A SIMULATION-BASED CAPACITY PLANNING MODEL: A CASE STUDY IN A CONTRACT FURNISHING SME

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ABSTRACT

The contract furnishing sector –stores, hotels and public facilities– is characterized for working under a MTO philosophy, having worldwide clients, a flexible and highly manual process and a high mix of products. In the presence of these sources of variability, the lack of a proactive planning drives to outsourcing and cost overruns. This paper presents a case study of capacity assessment in a Spanish SME of manufacturing, distribution and assembly of contract furnishing. To do so, a Monte Carlo simulation approach was adopted, with stochastic values for demand, process and product parameters. Based on historical data and expert interviews a spreadsheet-based model was proposed in order to represent the variability. As a result, capacity anticipation under different scenarios was provided: (i) at present conditions, (ii) with an increased demand and, (iii) in case of a change in the type of production orders.

Keywords: Capacity Planning, Monte Carlo Simulation, Demand Forecasting, Contract Sector, SME

1. INTRODUCTION

Contract furnishing sector is made up by companies that offer a complete furnishing service to hotels, stores, offices and public buildings, including design, manufacturing, distribution and final on-site assembly. These companies typically work under a Make to Order (MTO) philosophy, meaning that the manufacturing starts only after a customer's order is received.

The case study is a family-owned Spanish medium enterprise. Its main client is one of the world's largest fashion distributors representing circa 60% of the company's production and sales. Being a SME and having powerful worldwide clients is a complex balance; failing or even delaying an order is not an option. However, projects' planning is usually carried out in a reactive manner making subcontracting necessary in order to meet the tight deadlines.

Uncertainty is a well-known characteristic of make-to-order (MTO) philosophy based companies. It is difficult (if not impossible) to predict the time at which a customer will place an order, the order due date, its quantity and nature and accordingly, the process and material requirements to fulfil it. Generally, orders' uncertainty affects more to SMEs because of their weaker negotiation position (Achanga, 2006). Usually, diversifying is a way to reduce the impact of such condition. For instance, civil engineering companies try to combine projects for public clients with other works for private ones. Also shipyards do the same by offering both ship repairing and maintenance activities and new shipbuilding. However, this product variability and simultaneous production with shared resources make the planning and scheduling problem even more complicated. The available effective capacity to be used during the execution depends on the operational dynamics, which in turn depends on planning decisions. This circularity in planning is more complex in unsynchronised shops where the variety of products follows diverse routings (Albey and Bilge 2011). All these factors - uncertainty in demand, product variability, simultaneous conditions and diverse routings- are present in the normal activity of this case study.

As said before, the short period of time between the effective confirmation of an order and the moment the manufacturing process actually starts does not allow a proactive planning. The impact on the production levels may lead to bottleneck formations, subcontracting, difficulties to meet the due dates and expensive raw material acquisition. In other words, competitiveness relies on efficient production and capacity planning.

Clearly, deterministic processing times and deterministic demand rates based models are inappropriate to consider uncertainty in models. Mula et al. (2006) have carried out a literature review of the uncertainty treatment on production planning models. The use of simulation in production planning has been considered for several authors in the literature. For instance, Albey and Bilge (2011) state that simulation is a “natural solution” to represent the complex dynamic operational behaviour of unsynchronised shops. Several works propose simulation production planning. Hung and Leachman (1996) collect flow time statistics instead of machine capacities while simulating a production plan. Byrne and Bakir (1999) solve a multi-period multi-product production planning problem by using a hybrid simulation-analytical approach. Kim and Kim (2001) update both machine capacities and flow times by collecting relevant statistics during simulation.

However, Buxey (2005) points out three reasons why business has ignored researcher’s efforts so far. Those are basically related to (i) their huge need of data –impossible, difficult or expensive–, (ii) to the model underlying assumptions which make them inappropriate for the process or (iii) because they are too complex and they are seen as worthless by the managers. Moreover, empirical evidence shows that practitioners using advanced planning methods are on average less satisfied with their plans than those who use simpler and less accurate methods (Jonhson and Mattson 2003). In that sense, Tenhiälä (2011) links appropriate capacity planning techniques with process types, set-up and nature. He also highlights the wide use of non-systematic planning methods and claims that optimization is not always desirable in complex real-world planning situations so more pragmatic research in operations management is needed.

Considering these circumstances, the main goal of the study was obtaining an estimate for the fitted allocation of production resources (both in time and quantity) for the following year under two plausible demand scenarios:

1. The next year presents the same tendency than the previous ones.
2. Changes in the type of orders may occur:
    a. There is the possibility of establishing an important contract with a chain of resort hotels, increasing the workload around a 20%.
    b. Their main client may change the type of order, from the complete interior store manufacturing one to the partial refurbishing of actual stores, which would mean smaller orders (-25%)

To do so, we decided to build a spreadsheet-based simulation model aiming at representing how demand implied workload on the different work centres. Variability modelling is obtained from historical data-based probability distributions for demand, process and product parameters. Monte Carlo simulation is then used for the risk assessment of the solutions provided.

2. CASE STUDY

Demand is composed of several components. On the one hand, 60 % of production is dedicated to their main client. Although time deadlines are strict, at least orders are given with a certain level of anticipation. On the other hand, 40 % of production serves a variety of hotels, stores and business with more flexibility in due dates, but with much more uncertainty both in its amount and nature and in its occurrence. After a failed statistical attempt of characterizing this sort of demand, it was decided not to include it within the scope of the study. Besides, due to the possibility of delay in these type of order deliveries, it has been considered that the company’s capacity estimation is mainly influenced by the rest of the “predictable” orders workload. From now on, demand and orders will refer to the main client’s one.

The normal company’s operating scheme is now briefly described. The whole process starts when the fashion distributor provides the furnishing company with its own interior designs catalogue for all the stores of the year. This catalogue allows a basic preliminary estimate of materials as well as an early and conceptual technical design of the furnishing elements. From that moment on, specific orders may be placed in the form of a store plan, between 10 weeks -normal order- and 5 weeks -urgent order- before the opening date, where all the furnishings should be assembled and ready to be used.

Once the order arrives, the number of pieces of furniture and the amount and type of materials is calculated by the Technical Department. Then, the material supplying and the generation of production orders (in term of parts’ groups that are manufactured together) may start. From that time, the manufacturing process takes place sequentially through four manufacturing sections. Each of them, with different machines, operators and responsible, is now described. Also a fifth section is included, although it does not take place within the production plant.

1. Machining, comprising cutting and machining operations (drills, shapers, CNC machining centre, etc.).
2. Finishing, consisting of sanding, varnishing and automatic and manual painting operations.
3. Cabinet making, where carving operations, assembly and subassembly take place. They are the most qualified and experienced workers.
4. Packing, that can be either automatic or manual packing. All the finished packages are placed on the storage area until the whole order is ready so it can be dispatched.
5. Assembly. Finally, the pieces of furniture and the assembly workers are sent to the final location. Currently, the cabinetmakers are also in charge of these operations.

Some of the reasons for the complexity when applying a planning method are described now:

- There is a high uncertainty on demand, considering that orders are different in quantities and due dates.

- The manufacturing process is defined in the literature as an HMLVS, i.e. High-Mix Low-Volume Simultaneous production (Prasad, 2011). Its main characteristic is that product mix and bottlenecks keep changing frequently over time.
- Distribution and final assembly take place out of the manufacturing plant, increasing the uncertainty due to unpredictable external events. Besides, assembly and cabinet-making compete for the same resources.

3. APPROACHING THE PROBLEM

The followed methodology is shown in Figure 1. From historical demand data (2003-2010) we tried to determine the number and dates of the orders that could be usually expected any year, according to the past events. The same information was used for determining how project usually developed throughout the process operations. From its analysis, probability distributions are obtained in order to represent the following events:

- Monthly probability of a particular number of order deliveries.
- For each order:
    - Sizing. Distribution of the global amount of hours and its allocation among the different main operations.
    - Timing. Distribution of the operations durations and their respective delays.

Probability distributions are the input data of the model. Regarding the system modelling, time and process considerations have to be regarded. On the one hand, a marketing medium term approach (one year) has been proposed as a useful way of linking the managerial issues with the production requirements. Intermediate-range planning is facilitated by aggregating the many products of a company into a single unit of output (Aggregate Production Unit). In our case, each order will be translated into working hours. Also, we have considered as the planning period time the working week, because it is the usual unit in which production activities are referred within the company. On the other hand, the process has been divided in their main operations, that is to say, Machining, Finishing, Cabinetmakers, Packing and Assembly. A backward scheduling has been adopted, starting from the assembly tasks and finishing in the machining.

The resulting workload -the output data- is then analysed both in its quantity (maximum and average) and attending to its distribution along the year. The workload sizing and timing will be the basis of the capacity planning. Decisions regarding capacity planning have different risk implications. For the assessment of capacity planning, three different parameters will be used:

1. Number of operators, related to the direct manufacturing costs.
2. Failure probability, related to the risk of a plan. It is calculated as the number of weeks where the required workload exceeds the available workload (given a certain capacity level).
3. Occupation level. The average occupation level is related with the efficiency of the plan.

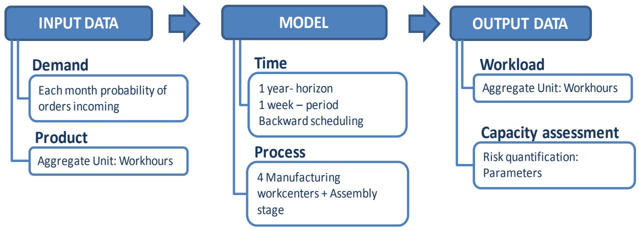


Figure 1: Model Development

4. MODEL DEVELOPMENT

Attending to the eight years record, when characterizing the occurrence of demand in terms of how likely is to have a fixed due date, a set of five month's behaviours within a year was identified. Autocorrelation tests were performed without leading to the identification of any significant pattern. By means of Maximum Likelihood Estimation five Poisson distributions were found to model the orders fulfilment process. When one or more orders are initially expected to be fulfilled in the same month, we have considered that they all will have to be ready for the first week (so assuming a worst case). As a result of the demand estimation, at each simulation N-orders arrive at a certain delivery week (D_W)

The amount of manufacturing and assembly hours (H) is composed of two terms. First, the average value was obtained from historical data and verified with the responsible of the Production Department. Then, a variable noise was modelled. The distribution of total hours in each process sector was quite regular (distribution of orders in work centres is shown in Figure 2). In order to simplify the model it was considered fixed (p1, p2, p3, p4 y p5).

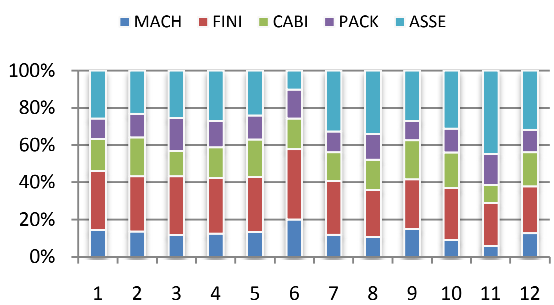


Figure 2: Monthly Distribution for the 2006 Year Orders Attending to the Defined Process Sectors

Given a certain delivery week, (D_W), the process scheduling is established backwards. Accordingly, the variety on operations lengths was modelled. For example, most times (63% of frequency) an order machining takes place in four weeks. During these four weeks, 32% of the machining hours happen the first week, 41% the second, 15% the third and 13% the fourth. However, 37% of times it takes place in three weeks. This has been done for all the work centres of the process.

In addition, production orders have to go through the whole process in a certain order attending to technological constraints. The sequential progress of the order is characterized by the following parameters:

- x: End of packing – start of assembly delay.
- r1: Start of cabinetmaker work – start of packing delay.
- r2: Start of finishing – start of cabinet maker work delay.
- r3: Start of machining – start of finishing delay

The variety on delays between operations has been modelled in the same way as the variety on lengths. Graphically, the evolution of an production order is depicted in Figure 3.

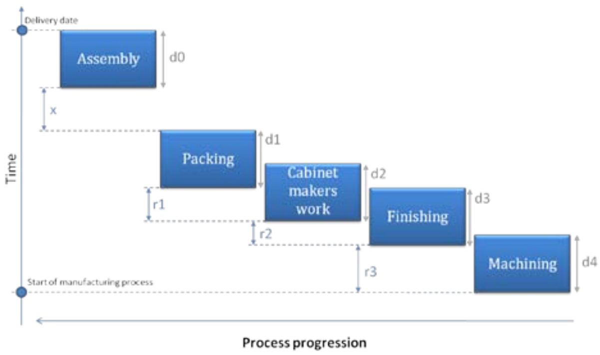


Figure 3. Process Evolution (for the Centres, including the Assembly).

Each order has to progress along the different operations according to the evolution parameters (x, d1, r1, d2, r2, d3, r3 and d4). Those different operations take a fixed rate of the global H, (p1, p2, p3, p4 and p5), so the amount of hours of each process (d_{in}) can be obtained as a vector:

$$d_{in}= HT\ (p1, p2, p3, p4, p5) \qquad (1)$$

All the production sequence is included in a 5xD matrix (M), where the dimension depends on the final duration of the manufacturing and assembly process, as it follows:

$$D= d0 + x+d1+ r1 + r2 + r3 \qquad (2)$$

Each element on M is the fraction of the corresponding production department dedicated hours (in columns) for a particular week (in rows). This way, M shows the evolution of the different operations for a single order.

As a result, the number of hours per operation, week and order $(K)_i$ can be obtained:

$$(K)_i=d_{in}\ .\ M \qquad (3)$$

The global amount of work, K_t is the composition of each K_i in a common time axis. The workload (Q), a 52x5 matrix, is obtained by adding the same operations each week.

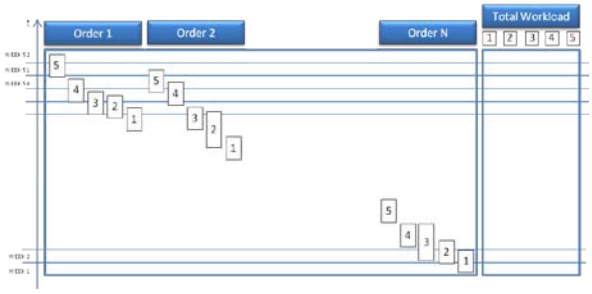


Figure 4: Workload Matrix Composition

In the same execution, there is a variation in terms of amount of hours, operations lengths and delays. Between two successive runs there is variation in terms of different number of incoming orders and their corresponding delivery date. So, we can talk of an inter and intra- year variation.

5. RESULTS

5.1. Workload sizing

The average workload, in hours per week, is the average of the average workload of each operation. The maximum workload is the average of the maximum values. The obtained distributions for average and maximum cabinet makers workload after 1000 simulations are shown in Figure 5. The results for the rest of departments are described on Table 1.

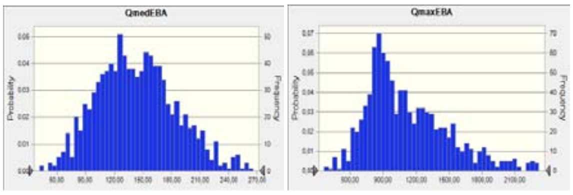


Figure 5. Average (left) and Maximum (right) Distribution of Workload for the Cabinet Department.

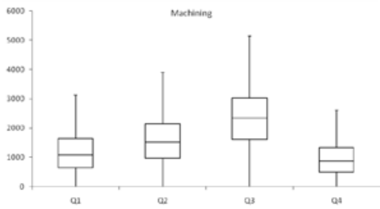
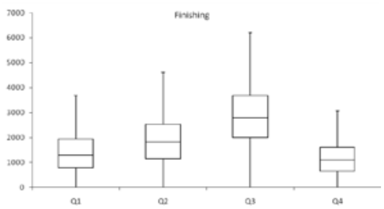
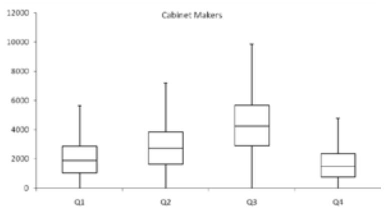
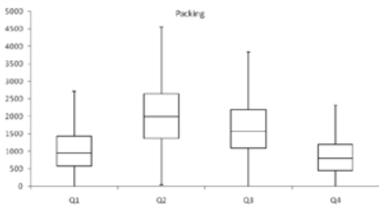
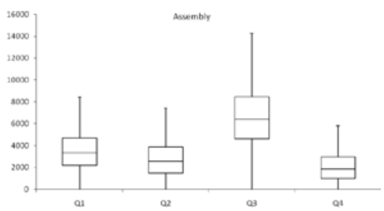
Table 1. Average and maximum workload per year

Workload	Mac	Fin	Cab	Pac	Asse
Average (h/week)	120.2	145.4	216.8	110.6	294,52
Max (h/week)	548.7	616.6	1597.0	449.3	3268.9

However, as a result of (i) the variability in number of hours and time evolution for every order, and (ii) the seasonable behaviour of the demand, one single value is not accurate enough to describe the expected workload. Therefore, results will be presented dividing in quarters of year (Q1, Q2, Q3 and Q4) and a range of more likely values (range of 50% confidence level) are presented together with a boxplot. In Table 2, for instance, machining workload in the first thirteen weeks has been between 643 hours and 1636 hours in 500 of the 1000 simulations.

As it can be noticed, second and third quarters of the year show the greater values of both workload and variability in all the departments except in assembly. More details in the year distribution of the workload will be found in section 5.2.

Table 2. Workload's Departments by Quarter

D.	Range	
M.	Q1 643-1636 Q2 977- 2148 Q3 1618-3027 Q4 493-1340	
F	Q1 782-1942 Q2 1148-2530 Q3 2005-3687 Q4 645-1611	
C	Q1 1054-2891 Q2 1644-3868 Q3 2912-5682 Q4 776-2374	
P	Q1 1054-2891 Q2 1644-3868 Q3 2912-5682 Q4 776-2374	
A	Q1 2192-4680 Q2 1466-3859 Q3 4611-8471 Q4 1027-2949	

5.2. Workload timing

Yearly workload distribution (along 52 weeks) is now showed for the different departments on Figure 6. On Table 3 all operations workload distribution is described in terms of shape and Coefficient of Variation (CV), and maximum and minimum level of occupations.

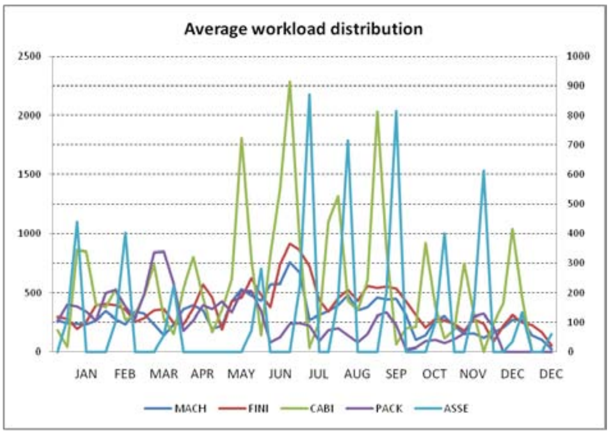


Figure 6: Year Workload Distribution for the different Departments

Table 3: Operation Workload Distribution: CV, Shape, Maximum and Minimum Occupation

Op.	CV	Shape	Maximum Occupation.	Minimum Occupation
Mac	1,20	Smooth	August-September May-June	December
Fin	1,14	Smooth	May –July	December-January and April
Cab	1,64	Concentrated in short periods	One or two weeks in June, July and August	March and December
Pac	1,07	Smooth	End of July, beginning of August	End of October, beginning November
Asse	2,29	Concentrated in very short periods	One week in August and one in September	March-April

The different shapes of the workload are related to the tasks nature. For instance, cabinet makers and assembly respective workload appear in a more concentrated way. Besides, these end stages of the process strongly influence the product quality. According to both factors, these work centres are considered the most critical in the process.

Currently, assembly and cabinetmakers share the same labours. This condition aims at reducing the impact of the concentrated assembly works. However, it also implies that sometimes the end of the process is almost unfilled. As a result the work flow is sometimes interrupted. It has been advised to the managers to separate these work centres and to try to negotiate a resource pool (variable number of working hours that can be compensated with longer holiday days) with the workers.

The plant total workload can be obtained by adding the different operations (machining, finishing, cabinet makers and packing) each quarter. Results are shown on Figure 7.

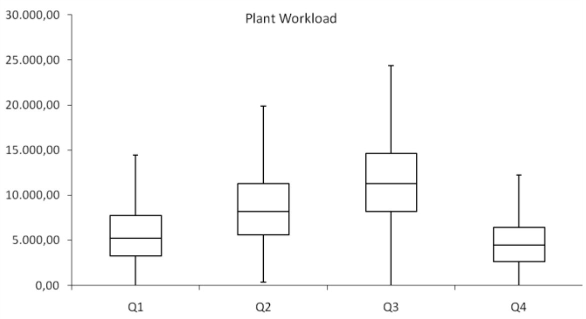


Figure 7: Plant Workload

First and fourth quarter of the year usually present the lowest level of work while the third quarter reaches its top. This information is useful for setting prices and hiring policies.

5.3. Capacity Estimation

According to the workload on each operation, different levels of capacity can be established. In a first approach, a constant annual level of capacity will be studied. Those levels have implications in terms of probability of risk, efficiency and of course, cost (parameters introduced on section 3). Capacity range for each department will be studied between a minimum and maximum level. The adopted criteria are that the minimum/maximum level for each department corresponds with covering the average/maximum workload values (Table 1).

The results are shown in Figure 8 (only for one operation). As it could be expected, the higher the number of operators is, the less the failure probability (lower blue line) and the occupation level are (red line).

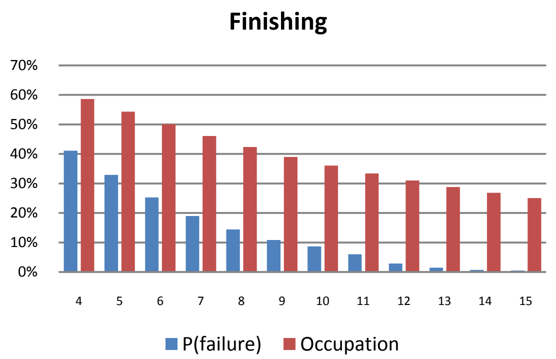


Figure 8: Operators in Machining as a Function of Failure Probability (lower bars) and Occupation Level (upper bars).

These graphs could be used for aiding in the decision process of establishing the capacity level. For example, the managers might decide that a 20% failure probability for the Finishing section is acceptable (one of five weeks the expected amount of work exceeds the Finishing capacity), which would imply that seven labours would be enough.

As it has been stated, each department workload reaches different levels and presents different behaviours. So, different capacity levels would be needed for meeting the same requirements (in terms of failure probability). However, experience shows that it is not necessary the same confidence level in all departments. For instance, a delay in machining would be much less severe than a delay in assembly. Being machining the first department, the excess of workload would probably be transferred to the following week without more consequences, while an excess of workload in assembly would probably lead to an eventual delay in the order. Accordingly, an operation cost indicator for each department can be built as follows:

$$C = n + 52 \cdot \frac{C_F}{C_H} \cdot P(failure) \qquad (1)$$

Being C an indicator of the cost of operating with n workers in a certain department, $\frac{C_F}{C_H}$ the relation between the cost of a failure and the cost of hiring an extra worker. This cost increases with the number of workers and decreases with the failure probability. We could say, for instance, that a single failure in Assembly would cost 3 times more than hiring an extra worker, while a failure in Machining would only cost 0.5 times more (these values have been chosen for illustration purposes, and do not have to be close to reality). When representing these expressions, in Figure 9, the optimum number of workers (7 for machining and 16 for assembly) is obtained.

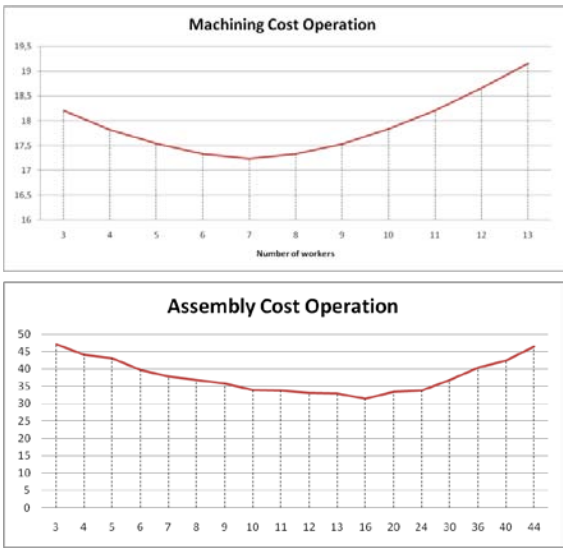


Figure 9. Machining and Assembly Cost Indicator depending on the Number of Workers.

5.4. Increased demand

According to the commercial department's expectations, a new contract with an important international hotel client would imply a 20% increase in the number of orders. As a result, the average workload is a 20 % higher compared to the previous situation. The maximum workload is 12-16 % higher (Figure 10), depending on the work centre. Assembly is the department that shows the higher increase of maximum workload. Referring to the CV, a smoothing effect in every task is observed. However, the lowest decrease in CV corresponds to the Assembly. It appears to be the strictest in its concentrated nature.

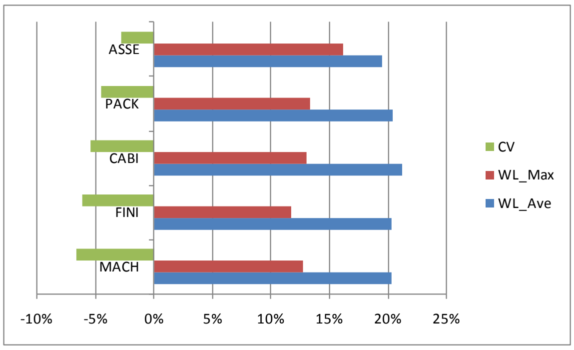


Figure 10: Workload Distribution when Demand increases 20%

5.5. Changes in the "order type"

Before a plausible change in the main client's type of works, from "complete new stores" to refurbishing existing ones, the Sales Department forecasts smaller projects (25% less, in average) but an increase in the number of orders (20%). Were this demand scenario, the workload would change as showed in Figure 11. The average workload decreases around a 10% per work centre. A similar smoothing effect in every task takes place. However, it is remarkable that the maximum workload decreases a 17% for the cabinet centers whilst the assembly only decreases a 14%. In fact, assembly has the lower decrease in maximum workload. It can be concluded that assembly department is more sensitive to changes in the number of orders than it is in the orders' size.

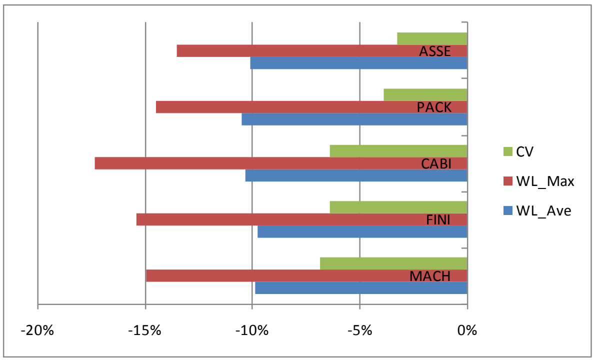


Figure 11: Workload Distribution when the Type of Order Changes.

6. VERIFICATION AND VALIDATION

For verification and validation purposes, the observed sample distribution (historical data) was compared with the modelled distributions in terms of four variables. The first is the number of orders, which accounts for demand level. The second is the total amount of workload hours per year. Yet the number of hour per quarter of year, week or department would have been a more accurate indicator for comparing results, this information was not available within the company's historical data. The third parameter accounts for the time gap between the start of the manufacturing and the final delivery. This value is obtained from the simulation as the addition of each operation estimate represented by different probability distributions. Then, it is compared to the historical time interval between the order incoming and the final delivery. Finally, the number of hours of each order is compared with the actual values from the database. The p-values for the null hypothesis of the averages being the same and the standard deviations being different are shown in Table 4 and Table 5. Model values for the average and standard deviations come from 1000 simulations so they were considered with a negligible error. They were then compared to the available number of observations (n) in the real data.

Table 4. Test T for Differences in Variable Means

Factors	Average Model	Average Data	N	p-value
Orders / year	15,1	15,28	7	0,956
Hours / year	46764,6	47867,1	7	0,903
Weeks / order	11,4	9,6	106	0,001
Hours / order	3094,6	3109,8	106	0,903

Table 5. Test χ for Differences in Variables Standard Deviations

Factors	Std. Dev. Model	Std. Dev. Data	n	p-value
Orders / year	3,8	6,9	7	0,003
Hours / year	12719,9	22976,2	7	0,003
Weeks / order	5,3	5,8	106	0,103
Hours / order	835,6	1275,0	106	0,001

It can be concluded that the estimations of demand per year, workload per year and workload per order averages do not significantly differ from those observed in the historical data (Table 4). On the other hand, significant differences were found in weeks per order average. This might be explained by the aforementioned differences in time durations, but further research should be conducted in order to assess the practical relevance of such a difference.

Significant differences in estimated standard deviations were found for all the tested variables (Table 5). This suggests that the model systematically underestimates variability levels in workload rates and, consequently, the forecasted failure probabilities. A plausible explanation is given by the way that the annual demand is generated. Although standard autocorrelation tests did not show any autocorrelation patterns in monthly orders, this is not a sufficient proof for independence. Only under actual independence among monthly demands, annual demand variability would be accurately estimated from monthly variability. Available data were not enough to conduct a more profound autocorrelation analysis. This shortcoming of the model can be corrected by adopting a more risk-averse position in the decision making process.

7. CONCLUSIONS

A workload and capacity planning based on historical data in a Spanish SME of manufacturing, distribution and assembly of contract furnishing has been presented. A simulation approach has been adopted in order to represent the high variability associated to their MTO philosophy and job-shop production schema. The spreadsheet-based model within a Monte Carlo simulation approach allows introducing stochastic values for demand, process and product parameters. As a result, workload estimation under different scenarios was provided. Also, by means of a set of three general performance parameters – labour costs, failure probability and occupation level- the assessment of the production resources necessary to cope with the corresponding workload is achieved. When complemented with overall cost information, this planning methodology can be the basis for optimised capacity estimation according to the nature of each department. This work aims at connecting the operational level with strategic considerations by means of a simple but comprehensive and precise tool for decision making.

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