Service level analysis for an automotive prototype manufacturing company through the application of discrete event modelling and simulation

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Abstract: This study addresses modelling and simulation as a tool for the analysis and evaluation of the design and manufacturing process of automotive prototypes. The application of these tools allows to visualise the process from a broader perspective and identify the downtimes that induce high variability to the process. Through the implemented simulation, the process cycle time is estimated given a certain level of service for each family of sequences identified in the sample. These results provide a quantitative reference of the response time according to the desired level of service for the process in general. In addition, an improvement scenario is provided through the implementation of a control monitor (KPI) in the critical activities that induce high variability to the process, which allows a 39% reduction in the magnitude of the lead times.

Keywords: supply chain; business analytics; discrete event simulation; Petri networks; CPN tool.

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1 Introduction

Over the years simulation has been applied to various sectors such as manufacturing, health, services, defence among many others. The relevance of implementing simulation techniques is a significant factor to consider in real-world applications because there is a growing need to address the complexities and interrelationships of companies (Jahangirian et al., 2010). Simulation is a quantitative method, which is used relatively frequently in business analytics, it allows obtaining estimated information for the evaluation and comparison of different operating scenarios, it is an effective tool to identify the causes and quantify the effects on the performance of a process individually or even at the supply chain level. There are several computational tools for the implementation of simulation models. Tools range from spreadsheet use to platforms for dynamic system simulation, discrete event simulation (DES), and simulation games. On the other hand, the type of simulation to be applied depends on the type of question that the model must answer (Kleijnen, 2003) and what type of information decision makers require.

Simulation techniques have proven to be a useful and valuable tool to design, analyse and evaluate the behaviour of manufacturing systems, due to their low cost, fast analysis and low risk (Mourtzis, 2020), they also allow companies to visualise their processes from a systematic perspective seeking a better understanding of the cause and effect between them in addition to allowing a better prediction of certain situations (Belda and Grande, 2009).

DES is applied to systems that can be represented by discrete mathematical logic models (Páez et al., 2011), which are associated with state automata, Petri nets, and event graphs (Tako and Robinson, 2018). DES models are the mathematical description of a system that allows studying the occurrence of events in processes (Álvarez, 2009), they use random numbers generated by advanced computational algorithms, which give a guarantee of unbiased and the creation of the stochastic component of the model. A DES can be performed when product information is available in an enterprise resource planning (ERP) system, a system that allows obtaining information to detect failures or drawbacks such as bottlenecks or delays in the production plan (Palma et al., 2009).

The elements that a DES model has are entities, attributes, variables, events, time, resources, and the statistical data warehouse. As a result of the model, linear functions or statistical probability distributions can be obtained such as uniform, exponential, gamma, binomial among others (Álvarez, 2009). Simulation provides knowledge and a greater understanding of a manufacturing system, influences cost reduction and production acceleration (Tako and Robinson, 2018), and serves to evaluate performance metrics (Páez et al., 2011). The analysis of the results obtained from the simulation aims to gain a better understanding of the behaviour of the system, draw conclusions about its performance, as well as provide information for the generation of recommendations about the system.

Simulation models are widely used in the literature, for example, in the work of Persson and Olhager (2002) a real case of the telecommunications industry is analysed, in which they seek to analyse and evaluate the relationships between quality, delivery times and cost in their supply chains, for this they used the Taylor II simulation software for discrete event simulations. On the other hand, in the work of Zhang and Zhang (2007) the simulation approach is used to evaluate the benefit of exchanging demand information in a three-tier model of the supply chain. Atieh et al. (2016) employed a hybrid approach of simulation and value stream mapping in the glass industry to detect bottlenecks. Heshmat et al. (2017) implemented simulation as a tool for the analysis, modelling and detection of the bottlenecks of a production line. Lugaresi and Matta (2018) present analysis in the context of current research on existing approaches to implement real-time simulation (RTS) concepts and their current state of development. Antonelli et al. (2018) implemented dynamic system simulation and discrete event simulation to evaluate the performance of a manufacturing system. Sang et al (2018) implement a simulation approach to analyse the rental housing supply chain inventory problem. A systematic and flexible process is proposed that efficiently provides critical decision making to support managers. Habibifar et al. (2019) develop a novel methodology based on the integration of simulation and data enveloping analysis for the optimisation of the performance of a production line of the pharmaceutical industry. Mostefaoui and Dahmani (2019) present the NB-DEVS approach for the modelling and simulation of complex systems involving imperfectly, they propose to integrate the naïve Bayesian network (NB) into DEVS formalism. This new approach permits to study the system when its behaviour is uncertain. Hamad (2020) developed a traffic simulation model to quantify the improvement in performance due to the reduction of vehicular traffic on a university campus. Mota et al. (2021) perform the analysis of the security area within an airport with particular restrictions. To improve capacity, different categories and policies for passenger processing were designed and evaluated through simulation models. Table 1 summarises a literature review extract on the application of simulation modelling in manufacturing and in other industrial domains.

Table 1 A literature review on the application of simulation modelling in industrial domains

Reference	*Scope*		*Application*	*Research design*	*Year of publication*
	Process	*SC*			
Heshmat et al.	•		Manufacturing system	Discrete event simulation (DES)	2017
Antonelli et al.	•		Manufacturing system	DES and SDS	2018
Mota et al.	•		Transport	Simulation approaches	2021
Habibifar et al.	•		Manufacturing system	Simulation and DEA	2019
Hamad	•		Transport	Simulation approaches	2020
Mostefaoui and Dahmani	•		Academic case	NB-DEVS approach	2019
Sang et al.		•	SCM/inventory	DES and SD	2018
Mota and Scala	•		Academic case/transport	DES	2019
Jahangirian et al.	•		Literature review/manufacturing	Simulation approaches	2010
Lugaresi and Matta	•		Literature review/manufacturing	Real-time simulation (RTS)	2018
Atieh et al.	•		Manufacturing system	VSM and Simulation approach	2016
Persson and Olhager		•	SCM/manufacturing	DES	2002
Zhang and Zhang		•	SCM	DES	2007

Currently, simulation has the challenge of being applied with big data in supply chains as a decision support system. Some examples of the exploration of these paradigms can be found in the recent academic literature, where simulation is highlighted as a useful and valuable tool that allows learning and testing the behaviour of systems.

This paper illustrates the application of simulation-based on discrete events as a tool for the analysis and evaluation of the prototype design and manufacturing process in which the problem of recurrent delays in the delivery of orders has been detected. The modelling of the system was initiated by the mapping and analysis of the process as it is, from the collection of real data that comprised 3 months of processed orders, the most relevant periods of inactivity observed between the execution of the tasks are identified and quantified, periods mainly attributable to the flow of information and the visibility of the process for the different actors, a situation that induces high variability, which hampers the completion of the production orders on time, and therefore by identifying these elements, it is possible to point out them as the critical or limiting factors in the process for the achievement of the agreed delivery dates.

The subsequent sections of this work are organised as follows. In Section 2, the description of the case study is provided. Section 3 introduces the simulation methodology. The formalisation of the models implemented using the CPN tools tool is illustrated in Section 4. In Section 5, the results obtained for each sequence and at the aggregate level are presented and discussed. Finally, the conclusions section describes in detail the interpretation and the usefulness of the obtained results, as well is provided with a list of potential future lines to exploit the information obtained and proposed models for the benefit of business operation and decision making.

2 Case study

2.1 Description of the problem

In a company dedicated to the automotive sector specialised in the manufacture of automotive parts, such as gasoline pumps, gears, alternators, ABS engines, among many others, another fundamental activity is carried out regarding the design and manufacture of prototypes for automotive components, the company has a specialised department in charge of the design and construction of the gasoline pump prototypes according to the specifications and parameters provided by the customers (assemblers). The process consists of a set of activities carried out by various areas that perform key activities for the completion of each project, as they are prototypes the procedures that are carried out are different from those of series production because it refers to new products or existing products that require modifications subject to certain specifications and parameters. The prototype design and manufacturing process begins once the client’s requirement is generated, so each area involved needs to develop its activities so that the process continues according to the plant’s planning.

The company under study faces a problem related to deliveries of prototype production orders, in which recurrent periods of inactivity and high variability between the end and the start of consecutive activities have been detected. Such alterations are presented due to interruptions in the flow of information between the areas, departments and personnel in charge of the process, which causes inconsistencies in the sequence and structure of the process, situations that currently represent the source of delays in the completion of each order and low processing time reliability.

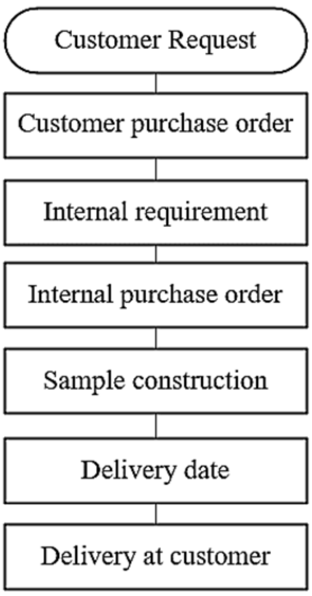
Following the above, this work reports the generation of a tool that allows the company to analyse and quantify the impact of variation and interruptions, which cause inconsistent and out-of-control process performance, to carry out improvement strategies for variability reduction. The proposed model can be adapted and reproduce the behaviour of the process under modified conditions, the above fulfils the purpose of offering the functionality to estimate effects of the potential improvement action designed to attack the sources of variability, and to establish a realistic (based on the actual capability) process cycle time for delivery (consistent lead time), and thus seeks to help to allow the achievement of the level of service expected by the company and customers.

2.2 Description of the system

The prototype design and manufacturing process begins when the customer (assemblers) sends the supplier its requirement where the specifications and components of the system required are indicated. Subsequently, the sales department receives the customer's request and works jointly with the engineering and purchasing departments, which are responsible for preparing the technical specifications and the quotation of the components and the final prototype, respectively. Finally, when the terms of both customers and the manufacturing company are accepted, the formal purchase order is issued, so that it is necessary to enter it into the company's data management system.

After the purchase order is entered, the raw material supply, programming, and adjustments to the production lines for the manufacture of the product are made, and once the prototype is ready, the product is inspected and validated to be sent to the customer. The above is illustrated in the following flow chart (Figure 1).

Figure 1 Should-be structure of the process flow



2.3 Assumptions for the simulations

According to the information provided and aligned to the concerns of the owner of the process, the scenario that is sought to be evaluated through the implementation of simulation models corresponds to the maximum time duration for the completion of the individual activities that constitute the process, see Table 1. However, it should be noted that the structure of the implemented models is easily configurable to evaluate other scenarios (empirical or fitted distributions included for those values).

Table 2 Maximum individual duration of process activities

Activities		*Duration (days)*
A	Customer requirement	1
B	Customer purchase order	7
C	Internal requirement	1
D	Internal purchase order	7
E	Sample construction	14
F	Verification and validation	3
G	Delivery date	7

3 Simulation model

In this section, the modelling of the system is presented, but first, the simulation methodology used is given, then some Gantt diagrams for the identified sequences are presented.

3.1 The simulation methodology

The implemented methodology comprises the steps intrinsic to a simulation project as proposed by Banks (1998), as shown in Figure 2, the methodology was developed in six phases. In phase 1, the problem to be treated and the description of the system to be analysed are formulated. In phase 2, the database is collected, consisting of a sample containing 3 months of processed orders. The areas and departments involved are analysed, as well as the activities they carry out, in which the execution times of each activity are provided by the personnel in charge (scenario to be analysed), the detailed mapping of the complete process is carried out through the construction of Gantt charts for each order that makes up the data sample, to identify the periods of inactivity between the end of one activity and the beginning of the next. From the analysis of the collected sample (Gantt charts), it was detected that the processed orders do not follow a single processing sequence, however, can be grouped into four families of sequences that characterise 80% of the data sample, which allows a specific study of each of the identified sequences. Later in phase 3, the process is modelled using coloured Petri nets (CPNs), for the implementation of the simulation model the CPN Tools software is used. Phase 4 corresponds to the pilot test to verify the logic of the model, as well as functionality tests, including the adjustment of the distribution of downtime between the end and start of consecutive activities. Consecutively in phase 5 with the information obtained from the simulation models is provided to the analysis and documentation of the results, which allow to visualise and quantify the waiting time of the process given the expected level of service, that is, the time to commit orders if a certain level of service is desired (measured as the accumulated percentage of orders completed in that time or less). Finally, phase 6 highlights the importance of the implementation of simulation models as a tool to evaluate the current manufacturing process of automotive prototypes, in addition to providing a tool whose purpose is to obtain information that allows establishing a standard delivery time associated with a certain level of service.

Figure 2 Simulation project flowchart

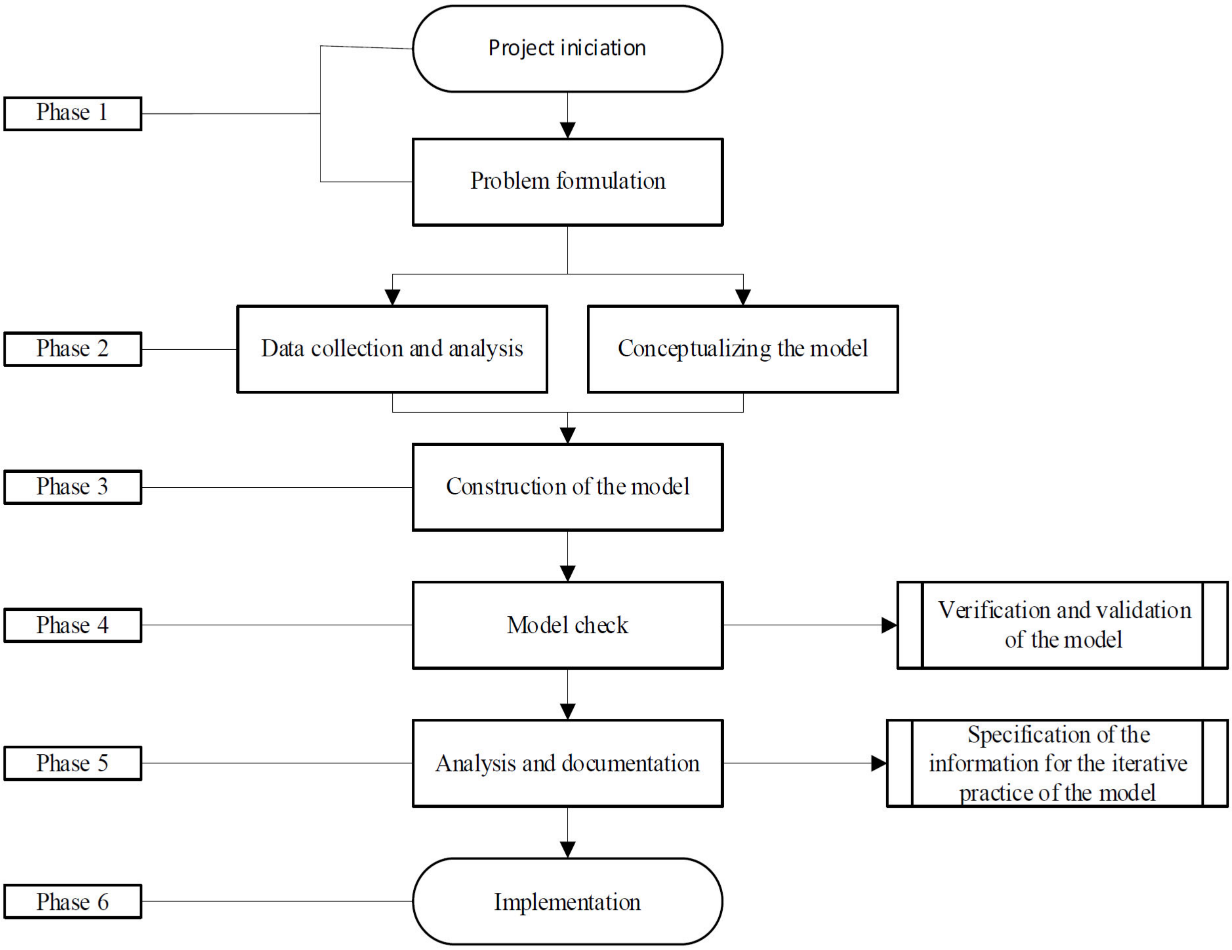


Figure 3 Gantt chart of an order processing according to sequence 1 (see online version for colours)

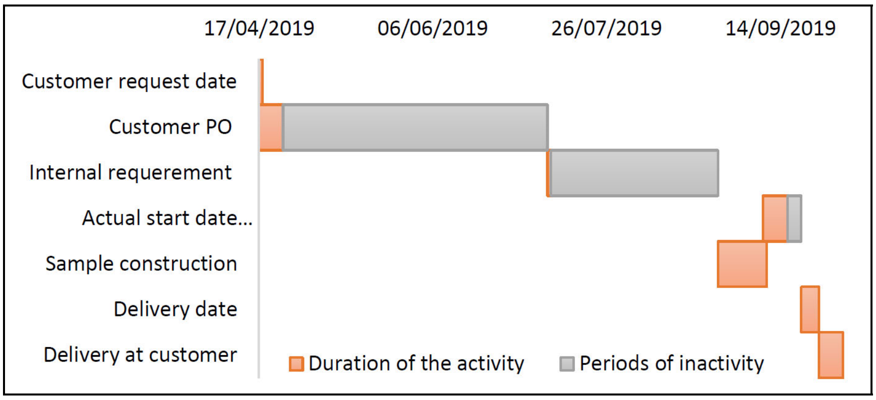


Figure 4 Gantt chart of an order processing according to sequence 2 (see online version for colours)

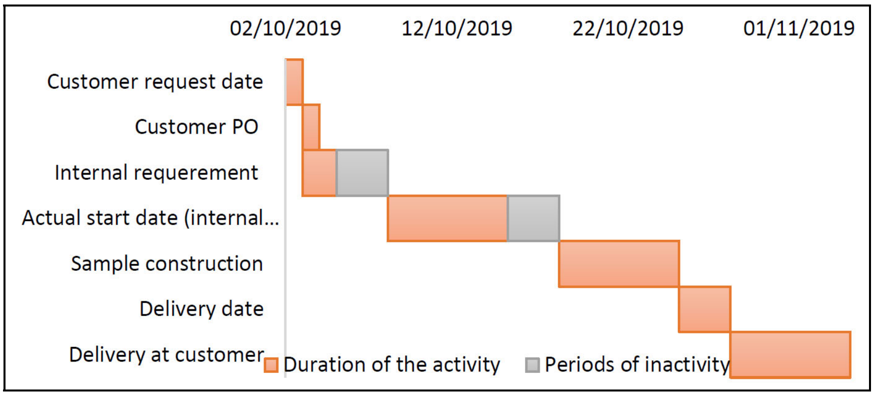


Figure 5 Gantt chart of an order processing according to sequence 3 (see online version for colours)

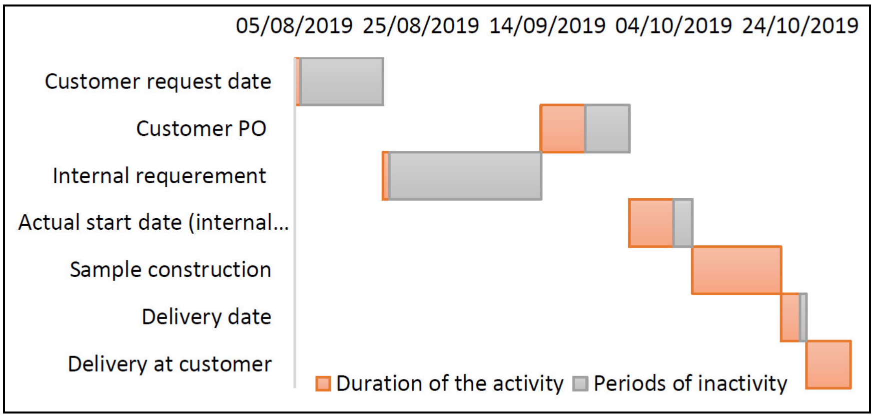
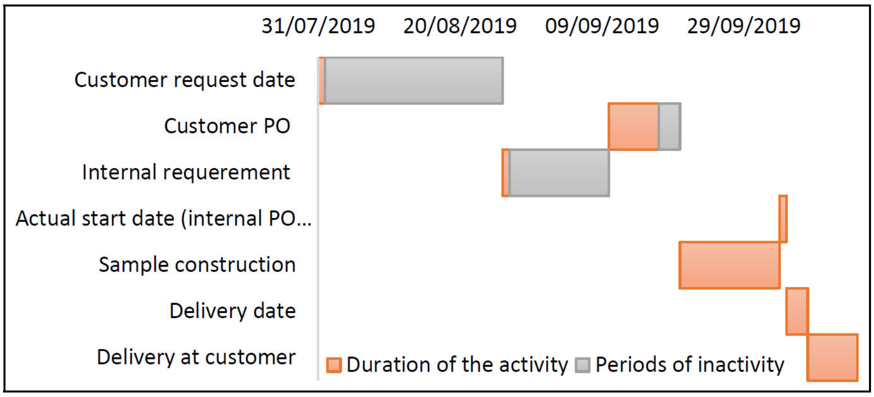


Figure 6 Gantt chart of an order processing according to sequence 4 (see online version for colours)



3.2 Process mapping

Based on the detailed flow mapping of each order of the sample, it was identified that the orders do not follow a single processing sequence, so the activities were grouped into macro activities (subsets of consecutive tasks) thus obtaining four families of sequences that encompass 80% of the processed orders, which allows a specific simulation model to be made for each of the sequences detected in the sample. Figures 3 to 6 show the processing structure of each identified sequence.

4 System modelling

The process modelling was performed using CPNs, which are a formalism for modelling and simulation of processes under a DES approach. For the implementation of the simulation model, CPN Tools is used, which is a fast simulator that can efficiently handle both untimed and timed CPN models.

Figure 7 Empirical distributions for gap values for each sequence

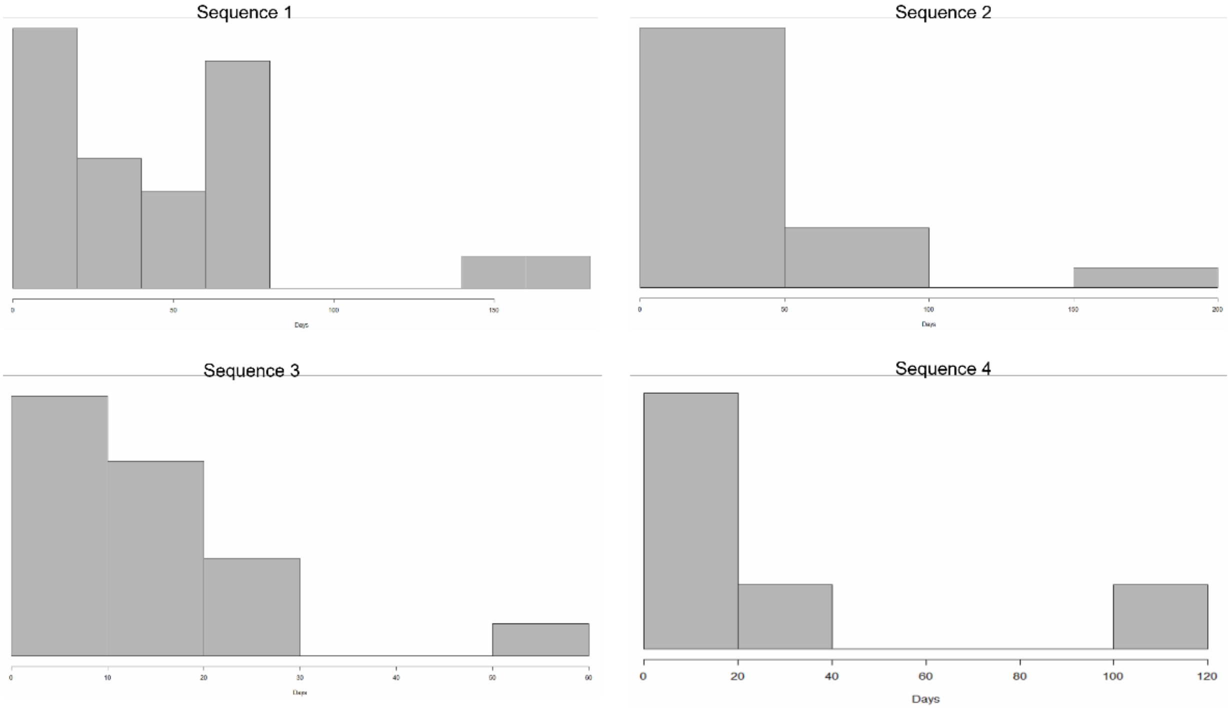
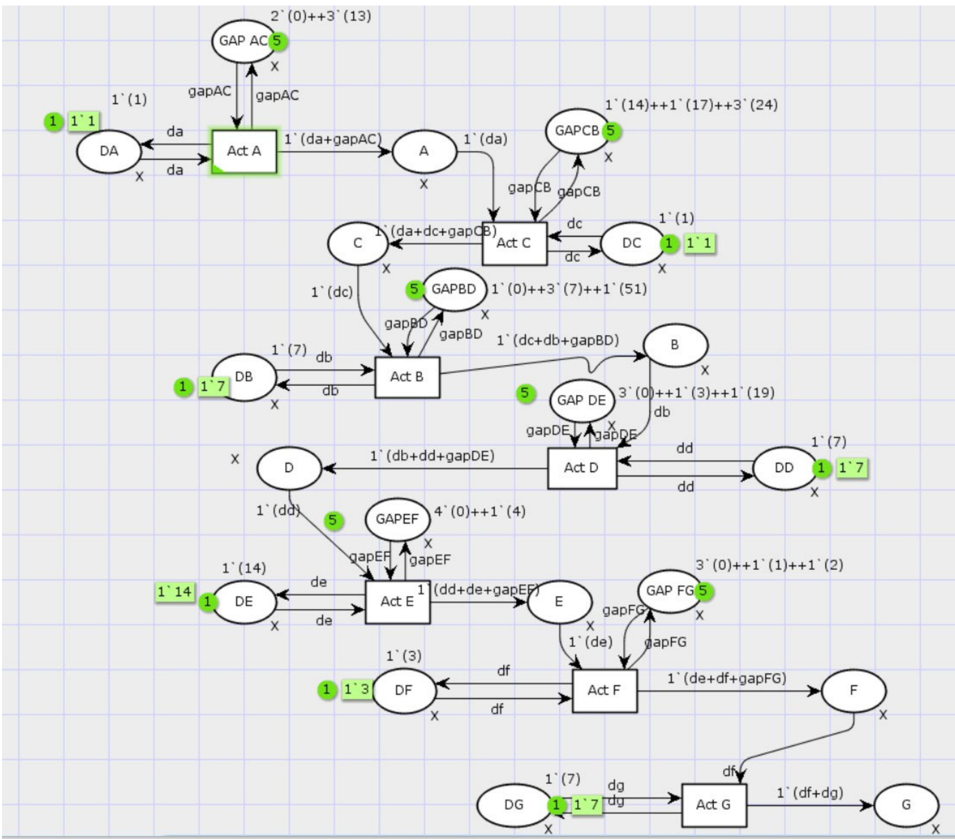


Figure 8 Model implemented in CPN tools for processing sequence 3 (see online version for colours)



To implement the model, the process flow of each sequence is converted to a diagram network, in which place nodes (circles that represent the system states), transitions (rectangles that represent actions or events that cause changes in the system), colours (units within the system) and their respective arcs that connect the information that is exchanged between the nodes are established.

The information used to simulate the performance of each macro activity corresponds to the maximum execution duration in days (scenario to be evaluated), as for the downtimes observed between each macro activity, these are modelled by an empirical distribution with the values observed in the sample of historical data identified for each detected sequence. The empirical distribution (illustrated in Figure 7), should be noted the presence of discontinuities, thus is used because in the verification and validation process (phase 4) the models that use these empirical distributions resemble better the real behaviour of the system (simulated lead times), however, tests were carried out with other distributions such as the uniform and triangular distribution.

Figure 8 presents the model (network diagram) for sequence 3, where the four components are identified: nodes places, transitions, colours, and arcs.

In the first instance, it is necessary to declare the model specifications; the input variables that are stored and used in the system, declared as *da*, *db*, *dc*, *dd*, *de*, *df*, *gapAB*, *gapBC*, *gapCE*, *gapED*, *gapDF*, *gapFG*, all integer variables, representing the maximum duration of each activity, after the execution of each activity (transition nodes *Act A*, *Act* B, *Act C*, …) the occurrence of a time lag between its completion and the start of the subsequent activity or activities are simulated, the duration of the accumulated process is recorded at each stage of the process in the nodes place *A*, *B*, *C*, *D*, *E*, *F*, and in the case of node *G*, the total time of information flow through the arcs in the direction of the nodes to conclude the whole process is quantified, the magnitude of the inactive times is simulated by implementing the values obtained in the Gantt diagrams, declared as nodes place in each transition where periods of inactivity were detected.

4.1 Detailed description of the model

The colours, places, and transitions of the model implemented in CPN tools are summarised in Tables 3, 4, and 5, respectively.

Table 3 Colours in the model

Colours	*Description*	
	Definition	*Explanation*
da, *db*, *dd*, *de*, *df*, *dg*	Int 1 … N	Colour represents the duration in days of activities, for example, 1′(1), where the activity is one day.
gapAB, *gapBC*, *gapCE*, *gapED*, *gapDF*, *gapFG*	Int 1 … N	Colour represents the duration in days of periods of inactivity between activities.

Table 4 Nodes place in the model

Description		
Node	*Colours*	*Operation*
DA	1′(*da*)	The token represents the average duration (days) of the execution of the request by the client.
DB	1′(*db*)	This token shows the average duration (days) of receipt of the purchase order.
DC	1′(*dc*)	Token sets the average duration (days) of order validation in the data management system.
DD	1′(*dd*)	The token plots the average duration (days) between the stock review and the start of manufacturing.
DE	1′(*de*)	This token defines the average duration (days) of manufacturing prototypes.
DF	1′(*df*)	This token defines the average duration (days) at which the estimated delivery date is sent to the customer.
DG	1′(*dg*)	The token defines the average duration (days) of receipt of delivery to the customer.
A	1′(*da* + *gapAB*)	This token quantifies the duration of activity A and the variation in the start and end of the quote for the purchase order.
B	1′(*da* + *db* + *gapBC*)	Token quantifies cumulative duration of predecessor activity (A) + activity B + downtime between term and start of the consecutive activity (C).
C	1′(*db* + *dc* + *gapCE*)	The token measures the cumulative duration of predecessor activity (B) + activity C + the downtime that exists between the term C and the start of E.
D	1′(*de* + *dd* + *gapDF*)	The token quantifies the cumulative duration of the predecessor activity (E) + activity D + the downtime that exists between the term D and the start of F.
E	1′(*dc* + *de* + *gapED*)	The token quantifies the cumulative duration of the predecessor activity (C) + activity E + the downtime between the term E and the start of D.
F	1′(*dd* + *df* + *gapFG*)	Token quantifies cumulative duration of predecessor activity (D) + F activity + downtime between term F and G start.
G	1′(*df* + *dg*)	The token quantifies the cumulative duration of the predecessor activity (F) + activity G.
GAPAB	*gapAB*	Token quantifies duration of inactivity time between activity A and B.

Table 4 Nodes place in the model (continued)

	Description	
Node	*Colours*	*Operation*
GAPBC	*gapBC*	Token quantifies duration of inactivity time between activity B and C.
GAPCE	*gapCE*	Token quantifies duration of inactivity time between activity C and E.
GAPED	*gaped*	Token quantifies duration of inactivity between activity E and D.
GAPDF	*gapDF*	Token quantifies duration of inactivity time between activity D and F.
GAPFG	*gapFG*	Token quantifies duration of inactivity time between activity F and G.

Table 5 Transition nodes in the model

Transition	*Explanation*
Act A	Simulates the completion of activity A (customer requirement).
Act B	Simulates the completion of activity B (purchase order).
Act C	Simulates the completion of activity C (internal notice).
Act D	Simulates the realisation of activity D (start date plant Toluca).
Act E	Simulates the realisation of activity E (manufacturing).
Act F	Simulates the realisation of activity F (validation and shipping).
Act G	Simulates the completion of activity G (completion of the process, and recording of the cumulative duration of predecessor activities).

5 Results

5.1 Model outcomes validation

The validation of the model outputs has been conducted by applying operational validation, which consists of determining if the behaviour of the outputs of the simulation model has the precision required for the intended purpose of the model (Sargent, 2013). For the case study, a hypothesis test was used considering the sample of available historical data. The output variable used for validation is lead time (Figures 9 and 10). A two-tailed t-test was performed to determine if the means differ significantly (real system lead time vs. simulated lead time), a 95% confidence level ($\alpha = 0.05$) was used to test the validity of the model. In this case, we define the null hypothesis H_0 that the model is valid for the acceptable range of accuracy under the set of testable conditions, while H_1 does not accept the validity of the model. Table 6 provides the result of the t-test where it can be seen that no significant differences are found between the values estimated by the model and the observed values ($p > 0.05$), so the validity of the simulation model (H_0) is not rejected.

Figure 9 Histogram of the observed lead time values (see online version for colours)

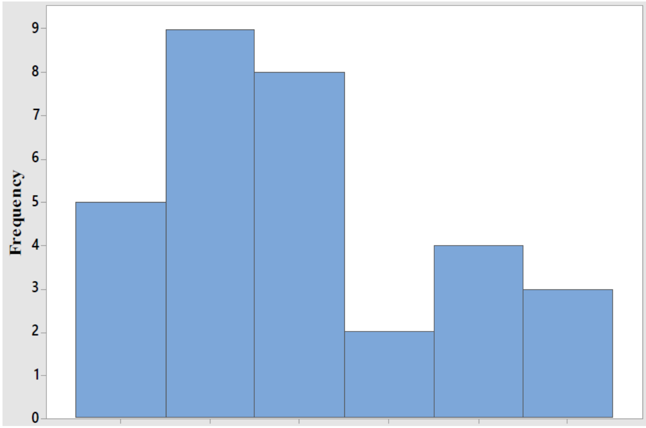


Figure 10 Histogram of simulated lead time values (see online version for colours)

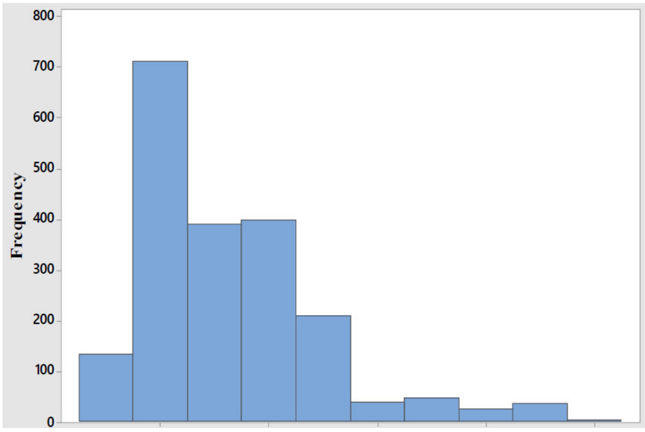


Table 6 T-test value (model validation)

System	*Mean*	*Standard deviation*	*p-value*
Real system	15.29	8.15	0.392
Simulation model	16.57	8.25	

5.2 Results for each modelled sequence

Through the use of CPN Tools, the results of the simulation of 500 orders were obtained following each of the four most frequent sequences found in the sample, the set of values obtained from the simulation allows building a cumulative distribution curve for each sequence with which it is possible to visualise and quantify the process lead time given the expected service level, i.e., the time to commit orders if a certain level of service is desired (measured as the cumulative percentage of orders completed in that time or less).

The cumulative distribution curves for the four most frequent sequences are shown below.

Figure 11 Cumulative distribution curve for the process duration for each of the 500 orders simulated under the four most frequent sequences (see online version for colours)

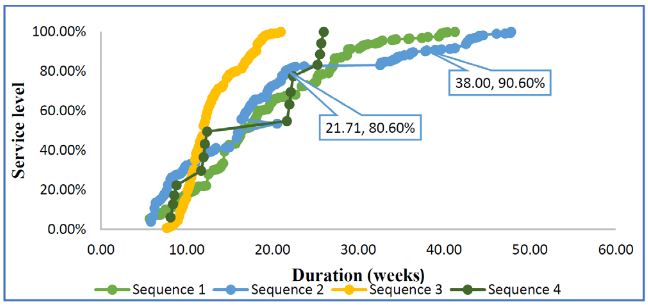


Figure 11 represents the simulated distribution curves for each of the four sequences identified in the historical data sample, where it can be observed that the performance required as service level (vertical axis) determines the processing time requested to complete the orders (horizontal axis) and meet the service level required by the company. For example, it can be seen in the graph for sequence 2 (cumulative distribution curve in blue) the process lead time for a service level of 80.6% is 21.7 weeks, however, if the company seeks to increase the service level for that sequence to 90.6% the expected process lead time increases to 38 weeks, which indicates in this particular case that assigning 10% more in the service level, implies an increase of 16.3 weeks in the required time to complete the process, On the other hand, to pass from 90 to 95% in the service level implies only an increase of 5.7 weeks, which represents 12% of additional time.

From the comparison of the performance among the four sequences, it is noticeable that each has a very different performance regarding time extension, with sequence 2 exhibiting the highest duration for the same service level and sequence 3 with the shortest time extension, for instance by exploring Figure 9, it is noticed that all the simulated orders for sequence 3 will be completed before 21 weeks (service level of 100%), meanwhile, for the same lead time extension, sequence 1, 2 and 4 provide a service level below 73% (in the best case, sequence 2), by exploring the sequence 4, it is identified that requires 26 weeks of lead time to offer the 100 % of service level, meanwhile, for the same lead time extension sequences 1 and 2 offers a service level below 85%.

Table 7 Service level scenarios and lead time extension in weeks

Sequences	*Service level scenarios*		
	Simulated process time required (weeks)		
	80%	*90%*	*Increase 10%*
1	26.64	28.79	2.15
2	21.7	38	16.3
3	15.72	17.93	2.21
4	23.86	25.64	1.78

Equivalently, an analysis of the time extension in the lead time to increase the service level from 80% to 90%, summarised in Table 7, provides the results for each of the sequences analysed.

From Table 7, clearly, sequence 2 demands special attention, a further evaluation of the convenience of offering a service level above 83%, this situation is also noticeable by exploring the plots (Figure 9), where the slope for sequence 2 exhibits a very different pattern.

5.3 *Aggregate simulation results for the four modelled sequences*

From the simulation of 2,000 orders comprising the simulation for each of the observed sequences representing 80% of the historical orders, it is possible to construct the aggregated cumulative distribution curve (Figure 12), in which it is possible to visualise and quantify the lead time based on the aggregated level of service desired by the company, i.e., the time in which it must commit its orders if this level of service is to be achieved, considering the overall orders processed through the four different sequences.

Figure 12 Cumulative distribution curve of process duration for each of the 2,000 simulated orders under the most frequent sequences (see online version for colours)

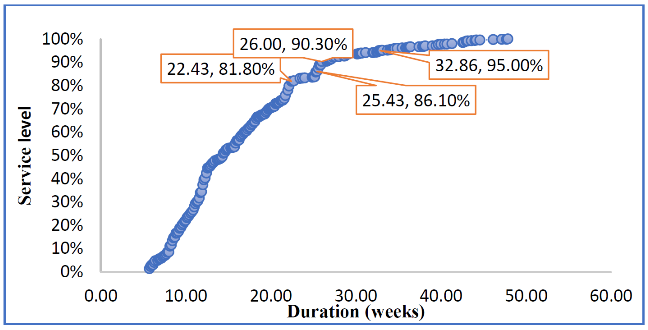


Figure 12 represents the cumulative curve of the duration of the current process for the most recurrent sequences, where it is observed that the process lead time to reach a service level of 81.8% is 22.43 weeks, however, if the company projects an increase in the service level to 86.1% the required process lead time increases to 25.43 weeks, which indicates a growth of 3 weeks. On the other hand, the simulated response time for a service level of 90.3% is 26 weeks and by increasing the service level to 95% the required process lead time rises to 32.86 weeks, which indicates a notable increase concerning that additional 5% of the service level.

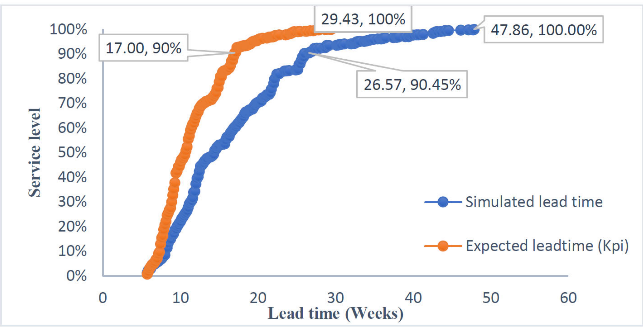
If the market imposes a shorter duration for the completion and delivery of orders, an analysis and improvement process must be deployed with emphasis on the most significant downtimes identified for each of the sequences, as reported in this analysis. It is worth mentioning that the impact, at the process level, for the improvements to be designed could be evaluated before their implementation through the update of the models presented here.

5.4 *Estimation of the effect of critical activities controls (indicators)*

Through the analysis and detailed mapping of the process, it was revealed that the most important downtimes are among the activities that comprise from the customer's requirement to the internal purchase order, which means that they are the areas that bring greater variability to the process and that is reflected in delays in the delivery of the prototypes. Regarding this point, the establishment of potential improvement actions in the process is sought to reduce downtime between the end and start of activities, as a response to this problem it is proposed to evaluate the implementation of a performance indicator (KPI) that allows monitoring the execution of the areas and the personnel in charge of the stages with greater downtime that reduce the response capacity of the process.

To analyse the impact of the performance indicator on the process, simulation models are executed for each sequence identified in the sample with the expected distributions for the activities included in the KPI, established as a maximum half of the time extension for the identified gaps, the establishment of this monitor allows to control in a preventive way the performance of the process, so an early detection of the occurrence of a gap between the end and start of activities means greater care is taken in the development of the process, which is reflected in the reduction of 39% in the magnitude of lead times. See Figure 13. This potential improvement is achievable by introducing the proposed KPI.

Figure 13 Simulated lead time vs. expected lead time (KPI) (see online version for colours)



6 Conclusions

CPNs provides significant advantages for its application in developing interpretable simulation models, this applicability has been proven and exhibited in several practical projects, as reported in the academic literature, comprising solutions proposed in process planning and management along with a straightforward interpretation and visualisation of the simulation models.

In this paper, the application of DES proved to be an effective tool that allows evaluating the current state of the company's prototyping process, besides contributing with a methodology whose purpose is to obtain information that allows establishing a standard lead time associated with a certain level of service. From the analysis and detailed mapping of the process it was possible to identify the sources of variability caused by periods of inactivity between the beginning and the end of consecutive activities which allowed to detect the critical activities in the process and the impact they generate in the process lead times, through the simulation implemented the improvement scenario was analysed through the implementation of control monitors (KPI) in the areas with the highest downtime allowing a 39% reduction in the magnitude of delivery times.

Future applications of the approach and tools presented in this work may include: its use to estimate changes in response time derived from the deployment of improvement proposals at the micro level (by sequence) to reduce variability in downtime, negotiation time, actions should enable to meet the commit delivery times consistently.

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