An integrated approach to develop a simulation model in manufacturing processes

M. Gallo, G. Guizzi, V. Zoppoli

Abstract— The present paper faces the problem of simplifying simulation tools management in their industrial applications. An approach to implement efficiently and effectively simulation models in manufacturing systems, as decision support system, is deployed. The framework proposed is very flexible and easy to use because of the building block architecture and the automatic model generation. This model is focused on operational decisions as those concerning with scheduling problems.

Keywords— Event-driven simulation, Quick modeling, Manufacturing process, Scheduling

I. Introduction

TODAY the markets are hardly testing the survival ability of numerous companies. The model of reactive, vital and competitive enterprise surely is composed of many parts: research and innovation, information technology, credit, purchases, quality, measures and controls, education, etc. The competitiveness in the mid/long term, for the manufacturing companies, surely is tied to their ability to innovate processes/products and in developing of marketing actions. In the short/mid term the competitiveness can be related to a recovery of efficiency and reorganization of the inner processes . So, the development of systems that allow a fast appraisal within alternatives decisions may result very helpful.

In a productive system, the high number of variables, their correlation, uncertainty and constraints increase the problem complexity. Whatever problem we must to face inside a company, from layout redesign, to the production lines balancing, from the scheduling problems to the maintenance, we must necessarily to face high complexity degrees of the system. The simulation of the productive system supplies an aid in the appraisal between alternative choices since, simulating the reality, it allows to evaluate the system dynamics.

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Unfortunately the simulation technique is rather complex in its management and it is somewhat onerous in terms of calculation power (or times of answer).

The proposed methodological approach aims to simplify the simulation tools management in their industrial applications. In the appraisal of alternative solutions often it is necessary to modify the simulation model structurally, these changes require an high burden in terms of development times. When the alternatives are multiple such burden increases meaningfully. Moreover, in the real applications, the decisional variables can assume values in a range and therefore we must choose the optimal values to set these last ones. At last there is a problem of information updating. To simulate the effect of a choice with data not updated can carry out to erroneous appraisals.

II. State of Art

Although simulation models can be discrete or continuous, we consider only the first kind of models as they are more used to model production systems.

In literature there are many discrete event simulation models for manufacturing systems and they can be classified as shown in Fig. 1 [16].

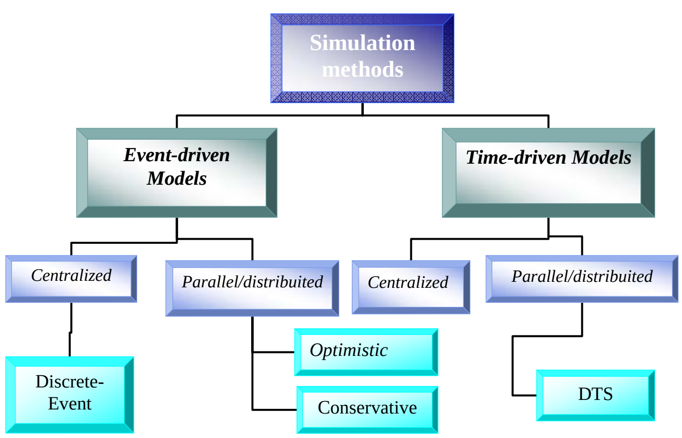


Figure 1: Simulation models classification [16]

In event driven simulations the system evolution is triggered by the occurrence of certain events so the simulation time progresses discontinuously. In time-driven simulations, instead, the scheduling of events depends on the simulation time, that increases with a constant rate.

Production systems can be modelled employing both the approaches. In the first case, the routing of parts is considered, while in the second the system is observed to different instants of time.

However, both the techniques require that at each observation the state of all the components of the model is modified. Most of developed models and commercial packages are, generally, focused on Discrete-Event Simulation (DES).

Nevertheless various recent applications have been developed using the Distributed Discreet-Event Simulation, that decomposes complex problems on more processors, and time-driven approaches (centralized or distributed).

Computer simulation of production and logistic systems has been, and is, widely used to face, efficiently and effectively, strategic and tactical problems. In particular simulation helps to investigate potential failure causes of a production system or to choose between design alternatives [8]. Consequently since the eighties many commercial modeling and simulation software have been developed and employed by major enterprises to support tactical and strategic decisions.

During the last few years a new and interesting application field of computer simulation is becoming that one connected to operational decisions, as tool supporting short-term planning and control activities of a logistic or manufacturing system. This kind of application implies the development and the use of simulation models much more detailed and updatable, in a very little expensive and fast way, according to the real system evolution. Moreover the integration of these models with enterprise information systems allows to carry out the so-called real-time simulation.

Besides, accelerating the simulation time, the designer can compare different project alternatives.

Examples of operational decisions to which computer simulation can be applied with clear advantages, are operations scheduling, capacity planning and production control [4].

The analysis of simulation applications as decision support system within production systems will be effected according to the scheme depicted in Fig. 2.

Various are the approaches developed to use computer simulation to support tactical and strategic decisions. Computer simulation is generally, employed to select the best system configuration.

Particularly, in literature it is possible to identify two different kind of implementation of simulation as tool to support strategic decisions: the first one concerns the design of new systems, the second is related to the analysis and the improvement of existing production systems.

The use of simulation is valuable when the system is complex and it is not easy to study its dynamics. Ceric et al. presented an approach to apply simulation to the development of a system for processing of solid waste installed in Zagreb, Craozia [24].

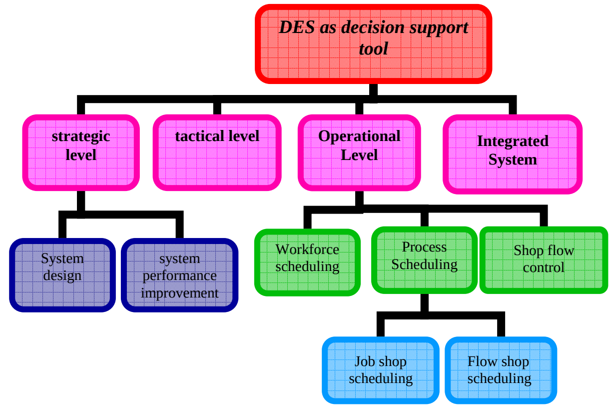


Figure 2. Classification of DES applications as DSS

The verification and validation of the model, carried out in parallel with its development, are independent (the real system does not exist yet) and they are based not on statistical analysis but on the face validity (consultation of experts).

The process of improving performance is a methodical analysis of the whole system in terms of interaction and interdependence of its elements. Different approaches are present in literature on the use of simulation models as a tool to improve the performance of a system.

Since simulation provides information about the critical elements of the system, their various interactions and their relationships with system performance, Alan et al. applied simulation to the performance improvement process[25].

Another approach aimed to evaluate and improve the system performance is that proposed by Ueno et al. [26]. As in the case analyzed by Alan et al., the simulation supports redesigning of the production process.

However, unlike previous approach, the authors use the simulation not to obtain an overall performance evaluation of the system, but to identify the bottlenecks of production lines. In this case, the simulation is seen as an alternative approach to the traditional ones. It has been shown that the technique used is more realistic and practical, especially if the system to analyze is complex.

The aim was, in this case, to determine a new system configuration that allows a certain level of production with a minimum cost.

The performance measures are the actual production rates which take into account setup times, reworks, blocking and starving conditions too.

Another application of simulation to the strategic decision-making process was presented by Kumar et al. [27] whose aim was to redesign a production system to improve its production rate.

In particular, the authors developed a DES system to design a semi-automated production line for plastic parts.

In this case, simulation is used to improve the existing process in terms of capacity. In addition, simulation allowed to estimate the effects on throughput resulting from the new configuration for the process and to set the parameters values that enable to maximize the throughput for the new configuration.

Fewer are the approaches that use simulation as a tool for tactical decision support. One of these is that shown by Watson et al. [28]. The authors faced the orders release scheduling problem in a make-to-order environment. Typically, orders releases in a multi-stage shop are carried out by the MRP module, that considers infinite capacity for resources and lead time for raw material and components based on historical data and past experience. These assumptions lead to a schedule often unfeasible that produces a lot of difficulties during the scheduling phase. The authors, to remove these restrictions, proposed an alternative approach, defined as Resource Planning Based on Queuing Simulation (qRP). This method generates orders releases through a backward explosion of the bill of material similar to that of MRP module except for the use of a simulation model for the system' queues.

The use of simulation, as support tool to the operational decision making process, allows to analyze, from a statistical point of view, the behavior of a production or logistic system, that is subjected generally to controllable and not controllable factors.

Through computer simulation it is possible to select those operational decisions that maximize an objective function or a system performance parameter, and to evaluate the effects of these decisions with the not controllable factors variability.

Process simulation enables to foresee its results and, if it is necessary (e.g. bottlenecks or overloads), to experiment alternative solutions that improve system performance [10].

In literature several problems have been tackled with simulation: workforce scheduling (Andersson et al. [1]), production planning and control of the shop floor (Smith et al. [19], Roy [15]).

As to production scheduling problems, the approaches for flow-shop systems (Vaydianathan et al. [20]) have to be separated from those for job-shop systems (Backer et al. [3], Palaniswami et al. [14], Selladurai et al. [17], Yang et al. [21], Sivakumar [17] Gupta and Sivakumar [7], Gupta et al. [6], Arakawa et al. [2]).

Further examples of the spreading of simulation technique as decision support system in manufacturing are the integrated simulation systems.

In some studies these systems have been employed at strategic level to define the configuration of the production system. Among these studies there is the contribution of Mosca et al. [13] in which the simulation model interacts in a dynamic way with a data collection system to generate a self-building structure for flow-shop systems.

Such approach is suitable for small enterprises, because reduces costs deriving from data collection, model development and its validation.

As to the application of simulation integrated systems to the support of tactical and operational decisions, there is in literature a larger number of very diversified studies.

All these applications are based on the consideration that simulation has to be integrated with ERP systems to carry out an evaluation of more detailed and realistic system performance.

Nevertheless the proposed structures are heterogeneous enough in terms of modality of integration and development of the simulation model.

Musselman et al. [22] developed a simulation-based scheduling function integrated with a ERP system. In this study based on the employment of the APS, production plan takes into account capacity constraints developing a so-called schedulable plan.

The role of simulation in APS systems is essential to get a more truly representation of the real situation.

Concannon et al. [5], instead, considered simulation as a tool to carry out consistent and correct production plans: simulation, thanks to the integration with ERP systems, enables to compensate their incapability to rapidly and efficiently adapt themselves to unexpected environment changes (breakdown, lack of materials etc.).

Marvel et al. [11] proposed a less complex structure that integrates, however, simulation model with production planning and scheduling automatic systems to improve their performance. In this case the aim of simulation is not only to validate capacity plan with a given stock level and demand, but also to size same parts of the production system itself. The proposed model, besides, enables to evaluate the production lines balancing and the problems connected with the backorders, and to compare several system configurations in a continuous improvement perspective.

More complete systems are those proposed by Metal et al. [12] and by Kuhen et al. [9] for job-shop processes.

Metan et al. [12], introduced a learning mechanism based on the interaction between simulation model and the environment. The model learns from the real system and from the environment, it builds a learning tree and selects for each period of scheduling the suitable dispatching rule from the tree.

The updating of the tree, that in such way follows the real system and environment conditions, is obtained by monitoring the performance of the tree itself with control charts. In this way the system gets the production scheduling integrated with the production control.

The most complete integrated system is that one proposed by Kuhen et al. [9]. In this case authors developed a tool supporting the production planning and control by the employment of Java and database applications (Simulation Based Job Shop Analyser). It enables to model and simulate the operation of a whatever job-shop system.

The study of the integration and interactions of production systems through simulation tool has been receiving an increasing attention. An example of this trend is the approach proposed by Ruiz-Torres and Nakatani [23]: they developed an integrated system based on simulation in a supply chain logic.

III. METHODOLOGICAL APPROACH

The aim of the research activity is to develop a simulation platform through a meta-model.

Through the parameterization of a database the meta-model produces in a fast way models of products and services production systems.

The management politics of routing, scheduling and sequencing are generically indicated through a function F(X) where X represents a matrix of state variables of the process during the simulation.

For this reason it is called simulation platform. In fact rather than to establish previously some functions to carry out the different tasks above mentioned, the platform is able to exploit technologies and models, already existing, integrating them.

From a technical viewpoint integration is obtained through the SOAP protocol (Simple Object Access Protocol). SOAP is a lightweight protocol for exchanging information in a decentralized and distributed environment. It is an XML-based protocol which aims to improve the data transfer on a remote system by removing the obstacles that limit the current distributed systems packages. The SOAP protocol is suitable to support a client-server architecture: the requested and processed data between clients and server are organized into SOAP messages and are transferred through the HTTP protocol or another transport protocol. SOAP messages are basically one-way transmissions from a sender to a recipient but are often combined to implement request-reply models.

The simulation platform can be represented as in Fig. 3.

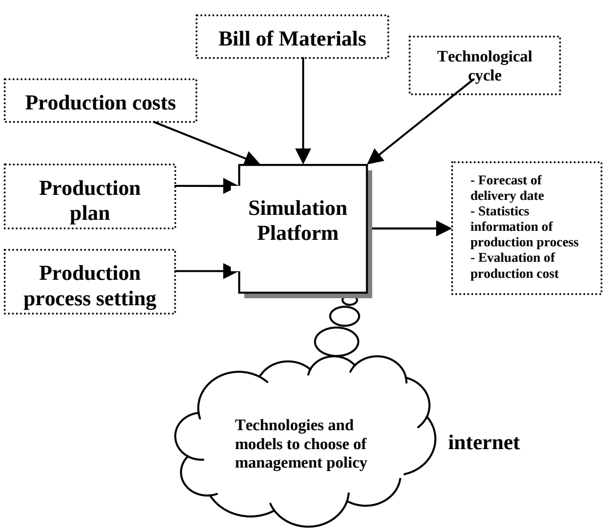


Figure 3. Block diagram of simulation platform.

The platform development requires a meaningful effort and the state of art on this topic doesn't underline similar approaches.

Once gained the simulation model, it is possible to carry out experiments to find the better combination of process control variables or to appraise changes to the production plan that would imply some backlogs.

At the end of simulation it is also possible to carry out an evaluation of the costs connected to each configuration and therefore to select the best system configuration. In this context DOE and ANOVA techniques represent either from a theoretical point of view or from an application point of view the main part of the research activity.

To modelling the production process it has been developed a data base that contains all the information for the parameterization and the recording of the results obtained from the simulation platform.

Particularly, to generalize the simulation model and therefore to make it applicable to several industrial contexts, we develop a simulation meta-model that characterizes the several states of a production order and automatically carries out a simulation model for the production process considered taking necessary information from a database ad hoc designed.

This database uses several sheets containing different data sets belonging to the following categories:

resources data;

jobs data;

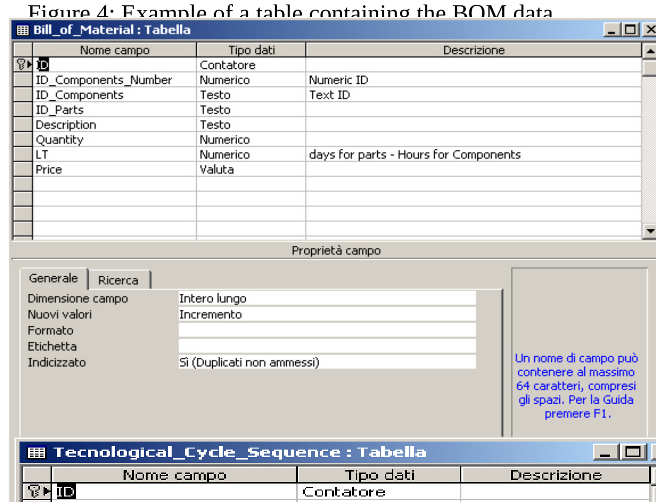
operational data.

The first data set gives information on the available machines: human resources required, capacity, setup time, quality control activities and the costs, including also the overtime costs.

This kind of information is static, since related to the production plant structure.

In Fig. 4, 5, 6 and 7 are shown some tables of the database implemented in MS ACCESS.

Figure 4: Example of a table containing the BOM data



Bill_of_Material : Tabella

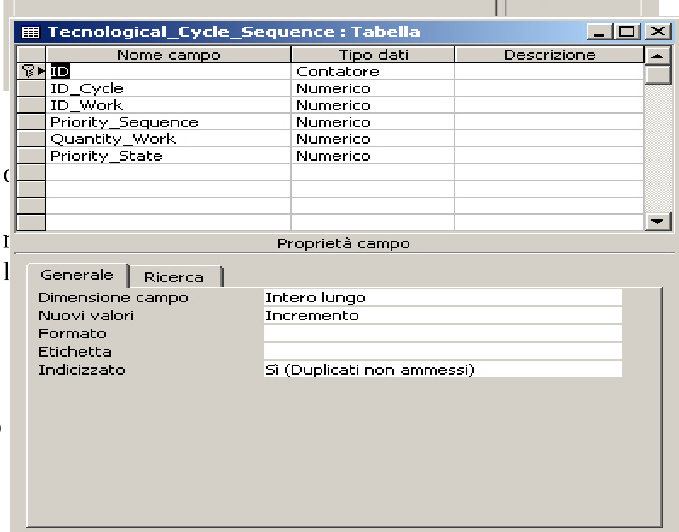
Nome campo	Tipo dati	Descrizione
ID	Contatore	
ID_Components_Number	Numerico	Numeric ID
ID_Components	Testo	Text ID
ID_Parts	Testo	
Description	Testo	
Quantity	Numerico	
LT	Numerico	days for parts - Hours for Components
Price	Valuta	

Proprietà campo

Generale | Ricerca

Dimensione campo	Intero lungo
Nuovi valori	Incremento
Formato	
Etichetta	
Indicizzato	Sì (Duplicati non ammessi)

Un nome di campo può contenere al massimo 64 caratteri, compresi gli spazi. Per la Guida premere F1.



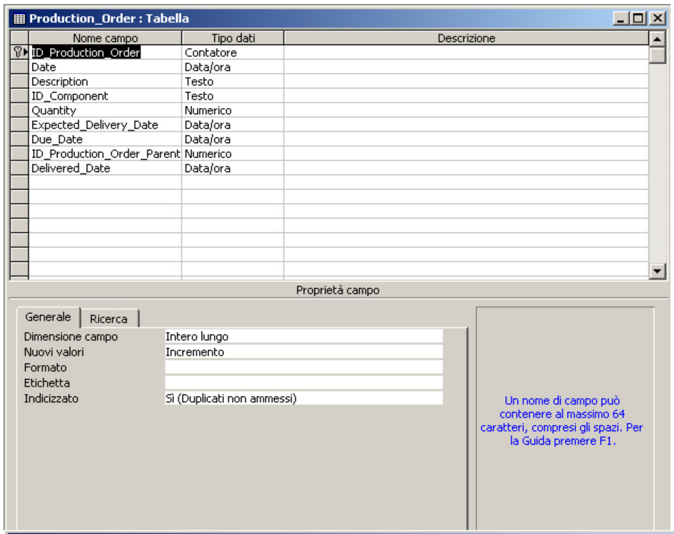
Tecnological_Cycle_Sequence : Tabella

Nome campo	Tipo dati	Descrizione
ID	Contatore	
ID_Cycle	Numerico	
ID_Work	Numerico	
Priority_Sequence	Numerico	
Quantity_Work	Numerico	
Priority_State	Numerico	

Proprietà campo

Generale | Ricerca

Dimensione campo	Intero lungo
Nuovi valori	Incremento
Formato	
Etichetta	
Indicizzato	Sì (Duplicati non ammessi)



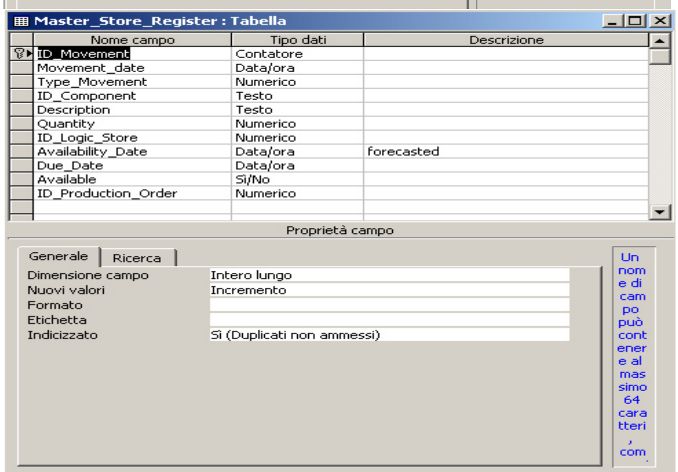


Figure 6: Example of a table containing production orders data

Figure 7: Example of a table containing Master Store Register data

The operational datasheet contains all load and unloading operations data for the central store and the logical stores defined for each production order, to properly manage the engages of products and components.

Besides the well-known benefits deriving from the employment of relational database for data management, as the simulation model is developed in an automatic way according to information in the database, it is possible to easily bring changes and update the production process model even in the case of great size problems (Fig. 8).

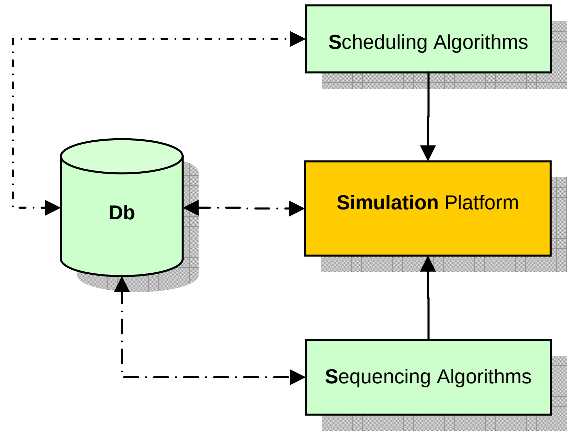


Figure 8: Logical scheme of simulation model operation

The aim of the study is to model and to simulate a job shop production system in an efficient and flexible way. Besides, thanks to the model definition through database, it is possible to simulate several alternative scenarios choosing the system configuration that is more flexible and able to solve the trade off between costs and customer service level.

The simulation model has been developed aiming to obtain a production planning system not exclusively focused on the production capacity saturation and costs minimization, but also on the customer satisfaction, implying already defined at order release time due dates. The input of the simulation model is a order portfolio, that is processed by a scheduling algorithm. At this point, using given information, the simulation model using a defined optimization algorithm carries out the orders sequencing and verifies the plan feasibility.

IV. Proposed Model

The proposed model can be spitted in three parts: the data base, the parametric simulation model, the algorithms to solve specific problems.

The data base contains all the information to generate the simulation model and to record the results of simulation runs. The data base is made up of the following tables:

Production Tables

Bill_of_Materials: it defines the bill of materials for each product.

Technological_Cycle: it defines the technological cycles.

Technological_Cycle_Sequence: it defines the working sequence for a technological cycle.

Work: it defines the operations to make a product. These operations can be linked to a technological cycle.

Resource: it defines the set of resources (i.e. machines) available in the plant.

Resource's_Works: it define the resources required for each operation.

Other_Resource: it defines other resources required for the items defined in the set “Resource” (i.e. manpower, tools).

Other_Resource_for_Resource: it links “Other Resource” to “Resource”.

Required_Material_in Cycle_Phases: it defines the required materials in a technological cycle (i.e. material consumption, spare parts).

Setup_Time: it defines the setup time needed to change the job which has to be processed.

Logic_Stores: Logic stores assigned to each production order (the logic store 0 is the central store).

Orders Tables

Production_Order: it defines the set of production orders

Purchase_Order: it defines the set of purchase orders.

Other Tables

Calendar: it defines the simulation calendar.

Weekly_Hours_Job: it defines the weekly working hours.

Events_Register: this table records the events so to monitor the jobs processing.

Measure_Units: it defines the units of measure used in all the tables.

Simulation_Register: this is a simulation register to record some information about each simulation run.

Warehouse and economic tables:

Master_Economic_Register: this table records all the economic movements (expenses & returns).

Master_Store_Register: this table records all the logical and physical warehouse movements (load & unload).

The database is developed using Microsoft Access. The simulation model is developed using Rockwell ARENA Professional 8.0. The simulation model and the database are interfaced by Microsoft ODBC.

The logical scheme of the simulation platform is represented in Fig. 9. The simulation model starts with the “Start” block. This block generates the specific production process model reading some information from database: available resources, technological cycles etc.. This procedure reads from the database the production orders too. Each order is represented by an entity. So the procedure generates an entity for each order and it sends them to the “Production_orders_wait_material” queue. The entities pass through the “VBA 2” block before they arrive to the queue. The “VBA 2” block verifies the availability of materials and, if necessary, it generate a production/purchase order using the main phases of MRP.

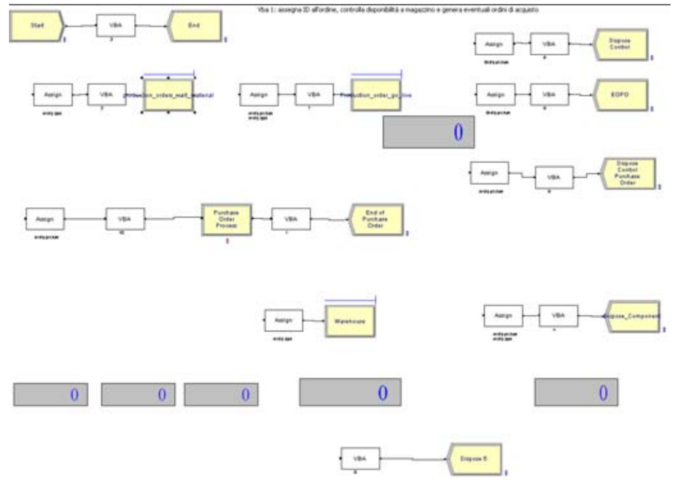


Figure 9: Logical scheme of simulation platform in ARENA.

If in the warehouse (Warehouse block) are available the materials required in the order, the order is delivered immediately and his life cycle finishes. Instead, if some materials are unavailable the system must generate a production order for these materials. So the system must verify the availability of components exploding the bill of materials.

If the components are available, the order passes to the “Production_order_go_live” queue and all the materials required will be sent to the previously generated model of the production process. When the production cycle ends, the products will be sent to the warehouse and the order passes to the “End_of_Production_Order” block. In the database, the order will turn out “delivered”.

If there is some components unavailable, the system generates purchase orders (if needed) and production orders for unavailable materials.

Therefore the order, that previously has launched them, will remain in the state “production_order_wait_material” until all the materials turn out “available” in warehouse. Periodically by the VBA(5) block, a “control entity” checks the availability of materials for waiting orders. When all the materials are available the order passes to “go_live” state and it follows the same path previously shown.

The production process model generated with the platform may have either work station or quality control station. Moreover, we can use some routing policy for the materials through a “Priority_State” defined for each resource. These policies may be defined by tools available in the market. These tools evaluate the priority state for each resource and the simulation goes on.

In the production process model we can use a costing model to evaluate the product cost (materials, machine, manpower).

During the production process simulation, in general, the system has to make some choices: what to produce, what technological cycle has to be chosen – between equivalent cycles – in producing a component, what machine to use – if there are different machines which can process the same item – in a technological cycle. All these variables, together with other decisional variables, may be optimized through some techniques as: genetic algorithm, linear/non linear programming, etc.

V. Conclusions and Future Developments

The methodological approach proposed has many advantages. The automatic generation of the production process model allows a quick development of the simulation model. Moreover, this approach allows to evaluate some alternatives: technological cycles, machines, resource allocation. So we can evaluate performance indicators of the process or economical. Techniques like Design Of Experiments (DOE) and ANalisys Of Variance are very important to evaluate the mix of the variables that strongly influence the objective function.

Another advantage of this approach is the building block architecture. The management policies and generally the decision making problems, are solved using a priority index (of a job, of a resource, etc.). These indexes may be evaluated through some tools that use techniques like neural networks, expert systems, etc.

At last, if we put all the results of the simulation in a database, we can carry out a data analysis at the end of simulation runs.

This approach can be used to solve scheduling problems. Usually when we solve this kind of problem, we try to cut production time and costs.

Another criterion may be searching more robust solutions. So may be very interesting to study the production process variability. This variability can't be modeled simply with aleatory variables. Often the problem is that the variables of the process aren't stochastically independent: previous events, time or other variables may influence them (aleatory functions).

In the industrial applications these cases may be very interesting, because there are some phenomena that have a low absolute occurrence probability, but they may have an high conditioned occurrence probability. This is the reason because, sometimes, production processes, apparently in statistical control, may reach a shift condition.

An indicator, widely used in practice, to detect weak signals that may bring the system drifting, is the FOR (Fall of Rate) defined as:

$$F.O.R.\% = \frac{D \cdot 100}{N}$$

where D is the number of defects found during the production process in a certain time interval and N is the number of products made in the same time interval.

Most of plant and production managers interviewed reported that the causes of these defects can be classified into 3 groups:

- Labour (50%)
- Production Process (20%)
- Quality of raw materials (30%)

Note that firms surveyed have flow shop production lines, with very automated processes and thus the defects linked to the production process depends primarily on the quality of materials and maintenance policies. If we consider a job shop production process, the percentages reported may suffer significant changes.

A substantial number of system drift cases are related to personnel. Some frequent causes are:

- negligence of various kind;
- weariness of workers, in particular towards the end of work shift;
- production information transfer errors.

Regarding the first cause, it is completely random and it is not easy to understand the laws that govern this phenomenon.

The second cause may be represented through a wear process and therefore with models traditionally used for mechanical components.

Production information transfer errors could be modelled using a Bernoulli process.

Let X_i a binary random variable for which the value of 1 indicates the event "information correctly transferred" and the value 0 indicates the event "information improperly transferred", and:

$$\Pr\{X_i = 1\} = 0.99$$
$$\Pr\{X_i = 0\} = 0.01$$

When a generic information is transferred through the various stages of the production process between different operators, the probability of correct information at the i-th transfer is:

$$\alpha(i) = \alpha(i-1) \cdot 0.99 + \left[1 - \alpha(i-1)\right] \cdot 0.01$$

It can be shown that after only 50 transfers this value reduces to about 0.7.

Regarding the defects induced by the quality of materials, a model in which raw material possess a certain degree of non-quality could be used.

This level can never decrease as a result of processing, activities, but can increase or, at most, remain unchanged. If the degree of non-quality increases above a certain threshold, the piece is discarded.

When a certain part passes through a process stage, the probability that its non-quality degree increases depends on the degree of non-quality already possessed by the part (raw material) and produced by the previous production stages. This increase, obviously, depends only on the non-quality degree of previous phases which are stochastically related to the current phase.

Considering a flow shop line consisting of m machines and letting

E_i the event "non-quality degree increase at i-th stage",

Xi the increase of non-quality degree produced by the i-th stage of the process (regardless of non-quality degrees due to other process stages)

a_i an amplification coefficient that takes into account of poor quality due to previous (production and/or procurement) phases, it results:

$$\Pr\{E_1 \mid X_0\} = \alpha_1,\ \Pr\{E_2 \mid X_0, X_1\} = \alpha_2,\ \ldots\ldots,$$
$$\Pr\{E_m \mid X_0, X_1, \ldots, X_m\} = \alpha_m$$

and

$$X_1 = a_0(X_0)\cdot X_0,\ X_2 = a_0(X_0)\cdot X_0 + a_1(X_0, X_1)\cdot X_1,$$
$$\ldots\ldots,\ X_m = a_0(X_0)\cdot X_0 + \ldots + a_m(X_0, X_1, \ldots, X_m)\cdot X_m$$

The evaluation of these correlations is rather difficult, but the advantages are certainly not negligible.

Both in flow-shop systems and job-shop systems it is always possible to choice between various sequence of operations to produce a certain product.

Clearly, exploiting the knowledge of correlations mentioned above, it would be possible to carry outa scheduling with better-quality products without changing machines, but only changing the sequence of technological processes.

Such a scheduling tends to improve product quality organizing resources in a different way, without the need for large investments.

The main advantages of this approach occur, however, in the case of job shop systems, as the system degrees of freedom are significantly greater.

Another interesting use of the platform aimes to optimize production planning for a production system with constrained capacity. In fact a fairly simple application to flowshop systems, using the simulation and the optimization tool embedded in ARENA (OptQuest), yielded interesting results.

The model uses two matrices:

- P(j,t): shows the amount of product j to be delivered during the period t.
- X(j,t): shows the amount of product j, which is to be launched in production in the period t.

Assuming the same technological cycle for all products j, the only difference is the manufacturing time, considering the developed simulation model (flow shop with two machines in series), we can optimize the matrix X(j, t), knowing when, how and what we have to produce in the different time buckets.

The optimization can be made on the basis of the following parameters:

Min! $\Sigma_{j=1..J} \Sigma_{t=1..T} [h_j \cdot I_{jt}] + \Sigma_{j=1..J} \Sigma_{t=1..T}[sc_j \cdot (Y_{jt})]$

subject to:

$\Sigma_{j=1..J} \Sigma_{t=1..T} IR_{jt}=0$

$\Sigma_{j=1..J} \Sigma_{t=1..T} X_{jt}>=1$

$\Sigma_{=1..t} X_j >= \Sigma_{=1..t} P_j \quad \forall j \in 1..J$ e $\forall t \in 1..T-1$

$\Sigma_{t=1..T} X_{jt} <= \Sigma_{t=1..T} P_{jt} \quad \forall j \in 1..J$

$X_{jt} \in N$

Where:

h_j : Holding costs for a unit of item j in a period ;

sc_j : Setup costs for a lot of item j;

I_{jt} : Stocks of item j at the end of the period t;

Y_{jt} : Binary setup variable (= 1, if there is setup for the item j in period t, 0 otherwise);

IR_{jt}: Number of item j not delivered at time t;

The example considers the scheduling of 2 products in 6 time bucket.

The demand for the product (P_{jt}) is as follow:

Item/Time	1	2	3	4	5	6
1	0	0	30	0	0	30
2	0	0	10	0	0	0

Running the optimization tool with 500 runs, a good solution is found after 22 simulations and after 327 simulations it gets the optimal solution.

The solution (X_{jt}) is as follow:

Item/Time	1	2	3	4	5	6
1	7	23	0	30	0	0
2	10	0	0	0	0	0

Fig. 10 shows the performance graph of the optimization process.

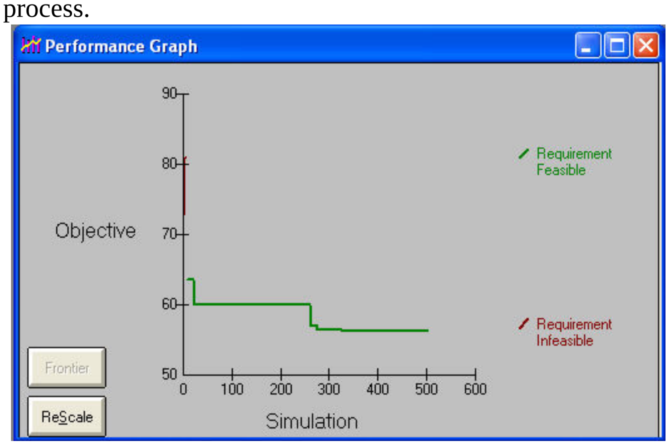


Figure 10. Performance graph of the optimization with OptQuest.

Of course, the test should be performed on more complex systems where the matrix X_{jt} has a greater dimensions.

These are some possible future development of the proposed platform.

VI. References

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