena. It corresponds to the more specific level of abstraction. To make better studies, we need to build meta-data which will be associated to specific events or behaviours of the production that might indicate a saturation of stock or a drift of the working time, for example. These behaviours can not be directly deduced from data.

A set of transformations has to be applied the data to obtain the expression of a certain behaviour under the form of a “phenomenon”. The next section will define what we call a phenomenon before showing how we can compute phenomena from our data.

## 4. PHENOMENA

A phenomenon is the expression of a particular behaviour. A phenomenon will be described by a set of attributes, and at least (Le Goc 2004):

- A name,
- A characterization of the location in the production line,
- Two dates:
  - A begin date
  - An end date

These phenomena have been defined in collaboration with experts of production, and in function of the goal of the analyses. A set of specific phenomena has been retained:

- Stock_Saturation,
- Workstation_Drift,
- Workstation_Instability,
- Not_Adapted_Workstation ,
- Out_Of_Bounds_Time, among others.

These phenomena can be deduced from the data provided by the data acquisition system.

For example if we consider the “Workstation_Drift” phenomenon, it is the expression of a drift of the production time on a workstation. We can observe it in the Poisson curves or the control charts with the study of processing duration ($d_3$) or the part presence duration ($d_1$).

More precisely, on the Poisson curves, a phenomenon of drift will be a possible translation of a drop in the “speed” and thus of a drop in the slope of the curve. On control charts, this phenomenon will be the translation of a regular increase in the execution times of a task in time (Figure 6).

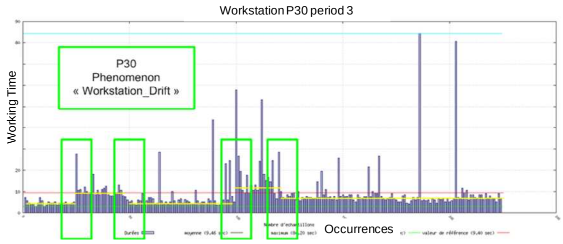


Figure 6: Visual observation of the "Workstation_Drift" phenomenon

To effectively compute occurrences of this phenomenon, we will calculate the slopes of the Poisson processes that are associated with this workstation during the considered time window. If we observe several slopes, named successively $\lambda_1$, $\lambda_2$, $\lambda_3$ ... and that these slopes are decreasing, then we can diagnose a “Workstation_Drift” phenomenon.

$$\forall \lambda_i, i \in [1,n], \text{IF } \lambda_i > \lambda_{i+1}$$
$$\text{THEN "Workstation\_Drift"}$$

In the same way, the list of the durations of processing on a workstation can be used to diagnose a “Workstation_Drift” phenomenon. It will be characterized by an increase of the average of durations.

$$\forall d_i, i \in [1,n], \text{IF Average}(d_1,...,d_k) < \text{Average}(d_{k+1},...,d_n)$$
$$\text{THEN "Worstation\_Drift"}$$

Let us consider the data in Figure 7:

| occurrence | date | added up durations | slope | lambdas |
|---|---|---|---|---|
| 1084 | 19/09/2007 19:01 | 18759881 | | |
| | | | 97771,96 | 0,00010233 |
| 1388 | 19/09/2007 20:00 | 21730557 | | |
| | | | 12599,15 | 0,00007937 |
| 1611 | 19/09/2007 20:53 | 14540168 | | |

Figure 7: Data of a post of the production line

The slopes values on this manual workstation lead us to say that we are in presence of a “Workstation_Drift” phenomenon from 20h00 to 20h53.

The idea is to calculate the slopes on a temporal horizon that is coherent with the production line speed and the considered station and to compare the slopes regularly. The algorithm to build occurrences of this phenomenon is depicted in Figure 8:

```
Constant : h time windows characterized by two dates d1 (begin) et d2 (end)
Constant : p tolerance
Variables : λ1 past slope, λ2 curent slope
Boolean : C Boolean uses to know if we are in Workstation drift period (1) or not (0)

Data :     NbOc (di) Number of pieces treated at time di
                     DC (di) Cumulated period of work at time di

Temporal loop on h
           Compute λ2 = (NbOc(d2) – NbOc (d1))/(DC(d2)-DC(d1))
           Compare λ1 et λ2
           IF the difference is upper than p
                  THEN IF  C = 0
                     THEN     Init occurrence of phenomenon Workstation_Drift
                              Begin date phenomenon = d1
                              C=1
           IF difference is lower than p
                     THEN IF C = 1
                              THEN     Stop occurrence of phenomenon Worstation_Drift
                                       End date phenomenon = d1
                                       C=0
           Make change the time, actualize d1 et d2
           Change value λ1 with value λ2
```

Figure 8: Algorithm for identifying the "Workstation_Drift" phenomenon

The application of this on data of Figure 6 will give us 4 occurrences of the “Workstation_Drift” phenomenon.

To have another example, let us consider the “Stock_Saturation” phenomenon. It can be deduced from data of post processing durations ($d_4$). Figure 9 shows an example of a time window for workstation P210 where we can observe 5 occurrences of this phenomenon.

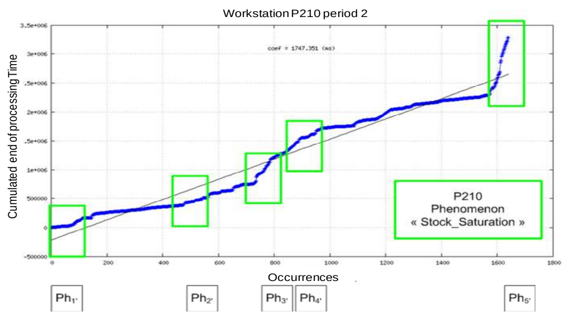


Figure 9: Example of the phenomena "Stock_Saturation"

It is important to remark that now we have to consider 5 occurrences of the “Stock_Sturation” phenomenon rather than all the data on the same time window. We make, also, the assumption that, if no phenomenon is detected, the behaviour of the production line is correct.

Therefore, because phenomena are meta-knowledge, we are able to build a sequence of phenomena, which contains more information than the original data but “lighter” than the original set.

The construction of phenomena is then a kind of discrete event abstraction (Le Goc 2004).

Post analysis may be performed on the phenomena sequence, by application of the stochastic approach to identify correlations which can exist between phenomena. Next subsection will show the bases of the stochastic approach and how we can use it to obtain fault models. These models will serve in the last step of our development to built action plans.

## 5. THE STOCHASTIC APPROACH: IDENTIFICATION OF FAULT MODELS

Once the log of phenomena obtained, new studies may be carried out.

New frequencies studies of the same type as described before may be made, but more especially we can carry out probabilistic studies, in order to identify if there exist correlations among phenomena, and the temporal constraints on these correlations.

The objective is to produce “fault models”. These models may be used to perform real time diagnosis, but also to define action plans and corrections on the production line. Fault models will probably reveal implicit links among the workstations of the considered line.

With this objective in mind, we will apply the stochastic approach (Le Goc, Bouché, Giambiasi 2006). This approach will permit the identification of sequential relations which can exist among phenomena and the computation of time constraints to label those sequential relations.

The stochastic approach is based on the representation of a sequence of discrete event classes in the dual forms of a homogeneous Markov chain and a superposition of Poisson processes.

We will use the BJT4S algorithm (BJT4S is the acronym of “Best Jump with Timed constraints For Signature”). The role of this algorithm is to identify the most important sequential relations from the Markov chain model and to compute timed constraints on these relations from the Poisson process model. The union of sequential relations and timed constraints constitutes a “signature”. It is an operational model of chronicle which its anticipating ratio is equal to or higher than 50% (the anticipating ratio is a measure of the quality of the model). A signature is a behavioural model representative of certain specific situations.

The application of the stochastic approach corresponds to the generic level of analysis of our project. The stochastic approach produces behavioural models that, according to our experience, are realistic indeed and can be used to make prediction or diagnosis for example.

Figure 10 shows an example of correlation between two phenomena detected on workstations P210 and P220 (See the production line in Figure 2). We detect the “Out_Of_Bounds_Time” phenomenon on workstation P220 and the “Stock_Saturation” phenomenon on workstation P210. It is easy to see that, if there is an important working time on workstation P220, the line will be slowed down and a consequence is the saturation of stock that can be observed on workstation P210.

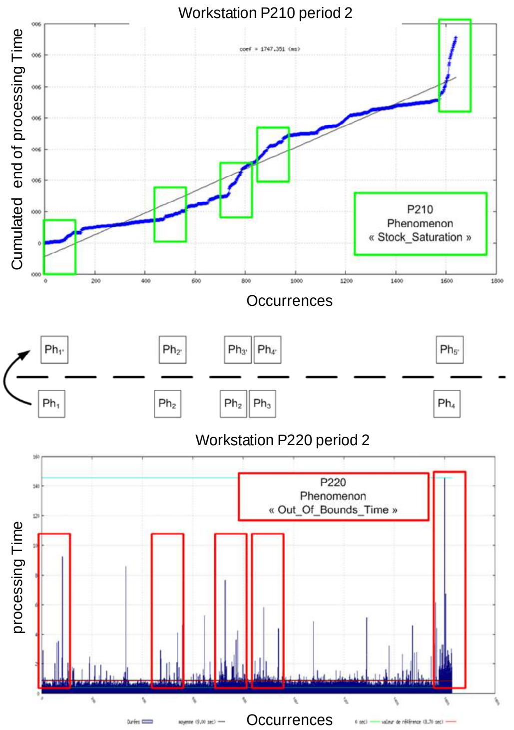


Figure 10: example of correlation between phenomena

Therefore, to improve performance of the line in this context, the problem will not be to eliminate the “Stock_Saturation” phenomenon but to improve the working time on workstation P220. With a single action we can act on two phenomena.

In our context, we make the assumption that the stochastic approach will permit to define global models like the one in Figure 11:

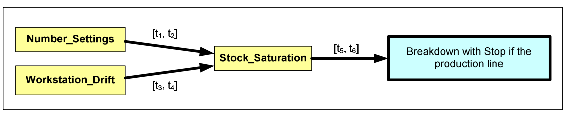


Figure 11 : Example of Breakdown Model

This model has to be read in the following way: If we observe an increase in the number of machine settings followed by a saturation of the stock in the time interval [$t_1$, $t_2$], or if we observe a drift in the behaviour of the workstation followed by a saturation of the stock in the time interval [$t_3$, $t_4$] then we have the risk to have a breakdown with the stop of the production line in the interval [$t_5$, $t_6$].

These models will be the base to the proposal of action plans to improve the performance of the production line in study.

They can also be used to make new studies, define new phenomena with high abstraction levels, etc. This phase will be described in more detail once the implementation of the algorithms for building phenomena will be achieved.

## 6. CONCLUSION

We have presented our global method based on a knowledge-based approach for the development of a software tool for modelling and analysis of production flows.

To the best of these authors understanding, the reasoning on the number of produced parts and the recommendations according to the three criteria, quality, maintenance and yield, have not been fully addressed yet. Also, the generic vs. specific analysis approach will make the tool flexible and available for use by the production staff on site (not necessarily at ease with other possible performance indicators) and decision makers.

The method we propose is based on data processing and data mining techniques. Different kind of techniques will be used: graphic representation of the production, identification of specific behaviours to identify phenomena, and research of correlations among them on the production line. Most of these techniques are based on statistical and probabilistic analyses. To carry on high level analyses, a stochastic approach is used to identify breakdown models.

Breakdown models can finally be used to propose action plans, which can be studied by simulation before implementation.

Therefore, last step of our project will be the development of a simulator. We will use it to compute the effects of the action plan. The principle will be to build new sequences of data with the specifications of the action plan and to introduce them in real data to compute the effects. If a proposition of an action has no effect, it is not necessary to implement it. Furthermore, if the implementation of that action does not produce significant improvements (according to the decision maker) in the quantity of good pieces that were produced, a non application of the action might be envisaged.

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