OPTIMIZATION OF THE OPERATION MANAGEMENT PROCESS OF A COMPANY IN THE ELECTRONIC MANUFACTURING SECTOR

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Abstract. The use of mathematical programming models for production planning has been proposed since the 1950s, being a widely applied tool, since it can provide optimal solutions for production planning problems. For manufacturing companies, it is a great challenge to plan in uncertain environments when there are large variations in planning parameters. Thus, the greatest difficulty in dealing with Mathematical Programming models in production planning is that, in general, with the intention of simulating reality through these models, it is necessary to estimate values for the planning parameters, which may not always be possible accurately, and consequently, the model's optimal solution may not represent the best solution to the problem. In this context, the classic approach to deal with a dynamic economic scenario is the use of robust optimization models, which propose a suboptimal solution in relation to the deterministic model. Therefore, the objective of this paper is to apply a robust optimization model in the operations management process of an electronic components manufacturing company. First, a content analysis was performed, then company data was collected, the model was proposed, and the results were analyzed. Results suggested more than 80% of the production should be done in anticipation. The optimal solution, at the lowest cost, was obtained from the minimal scenario. The worst and robust solution, bringing the highest cost, came from the intermediate scenario, proving that the production plan could be performed even with adversities on sight.

Keywords: Linear Programming, Robust Optimization, Operations Management.

1 Introduction

Carrying out production planning in manufacturing companies has progressively become a complex and expensive task. In addition, the increase in competition and market competitiveness has forced companies to increasingly seek production systems that are simultaneously effective and efficient, so that they can achieve their organizational objectives using the available resources in the best possible way. Or to put it another way, the organizational objectives of manufacturing companies incorporate at least one new challenge: Obtaining a good production decision-making system, which has the property of having a minimum cost.

Since the 1970s, sophisticated decision-making support systems have been implemented in a large number of medium and large organizations, such as Master Production Schedule - MPS, Material Requirements Planning - MRP, and Enterprise Resource Planning - ERP's. However, such models only provide viable solutions to the production planning problem, in the sense of not considering the fulfillment of some optimality criteria, consequently the quality of the solution found does not provide an adequate analysis both in relation to cost and in relation to sensitivity. In addition, the use of the MRP technique for large problems becomes unfeasible in relation to the amount of effort used to find a viable solution.

Given this scenario, Linear Programming (LP) models have been proposed and widely used to solve production planning problems. However, carrying out production planning efficiently is a great challenge, especially when, in the day-to-day experience of the factory floor, there is great variability in the parameters used in the models.

To deal with the fact that the parameters of the problem are subject to variations along the planning horizon, it is proposed the use of a robust approach, which is a worst-case technique, which seeks to reach viable solutions for a problem, considering the worst scenario of realization of uncertainties. In other words, it seeks to solve the mathematical model by minimizing the maximum deviation of the random variables chosen to be analyzed in the model [1].

Therefore, the modeling of the production planning problem through a robust approach arises from the need to consider the action of uncertainties in the model parameters, and with its use, a suboptimal solution is considered in relation to the value estimated by the deterministic problem, where, in general, the parameters are estimated using means, without association to a specific standard deviation, as in the robust approach [2].

This paper seeks to model the production planning problem considering the concepts of robust optimization in a company in the electronic equipment manufacturing segment, in order to provide the planner with greater security in decision-making in the face of the variability of the economic scenario in the environment where the company operates. To do so, a content analysis was first performed in the literature, to identify related works and possible gaps in the literature in relation to robust optimization, then a mathematical model was proposed, data collected in the company and the main results analyzed with the help of the Lingo software.

2 Robust Optimization

Real-life optimization problems often contain uncertain data, e.g., demand variability, cycle times, setup times, productive capacity, etc. The reasons for these uncertainties in the data could come from measurement/estimation errors that come from lack of exact knowledge of the parameters of the mathematical model or because of the business' dynamics.

There are two distinct approaches for dealing with data uncertainty in optimization: robust and stochastic optimization. Stochastic optimization assumes an important premise, which is that the true probability distribution of uncertain data must be known or estimated. Robust optimization, on the other hand, does not assume that the probability distributions are known, but assumes that the uncertain data resides in a set of uncertainties [3].

Robust optimization is a relatively young research field and has been mainly developed in the last 15 years. Especially in the last 5 years, there have been many publications that show the value of robust optimization in applications in many fields including finance, management science, supply chain, healthcare and engineering ([4]; [5]; [6]; [7]; [8]; [9]; [10]; [11]; [12]; [13]; [14]).

In general, two types of uncertainty sources are considered in robust optimization problems: uncertainty in constraints and in the objective function. In the first case, the variation of the model's parameters can cause an infeasible solution, while, in the second, the variations in the objective function parameters can lead to solutions considered optimal to be very far from the best solution.

The classic optimization problem consists of minimizing (or maximizing) an objective function, subject to a set of constraints:

$$\begin{array}{ll} & f(x) \\ \text{Subject to:} & g(x) \leq 0 \\ & h(x) = 0 \end{array} \quad (1)$$

Where: $f(x): R^n \rightarrow R$, $f(x) \in c^1(R^n)$, $g(x): R^n \rightarrow R^p$, $g(x) \in c^1(R^n)$ and $h(x): R^n \rightarrow R^m$, $h(x) \in c^1(R^n)$.

The uncertainties can be either in the objective function, $f(x)$, or in the inequality constraints, $g(x)$, or equality constraints, $h(x)$.

A possible treatment for the problem is to analyze the worst case, that is, to determine the solution that minimizes the maximum possible objective function when considering all possible instances of the problem. That is, the robust optimization problem is fundamentally a minimax problem.

Thus, to robustly minimize the model (1), with uncertainties that may be present both in the objective function, which will be called: $f(x, \alpha_f)$, as in the restrictions of inequality and equality, which will be called as $g(x, \alpha_g)$, $h(x, \alpha_h)$, respectively, where these uncertainties can oscillate over a continuous vector set, $\Omega_f \in [\bar{\alpha}_f \pm \varepsilon_f]$, $\Omega_g \in [\bar{\alpha}_g \pm \varepsilon_g]$ e $\Omega_h \in [\bar{\alpha}_h \pm \varepsilon_h]$, respectively, there is the following problem (2).

$$F(x, \alpha_f)$$

$$S.t. \quad F(x, \alpha_f) = \{ f(x, \alpha_f) | g(x, \alpha_g) \leq 0; h(x, \alpha_h) = 0 \} \quad (2)$$

Thus, a robust optimization model can be developed by applying the minimax concept.

The minimax concept allows the planner to obtain a robust production planning model capable of incorporating variations in the planning parameters. Since these variations occurred under a given set of analyzed uncertainty, the formulated planning will still remain feasible, thus, there is no need for a production re-planning.

Depending on the adopted range of uncertainty level, that is, the level of confidence that the manager decides to consider, the objective function may deteriorate if the adopted range is considerably wide. However, it ensures that the model remains feasible in the range of variation of the considered uncertain parameters, bringing a solution suboptimal. This fact is called the price of robustness [1].

[2] robust model was the pioneer in robust optimization, and it is extremely conservative, in the sense that the value of the objective function deteriorates too much to guarantee the robustness, in terms of feasibility, of the solution.

[2] used the term “uncertainty box” to refer to the space of realization of uncertain parameters in the model, that is, the vector space has as its center an average vector that can vary symmetrically over a given range (deviation) along the "box". The advantage of this approach is the simplicity of its application. The disadvantage is the high level of conservatism.

3 Content Analysis

A content analysis was performed on the Scopus database, no year restriction, with the terms “Production Planning Problem”, “Mathematical Model” and “Robust”. Only 9 scientific articles were obtained that deal with production planning via robust optimization. 4 of them analyzed “demand” as an uncertain parameter, or robust parameter, 3 of them analyzed the “production level”, 1 analyzed the “budget available for production” and 1 the “assembly time”. With that, we verified a gap in the literature regarding robust optimization analysis in parameters associated with production capacity.

Table 1. Index descriptions and symbols.

Title	Authors	Year	Source	Robust Parameter
Energy and carbon-constrained production planning with parametric uncertainties [15]	Chaturvedi, N.D., Kumawat, P.K., Keshari, A.K.	2021	IFAC-PapersOnLine	Budget
Robust optimization approach to production system with failure in rework and breakdown under uncertainty: Evolutionary methods [16]	Rabbani, M., Manavizadeh, N., Aghozi, N.S.H.	2015	Assembly Automation	Demand
A minimax p-robust optimization approach for planning under uncertainty [17]	Seo, K.-K., Kim, J., Chung, B.D.	2015	Journal of Advanced Mechanical Design, Systems and Manufacturing	Demand
A robust optimization model for multi-product two-stage capacitated production planning under uncertainty [18]	Rahmani, D., Ramezanian, R., Fattahi, P., Heydari, M.	2013	Applied Mathematical Modelling	Production Cost and Demand
Semiconductor production planning using robust optimization [19]	Ng, T.S., Fowler, J.	2007	IEEM 2007: 2007 IEEE International Conference on Industrial Engineering and Engineering Management	Production
A robust optimization model for multi-site production planning problem in an uncertain environment [20]	Leung, S.C.H., Tsang, S.O.S., Ng, W.L., Wu, Y.	2007	European Journal of Operational Research	Production loading plan and workforce level
A robust optimization model for production planning of perishable products [21]	Leung, S.C.H., Lai, K.K., Ng, W.-L., Wu, Y.	2007	Journal of the Operational Research Society	Production loading plan
A robust dynamic planning strategy for lot-sizing problems with stochastic demands [22]	Raa, B., Aghezzaf, E.H.	2005	Journal of Intelligent Manufacturing	Demand
Robust production planning for a two-stage production system [23]	Morikawa, Katsumi, Nakamura, Nobuto	1996	Proceedings of the Japan/USA Symposium on Flexible Automation	Assembly time

4 Application of robust optimization concept

4.1 Company description

Company M, founded in 2012, operates in the electronics manufacturing sector, specializing in the assembly of Surface Mount Device (SMD) components, integration of electronic products and formation of Plated-through Holes (PTH) components. Its headquarters is in southern Brazil. Among a highly complex product portfolio, the products selected were WAFFER 371000490 (Product 1) and WAFFER 371000493 (Product 2), for being both heavily demanded items, with a monthly output, from 1 to 2 batches of 1200 pieces.

4.2 Mathematical Model

[24], [25], [26], [27], [28] presented models that were used as a basis for modeling the production problem developed in this work.

$$Z = \sum_{i=1}^{U} \sum_{j=0}^{M} \sum_{k=1}^{Q} \left(T_{ik} X_{ijk}\right) * V_{ik} + H_{jk} W_k + A_{jk} Y_k + (X_{ijQ} - D_{ij}) Z_i + \left(G_{ik} X_{ij}\right. \tag{O.F}$$

$$\sum_{j=0}^{M} X_{ijk_i} = \sum_{j=0}^{M} D_{ij} \qquad \forall i,\ k = Q \tag{3}$$

$$X_{ijk} \geq D_{ij} \qquad \forall i, j = 0,\ k = Q \tag{4}$$

$$\sum_{j-1}^{j} X_{ijk} \geq D_{ij} \qquad \forall i, j = 1, 2, \dots, M,\ k = Q \tag{5}$$

$$X_{ijk} = X_{ijQ} \qquad \forall i,\ \forall j,\ k = 1, 2, \dots, Q - 1 \tag{6}$$

$$H_{jk} \leq 7200 \qquad \forall j, \forall k \tag{7}$$

$$\sum_{i=1}^{U} \sum_{k=1}^{Q} \left(T_{ik} + G_{ik}\right) X_{ijk} \geq \sum_{k=1}^{Q} O_k \overline{N_k} \qquad \forall j,\ O_k = 0 \tag{8}$$

$$\sum_{i=1}^{U} (T_{ik} + G_{ik}) X_{ijk} \leq \overline{N_k} + H_{jk} + A_{jk} \qquad \forall j, \forall k \tag{9}$$

$$\sum_{k=1}^{Q} (T_{ik} + G_{ik}) X_{ijk} \leq \overline{N_Q} + H_{jQ} + A_{jQ} \qquad \forall i, \forall j \tag{10}$$

$$T_{11} X_{1j1} + T_{12} X_{1j2} + T_{21} X_{2j1} + T_{22} X_{2j2} \leq \overline{N_1} + H_{j1} + A_{j1} \qquad \forall j \tag{11}$$

$$X_{ijk}, H_{jk}, A_{jk} \geq 0 \tag{12}$$

The constraints and objective function presented below represent the result of modeling the scenario found in the production problem of company M, after numerical experiments and validations.

Where $Z: R^n \rightarrow R$, $T_{ik} \in R^n$, $X_{ijk} \in R^n$, $H_{jk} \in R^n$, $W_k \in R^n$, $A_{jk} \in R^n$, $Y_k \in R^n$, $D_{ij} \in R^m$, $Z_i \in R^n$, $\alpha_{ik} \in R$, $G_{ik} \in R^n$, $O_k \in R^n$, $N_k \in R^n$.

Above, you can see the cost-minimizing objective function (O.F.), (3) General demand Constraint, (4) Demand constraint per period, (5) Demand constraint considering stock, (6) Bottleneck-guided Production and Work-In-Process Inventory Block constraint, (7) Maximum working hours constraint, (8) Productive Capacity Minimal Occupation, (9) Pure Capacity Constraint, (10) Per Product Capacity Constraint, (11) Single Resource Constraint, (12) non-Negativity.

Input data to what is described below, were given by the Production Planner, who already had most of the information, such as nominal capacity, minimum occupation, processing time and product setup. Altogether, 47 data entries were received and all of them were used. Due to internal reasons, information about product and processes were not available, therefore, cost data used in this model were all arbitrarily chosen. Index descriptions are: ***i***, ***j*** and ***k*** indicate, respectively, the product, period and process.

Table 2. Variables descriptions and symbols.

Variable Name	Variable Type	Description	Symbol
Outsourced hours	Continuous	Additional production capacity of *j* product in *k* process, given in seconds, by purchased outsourced work.	A_{jk}
Production	Continuous	Amount of *i* products, that passed through *k* process, during *j* period, given in products units	X_{ijk}
Overworked hours	Continuous	Additional production capacity of *j* product in *k* process, given in seconds, by overworked hours.	H_{jk}

Table 3. Parameters description and symbols.

Parameter	Description	Symbol
Nominal Capacity	Nominal process *k* production capacity, given in hours. Robustness is further applied in this value, so it is noted with a line on its top.	$\overline{N}_k$
Minimum Occupation	Minimum desired occupation ratio, for each process *k*.	$\mathbf{O_k}$
Processing Time	Passing-thru time spent by product *i* in process *k*, given in hours.	$\mathbf{T_{ik}}$

Nominal Process Cost	Processing cost of a single product *i* unit, on process *k*, given in reais (Brazilian currency).	$\mathbf{V_{ik}}$
Overtime Process Cost	Process *k* additional cost, during overtime working hours, given in reais.	$\mathbf{W_k}$
Outsourced Process Cost	Process *k* additional cost, during outsourced hired hours, given in reais.	$\mathbf{Y_k}$
Inventory Cost	Stocking cost for a single product *i* unit, over a period.	$\mathbf{Z_i}$
Product Setup Time	Time spent setting the process *k* for product *i* production.	$\mathbf{G_{ik}}$
Setup Time Cost	Cost of time spent setting process *k* in order to produce product *i*	$\boldsymbol{\alpha_{ik}}$

4.3 Results

Results were obtained using Microsoft Excel data export functionality of Lingo software, performing a direct extraction to the desired tables, but only objective function (cost-minimization) results will be presented in this study, due to page limitation.

After disturbing model's robust parameter, which was nominal capacity, $\overline{N}_k$, intermediate capacity scenario presented the robust solution.

Table 4. Scenario comparison

Scenario	Objective Function value	Ranking
Intermediate	$2.665.193,30	Robust
Possible	$2.665.053,77	Sub-optimal
Minimum	$2.662.980,37	Optimal

Under another circumstances, for instance, model could have chosen to produce the whole 1200 pieces in only one day or break it into daily production. This is possible due to the gap between order placement by the customer and delivery date, which is 11 days as informed by the company and represented here as 11 periods of production (0 to 10).

The productive capacity, in the 3 possible scenarios, was affected by the decision to hire overtime in the exact same amount, and in the same periods.

There are the values of 7200 seconds, or two additional hours, totaling 62 contracted overtime, over periods 5, 6, 7, 8, 9 and 10 for all machines, and for machine 2 in the zero period.

5 Final Considerations

It was possible to analyze and extract a large amount of data and information from company's current scenario, enough to generate a feasible model. Even if not trustful to the daily reality of the company. Results that met the proposed demand for the planning periods were obtained, even with a sub optimal solution.

Results shows that Robust Linear Programming is an option, when Materials Requirement Planning, Manufacturing Resource Planning and Enterprise Resource Planning costs and flexibility does not match companies demand.

Also, Robust Linear Planning is not limited to deliver a production plan that only complies with all the plant's capabilities, such as models previously said. Through Robust Linear Programming, it is possible to obtain optimized solutions for minimizing production time, or reducing costs as seen in this work. All of this, with the use of an economically viable tool, especially when compared to the Materials Requirement Planning solutions offered in the market.

Small-scale industries, which may struggle with less resources and lower budget, could improve results by using practices that build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation, becoming more competitive when lowering the costs of production planning and mitigating production planning infeasibility risks, making it possible to small-scale industries have a better portion of total industry value added.

Implications for practices are related to United Nation Sustainable Development Goals (UN SDG) no. 9 and 13. Indicator 9.3.1 verifies small-scale industries participation in total industry value added, and indicator 9.4.1 checks on the CO2 emission per unit of value added. Indicator 13.2.2 look towards total greenhouse emissions per year ([29]; [30]).

Lowering general CO2 emissions or emissions per unit of value added could be incorporated in the mathematical model, defining which level of emission is desired or helping analyze the impacts on production when minimizing emission.

Furthermore, this study offers a glimpse of what could be another meaningful application of Operations Research, by showing practical results, validating what previous authors already proposed and mathematically modeling a production process.

Future studies are suggested, applying it to a greater mix of products, with more extensive bills of materials and in other sectors of the industry, which operate with pushed production. The development of solutions to the same problem, however based on methods of decision-making processes, appear as possible proposals for improvement.

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