

Robust optimization for tactical capacity planning in ETO industry subject to uncertain costs

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RESUMO

Na engenharia sob encomenda (ETO), a incerteza de custo tem a sua relevância dado que os preços dos produtos são definidos no início do desenvolvimento dos projetos. Não obstante, existe uma lacuna entre teoria e prática na aplicação de ferramentas de apoio à decisão que incorporam incertezas no planejamento. Portanto, este trabalho estende uma pesquisa-ação relativa a um contexto industrial ETO, onde um modelo de otimização robusta, considerando incertezas de processo, foi aplicado. A contribuição se refere a uma adaptação deste modelo considerando custos incertos. Uma análise de sensibilidade foi empregada para identificar os principais impulsionadores da variabilidade do custo ótimo. O modelo robusto foi reformulado para incorporar a variabilidade dos parâmetros mais relevantes. Um exemplo numérico foi aplicado revelando os efeitos do nível de conservadorismo na solução ótima. As observações obtidas com esta aplicação poderão estimular acadêmicos e profissionais a investigar questões novas nessa área.

PALAVRAS CHAVE. Planejamento da produção, incerteza em custo, modelagem matemática

ABSTRACT

In Engineer-to-Order (ETO) context, cost uncertainty plays a major role as prices must be defined during at the early stages of project development. Notwithstanding, there is a research-practice gap on the application of decision support tools that incorporate information about uncertainty within ETO planning. To address this gap, this paper extends a previous action research relative to an ETO industrial situation where a robust optimization model considering process uncertainties was applied. The contribution given now refers to an adaptation of this model considering cost uncertainties. A sensitivity analysis was employed to identify the key drivers of variability of the optimal cost. A robust model was reformulated to incorporate the variability relative to the most relevant parameters. A numerical example was applied revealing the effects of the conservatism level on the optimal solution. The insights gained from this application may stimulate academics and practitioners to investigate news issues regarding this area.

KEYWORDS. Production planning, Cost uncertainty, mathematical modelling.

Paper topics: GAD & GP - OR in Administration & Production Management, IND - OR in Industry

1. Introduction

In this paper, one revisits the problem of tactical capacity planning applied to an Engineer-to-Order (ETO) industrial environment, initially tackled by [Carvalho et al., 2015], followed by the authors' subsequent work, [Carvalho et al., 2016], where uncertainty was taken into account and its interesting results concerning risk exposure mitigation strategies were obtained through robust optimization. Uncertainties on planning models affect due date achievement, efficient resource allocation and the usage of nonregular workforce, [Tolio e Urgo, 2007], impacting the stability and performance of a production system.

In order to avoid generated plans to be reviewed frequently or, even worse, to be worthless, [Bertsimas e Thiele, 2006; Aghezzaf et al., 2010], capacity planning methods able to evaluate before-hand the decisions effects on the production system are important tools at the tactical planning level, [Giebels, 2000; Gademann e Schutten, 2005; Hans et al., 2007; Montreuil et al., 2013]. Their applicability are even more relevant in case the planning tasks cope with the variability of model parameters in the context of multi-projects settings with inherent considerable uncertainty (like ETO case), [Herroelen e Leus, 2004; Tolio e Urgo, 2007; Chtourou e Haouari, 2008; Deblaere et al., 2011; Alfieri et al., 2012; Artigues et al., 2013].

In the ETO tactical planning context, the decision process about incoming projects and customer's inquiries might be highly dependent on different sources of variability such as production processing times (Carvalho et al., 2016). Furthermore, in this context, prices must be defined during the bidding process and the early stages of project development, which makes cost estimation a key issue to avoid profit loss, [Hooshmand et al., 2016]. According to these authors and to [Martin et al., 2007], the involved cost estimate accuracy varies along the design steps.

Even though uncertainty associated with ETO context plays a major role, the literature of tactical planning framework including uncertainties is not as extensive as the deterministic counterpart, [Carvalho et al., 2016]. Among the above thirty references listed in, [Carvalho et al., 2016], it should be pointed out that only two references tackle costs uncertainty, regardless of the customer delivery strategy context. To address this gap, this paper extends [Carvalho et al., 2015, 2016] research relative to a real-world ETO industrial situation where a robust optimization model considering process uncertainties was applied. In this paper, this alternative type of uncertainty, related to costs, is considered. The aim is to analyse the effects of having uncertain costs on the generated tactical plans. In addition, a robust optimization-based framework is proposed since it is assumed that costs are defined on intervals without information about cost probability distribution. This paper is organized as follows: in Section 2, a discussion concerning the issue of cost assessment on ETO setting is presented following by Section 3, where the main results are presented; Section 4 is devoted to the case study description as well as to numerical results discussions; and concluding remarks are highlighted in Section 5.

2. Costs involved in tactical planning on ETO settings

In ETO industrial settings, companies design and manufacture products with highly specific requirements leading to one-of-a-kind product, [Adrodegari et al., 2015]. To this end, product development tasks usually take place during ETO bidding phase, making it difficult to define the actual product cost, which influences the product price. This highlights the effort and works in the literature that aim at determining driving factors for product cost at early stages, [Molcho et al., 2014], in particular for ETO setting, [Kristjansdottir et al., 2017].

One approach to increase cost estimate accuracy is given through product configuration systems (PCS) in configure-to-order context and ETO as well, [Myrodiya et al., 2017]. Nevertheless, as pointed out by the authors, its adoption is still challenging due to for instance product modelling and data acquisition, in particular in ETO settings. In the real-world industrial application scenario studied by the authors in [Carvalho et al., 2016, 2015], the involved costs were defined accordingly its type: average hourly salary in regular and overtime regime; work centre hourly operation cost, capacity change, price of outsourcing and the plan generation was performed assuming a base value.

It is noteworthy, nonetheless, that earlier the development, worse is the cost estimate accuracy and bigger is the activities involved influence on the final product cost, [Hooshmand et al., 2016]. [Martin et al., 2007] illustrate that the accuracy of product cost in ETO setting lies, at best scenario, in the range of -5% to $+15\%$. Such a level of uncertainty motivates the present paper where a tactical capacity planning to cope with uncertainties on costs is proposed. The main results are based on robust optimization, instead of following stochastic, [Leung e Ng, 2007], or fuzzy [Demirli e Yimer, 2008] optimization approaches.

3. Proposed framework

In [Carvalho et al., 2016], it is developed a robust optimization model to support tactical capacity planning by optimally balancing demand with the available capacity in a real-world ETO industrial context. This model exploits capacity flexibility, admits the representation of a multiple processing stage production flow and incorporates process uncertainties when generating the capacity plans. It is a cost minimization formulation which involves several cost parameters which refer to the hourly production processing cost, the overtime cost, the average salary, the price of each part component and the capacity change cost (relative to hiring and firing employees).

In this studied context, the prices of the products are defined during the bidding process and are usually imposed by the customers. Therefore it is crucial to estimate as early as possible the overall production costs relative to the incoming demand. Although the cost parameters considered in [Carvalho et al., 2015] are deterministic, they are significantly sensitive to variability. For instance, the production hourly costs involve the consumption of energy and lubricants. Moreover, the average salary depends on the available workforce in each specific work centre. To address this problem, a reformulation of the former optimization model was developed to incorporate cost uncertainty. In this section, the main results are presented. Firstly, a sensitivity analysis is discussed in order to determine the most significant uncertain cost parameters followed by the presentation of the mathematical formulation employed to obtain the robust optimization model.

3.1. Pre-optimality analysis

Sensitivity analysis was used to identify the key drivers of variability of the optimal cost. A tornado diagram was developed to compare the relative importance of each uncertain cost parameter. Estimates of the low, nominal and high values for each parameter were needed to perform this analysis. One by one, each cost parameter was set to either its highest or lowest value while the others were kept at their respective nominal values. At each round, the uncertain value assumed either its lowest or highest bound value, the model was executed and the objective function output was tabulated. This process was repeated for each parameter.

In Table 1, it is presented a summary of the analysis. For each cost parameter listed row-wise, the columns refer to the base, minimum and maximum cost values. Subcontracting costs depends on each particular component.

Cost parameters	Nominal value	Lowest	Highest
Production cost	11	7	15
Overtime	50	45	55
Salary	4950	4450	5450
Capacity change	5000	4500	5500
Subcontracting price	component-wise price	$0.9 * \text{Value}$	$1.1 * \text{Value}$

Table 1: Cost parameters values considered for the sensitivity analysis.

In Figure 1, the results of sensitivity analysis performed are illustrated by means of the Tornado diagram. That is, the horizontal axis is related to the base total cost value, and its variation

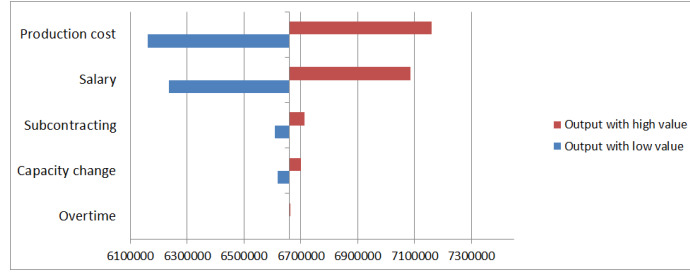


Figure 1: Tornado diagram of total costs variability given the cost parameters set to values in Table 1

is presented as coloured horizontal bars (positive as red and negative as blue) split according to the source of cost uncertainty along the vertical axis.

Based on Figure 1, it is noteworthy that the top cost parameters are production cost associated with the work centre followed by the average salary cost.

3.2. Optimization model

In the problem under study, the production hourly cost at work center w , originally given by the parameter CR_w , is remodelled by a symmetric and bounded random variable $\widetilde{CR}_w$ with unknown probability distribution taking values in the uncertainty set $[CR_w - dCR_w, CR_w + dCR_w]$, with parameter dCR_w describing the maximum possible deviation of the CR_w parameter from its nominal value. Furthermore, according to the same rationale, the average salary at work center w , initially given by the parameter CS_w , is also remodelled as a random variable $\widetilde{CS}_w$ defined on the uncertainty set $[CS_w - dCS_w, CS_w + dCS_w]$, whereas dCS_w refers to the maximum value of CS_w from its nominal value.

To formulate this problem considering uncertainty in this manner, let the variables k_w^{CR} and k_w^{CS} be the scaled deviation of $\widetilde{CR}_w$ and $\widetilde{CS}_w$ from their nominal values and defined as $k_w^{CR} = (\widetilde{CR}_w - CR_w)/dCR_w$ and $k_w^{CS} = (\widetilde{CS}_w - CS_w)/dCS_w$ respectively. Therefore, the stochastic version of the problem can be presented by modifying the budget constraint depending on the nominal values,

$$\begin{aligned} \Psi = & \sum_{a,w,t} [CR_w(r_{at} + o_{at}) + CO_w o_{at}] + \sum_{w,t} \left[CR_w(wr_{wt} + wo_{wt}) + CO_w wo_{wt} + CC(eh_{ttw} \right. \\ & \left. + \sum_l^t ef_{ltw}) + CS_w ea_{w,t} \right] + \sum_i PS_i(1 - d_i) \leq \epsilon, \end{aligned} \quad (1)$$

with the maximum allowed budget $\epsilon \in \mathbb{R}$, by the following one, which considers the uncertain parameters explicitly

$$\begin{aligned} \Psi + \sum_w dCR_w k_w^{CR} \left[\sum_{a,t} (r_{at} + o_{at}) + \sum_t (wr_{w,t} + wo_{w,t}) \right] \\ + \sum_w dCS_w k_w^{CS} \sum_t ea_{wt} \leq \epsilon. \end{aligned} \quad (2)$$

Note that $\Psi \in \mathbb{R}$ means the objective function depending on nominal cost parameters, the additional terms are responsible for representing possible deviations that may occur.

The problem structure evidently suggests that – for each activity a , work centre w , and time instants l, t and part i – the decisions on r_{at} (number of regular hours), o_{at} (number of overtime hours), wr_{wt} (number of committed workload hours), wo_{wt} (number of committed workload hours), eh_{ttw} (total number of hired employees), ef_{ltw} (total number of fired employees between l and t),

ea_{wt} (boolean related to already started activity), and d_i must be made before the observation of realizations k_w^{CR} and k_w^{CS} . This consequently makes it hard to guarantee that a given solution will be feasible when these scaled deviations are observed.

According to the robust paradigm, it is assumed that the uncertain problem will be subject to the worst-case realization observed by the random parameters. The idea is to strengthen feasibility regardless of the realization of k_w^{CR} and k_w^{CS} within the given uncertainty interval. Therefore auxiliary problems are formulated to maximize the sum of all deviations over the set of all admissible realizations of the uncertain parameters, given an optimal decision.

For the sake of explanation, consider in the first place only the uncertainties relative to the production costs. In this sense, given the optimal solution $(r_{at}^*, o_{at}^*, wr_{wt}^*, wo_{wt}^*)$, a protection function may be defined as

$$\begin{aligned} \max_{k_w^{CR}} \quad & \sum_w dCR_w \left[\sum_{a,t} (r_{at}^* + o_{at}^*) + \sum_t (wr_{wt}^* + wo_{wt}^*) \right] k_w^{CR} \\ \text{s.t.} \quad & \sum_w k_w^{CR} \leq \Gamma^{CR}, \quad \forall w, \\ & 0 \leq k_w^{CR} \leq 1. \end{aligned} \quad (3)$$

The parameter Γ^{CR} can be defined as the upper bounds on the number of uncertain parameters that can deviate from their nominal values. It belongs to the set $\Gamma^{CR} \in \{0, \dots, |K|\}$, where $|K|$ means the cardinality of the set of work centres). Note that in case $\Gamma^{CR} = 0$, one has no uncertainty considered and, on the contrary, $\Gamma^{CR} = |K|$, one allows all uncertainties to take its highest values. These parameters are introduced to adjust the conservatism level of the optimal solution.

Let the dual of the optimization Problem 3 be defined as follows

$$\begin{aligned} \min_{\mu_w^{CR}, \lambda^{CR}} \quad & \sum_w \mu_w^{CR} + \lambda^{CR} \Gamma^{CR} \\ \text{s.t.} \quad & \mu_w^{CR} + \lambda^{CR} \geq dCR_w \left[\sum_{a,t} (r_{at} + o_{at}) + \sum_t (wr_{wt} + wo_{wt}) \right], \quad (4) \\ & \mu_w^{CR} \geq 0, \quad \forall w, \\ & \lambda^{CR} \geq 0, \end{aligned}$$

where λ^{CR} and μ^{CR} are the dual variables associated with Constraint (3).

Following the same reasoning for defining the dual of protection function in the average salary uncertain parameter, one has the dual the protection function defined as

$$\begin{aligned} \max_{k_w^{CS}} \quad & \sum_w dCS_w \left(\sum_t ea_{wt} \right) k_w^{CS} \\ \text{s.t.} \quad & \sum_w k_w^{CS} \leq \Gamma^{CS}, \\ & 0 \leq k_w^{CS} \leq 1, \quad \forall w \end{aligned} \quad (5)$$

which has the following problem as its dual

$$\begin{aligned}
& \min_{\mu_w^{CS}, \lambda^{CS}} \sum_w \mu_w^{CS} + \lambda^{CS} \Gamma^{CS} \\
& \text{s.t.} \\
& \mu_w^{CS} + \lambda^{CS} \geq dCS_w \left(\sum_t ea_{wt} \right), \forall w, \\
& \mu_w^{CS} \geq 0, \\
& \lambda^{CS} \geq 0.
\end{aligned} \tag{6}$$

By combining the production cost and average salary protection function, Constraints (4)-(6), with budget Constraint (2), one obtains the inner-problem in the two-level framework

$$\begin{aligned}
& \min_{\substack{\mu_w^{CS}, \lambda^{CS}, \mu_w^{CR}, \lambda^{CR}, \dots, \\ d_i, r_{at}, o_{at}, wr_{wt}, wo_{wt}}} \Psi \\
& \text{s.t.} \\
& \Psi + \sum_w \mu_w^{CR} + \lambda^{CR} \Gamma^{CR} + \sum_w \mu_w^{CS} + \lambda^{CS} \Gamma^{CS} \leq \epsilon, \\
& \mu_w^{CR} + \lambda^{CR} \geq dCR_w \left[\sum_{a,t} (r_{at} + o_{at}) + \sum_t (wr_{wt} + wo_{wt}) \right], \quad \forall w, \tag{7} \\
& \mu_w^{CR} \geq 0, \\
& \lambda^{CR} \geq 0, \\
& \mu_w^{CS} + \lambda^{CS} \geq dCS_w \left(\sum_t ea_{wt} \right), \\
& \mu_w^{CS} \geq 0, \\
& \lambda^{CS} \geq 0.
\end{aligned}$$

where it should be pointed out that the last three constraints are related to the salary cost protection function.

The proposed robust optimization model might be seen as an adaptation of the robust optimization model presented in [Carvalho et al., 2016], substituting the robust counterpart relative to uncertainties in the production time by uncertainties in cost parameters. Table 2 presents the additional parameters and variables included in this version.

4. Application

This section presents the results from applying the proposed robust model in a problem setting inspired in the original problem of [Carvalho et al., 2016]. Different scenarios based on this simplified situation were elaborated by varying the uncertainty budget parameters and analyzing the coherence of the model outputs in face of the input changes. The section ends with a discussion with the main insights gained from this application.

4.1. Numerical results and post-optimality analysis

In the set of experiments, the capacity related input parameters (which refers to the number of work centres, limit of working hours, limit of regular and overtime hours per employee) and cost parameters were extracted from [Carvalho et al., 2016]. Furthermore, this set considers a planning horizon of 18 months with 10 running projects, meaning 125 activities. It is assumed that none employee is initially allocated and with a limiting budget cost of $\epsilon = 7 \cdot 10^6$ monetary units. Additionally, the expected deviations relative to the key cost parameters budget level (production hourly cost and average salary) were considered to assess the robust formulation.

dCR_w	Parameter describing production hourly cost deviation at work centre w
dCS_w	Parameter describing employee average salary processing deviation operating at work centre w
Γ_w^{CR}	Uncertainty budget parameter of production hourly cost
Γ_w^{CS}	Uncertainty budget parameter relative to salary
k_w^{CR}	Scaled deviation regarding processing hourly cost uncertainty
k_w^{CS}	Scaled deviation regarding nominal salary uncertainty
μ_w^{CR}	Robustness variable relative to production hourly cost uncertainty
μ_w^{CS}	Robustness variable relative to salary (payroll cost)
λ^{CR}	Robustness variable relative to production hourly cost uncertainty
λ^{CS}	Robustness variable relative to salary (payroll cost) uncertainty

Table 2: Additional parameters and variables.

The uncertainty budget parameters Γ^{CR} and Γ^{CS} are assumed to belong to the set $\{0, \dots, 5\}$ (as there are five work centres). Figure 2 displays the effect of the variation of Γ^{CS} for each possible Γ^{CR} on the percentage increase of the optimal objective function value with respect to the nominal value. As expected, the solution provided by the deterministic model framework is retrieved by the robust one when both uncertainty budget parameters are set equal to zero. In addition, such a nominal solution is repeated when uncertainty is considered on one work centre, *i.e.*, $\Gamma^{CR} = 1$ or $\Gamma^{CS} = 1$). It is noteworthy that a solution of full subcontract plan, which refers to the 3.5% increase scenarios, verifies the budget limiting constraint when $\Gamma^{CR} \geq 2$ and $\Gamma^{CS} \geq 1$) or ($\Gamma^{CR} = 1$ and $\Gamma^{CS} \geq 2$). This plan represents the fully protected situation (conservative solution). There are also moderate solutions when ($\Gamma^{CR} = 0$ and $\Gamma^{CS} \geq 2$) and ($\Gamma^{CR} = 2$ and $\Gamma^{CS} = 0$) and ($\Gamma^{CR} = 1$ and $\Gamma^{CS} = 1$).

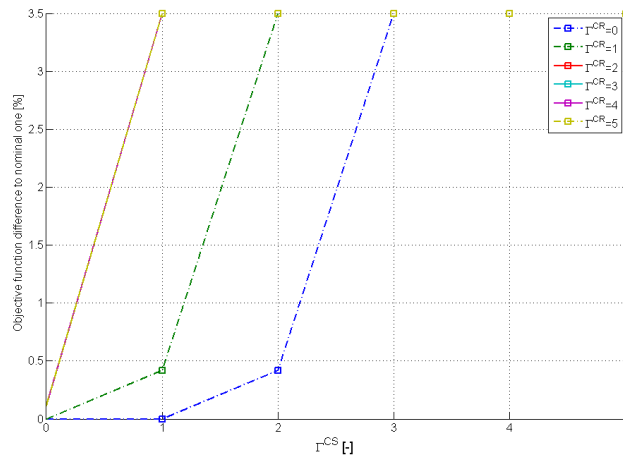


Figure 2: Total cost deviation regarding the nominal value by varying the salary cost uncertainty budget Γ^{SC} for fixed production cost Γ^{RC} .

The same reasoning of Section 3.1 is followed in order to assess the sensitivity of the

total cost optimal solution provided by the proposed robust optimization model, with respect to variation on cost parameters. Given the fact that such a model is formulated assuming uncertainty on production cost and average salary, the variation is initially applied on those two parameters, followed by the other costs.

The analysis is performed for two different situations, each one associated with the number of work stations considered uncertain. In Figure 3, one has the results for the conservative tuning with $\Gamma^{CS} = \Gamma^{RC} = 5$ and the moderate tuning is presented in Figure 4.

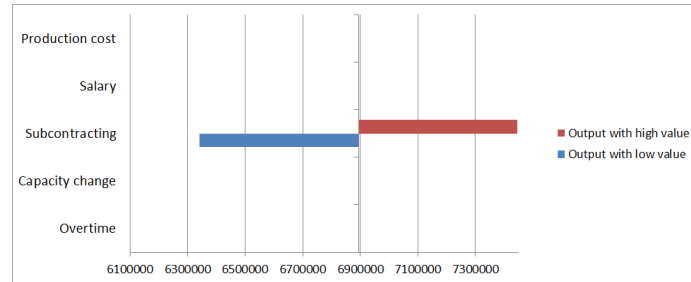


Figure 3: Tornado diagram of total cost variation regarding each cost parameter for conservative budget cost uncertainty tuning.

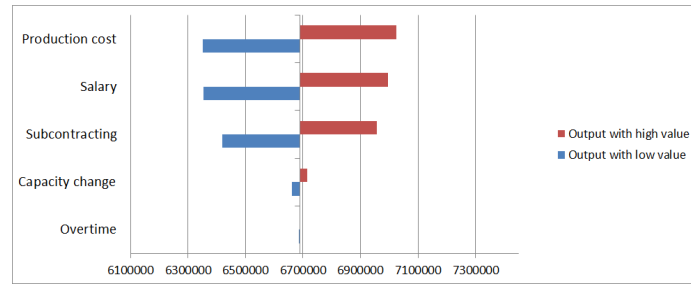


Figure 4: Tornado diagram of total cost variation regarding each cost parameter by employing the moderate budget cost uncertainty tuning.

4.2. Discussion

Note that the performed sensitivity analysis, considered as starting point, is interesting to rank the most relevant drivers of costs. This is in particular more interesting in applications where there are many cost parameters. The followed approach avoids over conservatism that would arise if uncertainties are assumed for all those parameters. In addition, it should be pointed out the proposed optimization model is able to cope with more structured cost uncertainties. That is, in case the product cost breakdown analysis is performed resulting on a detailed cost variability associated with each working centre, it is possible to straightforwardly deal with this case by applying the proposed framework. In the particular context of this case-study of ETO setting, some activities which are labour intensive ones (e.g. assembly and welding) are more subject to variability. Hence, the associated production costs costs are also more uncertain than operations that mainly depend on the use of machine (e.g. machining), [Carvalho et al., 2016].

For the fully protected situation, presented in Figure 3, the total cost does not change under the variation of production cost and average salary, as expected. In addition, it is possible to see that under the variation of subcontracted costs, one has the maximum budget constraint violated. This is due to the fact that the proposed optimization model did not take this variation into account. One approach to circumvent this issue would be to add additional protection constraints associated with such costs. Regarding the moderate tuning sensitivity analysis, Figure 4, one remarks that

variation of the total cost under the highest and lowest salaries and production costs are lower than the one of the deterministic model, exhibited in Figure 1.

5. Conclusions

In this paper, the problem of production planning for an ETO industrial setting under process uncertainties was studied. The main result was given by extending the robust optimization model of action research previously proposed to cope with cost uncertainties. The key cost parameters influencing the optimal total cost were identified through a sensitivity analysis followed by a robust optimization model considering the top two cost uncertainties. By means of a numerical example, one has illustrated the influence of the desired budget uncertain cost protection on the optimal total cost solution. It is showed that the higher is the protection level, the more robust is the model with respect to variabilities on the two considered costs. However, it is also discussed that the solution is less robust regarding other uncertainties such as outsourcing costs. As future works, it will be interesting to consider an additional step of model the variability of product cost breakdown into different types of activities and assess the performance of the proposed framework.

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