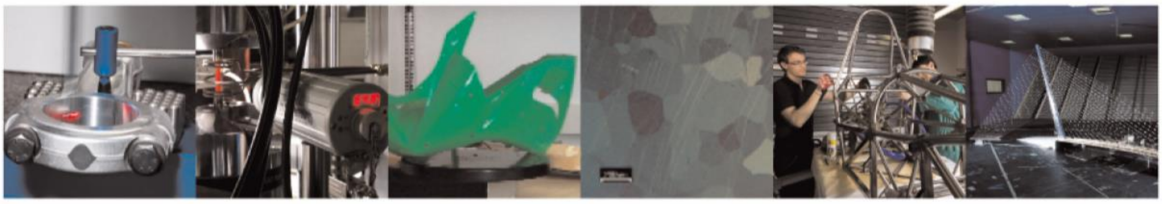

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Order allocation and sequencing with variable degree of uncertainty in aircraft manufacturing

Marcello Urgo[1], Jens Buergin[2,*], Tullio Tolio[1,3], Gisela Lanza[2]

1 Politecnico di Milano, Department of Mechanical Engineering, Milan, Italy.
2 Karlsruhe Institute of Technology, wbk Institute of Production Science, Karlsruhe, Germany.
3 ITIA-CNR, Institute of Industrial Technology and Automation, National Research Council, Milan, Italy.

Aircraft manufacturers are challenged with increasing demand requiring customers to place orders months in advance respect to the time aircrafts will be operative. Consequently, customers decide aircraft's size but have additional time to select cabin fittings. Nevertheless, manufacturers must promise a delivery time, regardless real aircraft configuration and resource availability at the production sites. We propose a novel framework for order allocation and sequencing in aircraft manufacturing minimizing the risk for manufacturing costs. Different degrees of uncertainty affecting products, work content and resources are considered as time advances and decisions to be taken change. An industrial application is also presented.

Planning, Manufacturing network, Uncertainty

1. Introduction and Problem Statement

The demand for new aircrafts has been growing consistently in the last years and seems not likely to slow down in the future, with companies from China, and Middle East leading the race for new orders [1]. The forecasts at Airbus say that, in the next 20 years, the market will ask for about 35-thousand new aircrafts above 100 seats (or above 10 tonnes for freighters) [1]. Despite the ups and downs of the world's economy and the fuel prices, the air travel has proven to be a resilient market, and robust growth is expected to continue in the future [2]. According to analysts [3], order books are bulging both at Airbus and Boeing, the biggest players in the market. The European firm's current backlog of 6400 planes will take about a decade to deliver while Boeing's 5800 will need about eight years [7]. Although being an extremely positive economic situation for aircraft manufacturers, this also entails consistent difficulties from the manufacturing point of view. Due to the impossibility and the high risk for a rapid increase of production capacity, planning is a key factor of success.

While planning their business strategy, airline companies must place orders for new aircrafts many months in advance. At Airbus, they select the class of the aircraft to be delivered, e.g. the A320 family, as well as its derivatives (A318, A319, A320, and A321). Customers are also provided a wide range of personalization of the aircrafts and are given additional time to go into the details of the aircraft's configuration, specifically in terms of the cabin fittings (seats, lavatories, galleys, etc.). Grounding on the aircrafts' delivery times (year and quarter) agreed with the customers, a mid-term planning of the associated manufacturing activities is defined to allocate the production of aircrafts to production sites and match the capacity over the considered time periods but, due to the lack of a detailed definition of the aircrafts' configurations, uncertainty must be taken into consideration.

At the time orders have to be sequenced, the definition of the configuration items impacting the workload is complete and manufacturing operations must comply with the delivery dates agreed with the customers months in advance, irrespective of the actual workload and amount of resource (personnel) available as well as the availability of parts and components.

In this paper, we address a novel framework for order allocation and sequencing in aircraft manufacturing. At the order allocation phase, the manufacturing of the aircrafts is assigned to the available production sites for final assembly taking into consideration specific technological and regional constraints. The allocation of orders must comply with the delivery times agreed with the customers and match resource and lead-time constraints. Due to the incomplete definition of the aircraft configuration, the associated uncertainty must be taken into consideration, with the aim at minimizing the deviations respect to the expected availability of production resources.

At the aircraft sequencing phase, the characteristics of the aircrafts are completely defined and, consequently, also the resource requests of the associated assembling activities. On the contrary, the uncertainty affects the availability of production resources, specifically workers, and sequencing must guarantee the timely delivery of aircrafts coping with these sources of uncertainty. The focus of the approach is on the final assembly line, i.e., the first part of the assembly process organized as a paced flow shop. The definition of the sequence is aimed at minimizing the risk associated to the so-called *residual work content*, i.e., the workload that cannot be completed within the cycle time of the assembly process and must be shifted in the stations following the flow shop and/or managed at the end of the assembly process.

The paper is organized as follows: Section 2 presents an analysis of the literature and the identification of the degrees of innovation for the proposed framework; Section 3 presents a formalization of the uncertainty associated to the order allocation and sequencing while Section 4 describes the solution approach in details; in Section 5 an application to the Airbus industrial case is presented while Section 6 reports the conclusions and future developments.

2. Literature review

The personalization of products has become a key competitive factor for companies [4], in particular for high value and complex products. Customers can configure their products according to their individual preferences by selecting specific options that are combined into a specific and often unique product variant. With the aim at providing their customers additional flexibility in selecting the desired customization of the products, manufacturers often offer additional flexibility to choose product options as late as possible. Due to this, planning decisions taken before the customization phase is closed may be conducted under uncertainty, entailing the need for robust planning [5].

In robust optimisation, uncertainty can be modelled through scenarios [6][7] pursuing robustness providing a feasible solution for all the scenarios taken into consideration [8]. A possible solution technique is stochastic programming, specifically two- (or multi-) stage programs with recourse, where corrective actions are planned based on first-stage decisions after uncertainty is disclosed [7]. The proposed approach takes advantages from these techniques proposing a different perspective, where the major source of uncertainty is caused by the late definition of products' characteristics (due to personalization, upselling, etc.) with the aim at proposing a robust allocation of orders to production sites and to periods. Current approaches for the assignment of orders to periods or sites either neglect complete product configurations or assume that they are certain.

In relation to the sequencing problem, the manufacturing environment under study is a flow shop. The flow shop scheduling is in general a NP-hard problem (except for the simple case of 2-machines systems and some particular cases of the 3- machines systems), hence, most of the research efforts have been devoted to the development of heuristic approaches rather than exact ones, most of them focusing on deterministic problems. A survey of the research results for flow shop scheduling are provided in [9][10].

Robust scheduling approaches have been gaining increasingly importance in production scheduling research during recent years. The pursued objective is to obtain schedules being insensitive as much as possible to the occurrence of uncertain events causing potential disruptions in the schedule, thus protecting the decision-maker against the impact of unfavourable events [11][12].

When addressing robustness, risk plays an important role. The conditional value-at-risk (*CVaR*) is a measure of risk widely used in financial research applications, like portfolio optimization [13][14].

The proposed approach addresses the sequencing of aircrafts at a single production site aiming at minimizing the risk of not completing the requested manufacturing operations in the given cycle time. In addition, although different classes of uncertainty with different time scales are present, an integration of the two phases is operated under the assumption that, as the variability associated to the planning phase is reduced (due to the robust order allocation approach), then also the robustness of the sequencing phase is improved, thus mitigating the impact of uncertain events. Examples of scheduling approaches based on conditional value-at-risk or similar risk measures minimization can be found in [15][16], nevertheless, none of these approaches considers this class of objective functions.

3. Order allocation and sequencing under uncertainty

3.1. Uncertainty related to demand of product configurations

In the aerospace industry, the allocation of orders to periods and to final assembly sites is a mid-term planning task operated under incomplete or uncertain information on final product configurations and, thus, the associated workload [5].

Once the order of an aircraft is placed, its assembling phase is assigned to a production site and a period (month). Nevertheless, as mentioned before, customers can finalize the desired aircraft's options also after the placement of the order, hence, during this planning phase, the workload associated to this assignment is uncertain and can cause deviations of the workload in relation to the available resources at the production sites. To model this source of uncertainty, a scenario-based model can be used.

Grounding on the customer's characteristics (e.g., considering previous orders) a probability can be guessed for the different aircraft configurations. Hence, scenarios are generated, to model the impact of the alternative configurations in terms of workload. All the scenarios deriving from the orders are combined together, to form a comprehensive scenario model of the uncertainty affecting the order assignment problem, with the objective to support a robust approach. Due to the very large number of scenarios, a reduced model will be used, sampling a subset of the whole set of scenarios. In addition, a worst-case scenario is taken into account, i.e., the one where all the customers opt for the maximum workload configuration, since it determines the maximum possible workload at all the sites and periods.

3.2. Uncertainty related to availability of production resources

When addressing the scheduling of the production at the assembly sites, the uncertainty affecting the problem changes. As the delivery date approaches, customers are required to take a final decision for the aircrafts' configuration, completely resolving the uncertainty affecting the associated workload. On the contrary, at the production site, the complexity of the assembly process entails a wide range of uncertain factors that can influence the timely execution of the assembly process.

Deciding the sequence to be used to assemble the aircrafts and, assigning orders to the assembly lines of a production site, entails the definition of the time when each aircraft will go out of an assembly line towards the final painting operations and, finally, to the delivery to the customer. At this stage, many sources of uncertainty could affect the assembly process, namely the availability of resources (specifically workers), the availability of parts and components and the possible non-conformities. In this work, we will mainly address uncertainty associated to the availability of workers, due its relevance and the relatively good availability of historical data. Stochastic fluctuations of workforce availability can be caused by personnel sickness, absenteeism or lack of personnel with specific skills. Since the assembly lines are paced, a lack of workforce with respect to the planned availability severely affects the completion of all the scheduled assembly operations. In addition, this risk is increased by the variable resource requests of the different aircrafts. A scenario model is generated also in this case, modelling the variability associated to the availability of resources in a given cycle time of the assembly line. Hence, the scenarios for all the cycles within the considered scheduling horizon are composed to obtain a comprehensive model of the uncertainty. Similarly to the previous case, due to the very large number of scenarios, a sampling approach is also adopted, obtaining a subset of the whole set of scenarios to support the robust sequencing approach.

3.3. Hierarchical uncertainty scheme

To summarize, we consider uncertainty affecting the global order allocation and local order sequencing in the production of large aircrafts. At the order allocation phase, both the characteristics of the orders and the availability of resources at the time the aircraft will be assembled are not completely known (Figure 1). Nevertheless, the availability of production resources is going to remain uncertain for a long time, since the time the aircraft will be assembled is far away in the future, hence, aggregate statistics (e.g., mean, variance, minimum, maximum, etc.) provide a reasonable model. On the contrary, the uncertainty affecting the characteristics of the products are going to be resolved earlier, hence, a more detailed model of the uncertainty is provided through scenarios.

When addressing the scheduling phase, aircrafts' configurations are completely known, hence no uncertainty model is needed anymore. On the contrary, the exact availability of production resources over time can vary, impacting the timely execution of the assembling operations. Also in this case, a scenario-based stochastic model is also fitted to provide a more detailed description of the uncertainty (Figure 1).

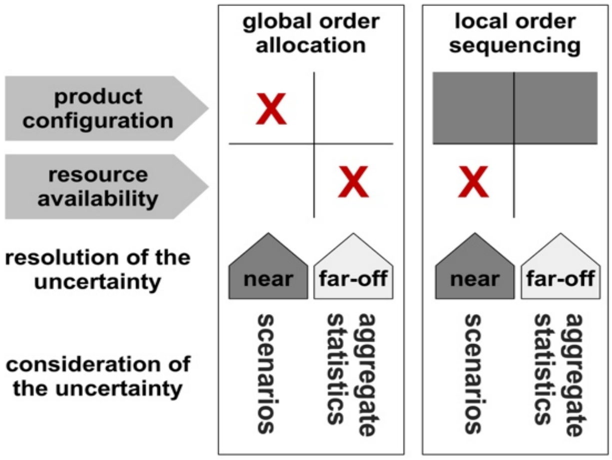

Figure 1. Uncertainty scheme.

Grounding on the framework described, the solution approach is organized in two steps. In the first one, orders are assigned to production sites and months, modelling the uncertainty associated to the aircrafts' configurations through scenarios. The aim is at minimizing a stochastic function of the difference between the aggregated workload and the expected resource capacity at each site in each month for the considered scenarios. This is done under the hypothesis that, as any of these deviations increases, it will be more difficult to manage by using the available resource flexibility at the production sites. Specific constraints are imposed to limit these deviations in terms of magnitude. Notice that, when an order is assigned, the time aircrafts will be put into production is far away; hence, addressing the uncertain availability of production resources in an aggregate way on a monthly basis, through an expected value, is likely to be suitable.

The second step addresses the sequencing of aircrafts in the final assembly lines, and the uncertainty associated to the availability of workers is modelled in detail through scenarios. Here, extreme cases are the most important factor to be addressed, rather than average values. In fact, an inadequate availability of resources implies the impossibility to complete the assembly process in a station within the cycle time, generating an amount of pending work that must be delayed to the following station propagating through the whole assembly line. The aim of the approach is to minimize a measure of risk, the *CVaR,* of the *residual work content (rwc)*, i.e., the workload that cannot be completed and must be delayed.

4. Solution Approach

4.1. Global order allocation

The global order allocation step is operated through a set of binary decision variables x_{ilt} assuming value 1 if an individual customer order *i* is allocated to site *l* in month *t*.

The number of orders to be assigned to each site and month is limited by the number of the available cycles of the assembly lines at that site K_{lt} as stated in (1).

$$\sum_{i \in I} x_{ilt} \leq K_{lt} \ \forall l, \forall t \qquad (1)$$

Grounding on the order assignment variable ***x***, the workload deviation $\Delta_{lts}(x)$ is calculated, modelling the difference between the available resources and the workload demand at site *l* in month *t* in scenario *s*. Keeping this difference low is one of the factors to be taken into consideration in the order assignment phase through an associated workload deviation cost. Moreover, additional aspects are considered. Order-related costs cover costs for material input, inventory of orders produced too early and penalties for orders delivered late in case of specific months preferred by the customers for delivery as well as penalties for orders delivered at sites different from the ones preferred by the customers. Order spacing costs cover costs accruing if more orders of the same customer are produced in the same month than preferred, thus entailing costs for holding them on inventory and considering penalty costs for delivering them in a later month. Finally, also smoothing specific part usage over the planning horizon is addressed [17], due to the difficulty for suppliers to fulfil peak requests of components in relation to fair usage rates from both the time and site points of view.

As one of these aspects, a comprehensive workload deviation cost function $C^{\Delta}(\boldsymbol{x})$ depending on ***x*** is minimized (2).

$$C^{\Delta}(\boldsymbol{x}) = \left[\sum_{s \in S'} p_s \left(\sum_{t \in T} \sum_{l \in L} C^{f}_{lts}(\Delta_{lts}(x))\right)\right] \qquad (2) + \sum_{l \in L} C^{c}_{l}(\max_{s,t}\{N(\Delta_{lts}(x))\}$$

The first term of the workload deviation costs addresses the direct costs associated to the workload deviation. Pursuing an analogy with the reconfiguration of manufacturing systems, they are modelled through flexibility costs $C^{f}_{lts}(\Delta_{lts}(x))$, a piecewise linear function considering the cost associated to workload deviation within a given flexibility limit, summing up over all sites, months and sampled scenarios S' out of S. As the aim of the approach is at minimizing the expected value of these cost, the sum is weighted with the scenario occurrence probabilities p_s.

To pursue robustness over the considered scenarios, corrective actions are considered addressing the qualification of temporary staff at the sites. This is modelled through the number of temporary workers $N\left(\Delta_{lts}(x)\right)$ required for handling the workload deviation falling outside the available flexibility at the site. This is a recourse action and we hypothesize that second-stage problems are always feasible, i.e., it is always possible to qualify the needed number of temporary staff. Hence, the second term mimics a changeability cost and aims at minimizing a function

C_l^c of the sum of the maximum number of temporary workers to be qualified to manage a workload beyond the available flexibility limit at all the sites over the considered months and scenarios, i.e. trying to mitigate the impact of the extreme scenarios.

4.2. Local order sequencing

The first part of the final assembly of aircrafts is operated in paced assembly lines dealing with a family of aircrafts, operating the assembly of structural components, which are equal for a given aircraft derivative, as well as those related to the specific options required by the customers, which may vary among single orders. Due to this, the workload on each station is affected by both the aircraft derivative and the configuration of each order.

We consider a set of assembly lines Ψ, each of them consisting of *m* stations operating a batch of operations within a given cycle time. A set of independent jobs *J* have to be processed in an assembly line entailing a workload nwl_{jm}, i.e., the amount of equivalent man hours required by job *j* in station *m*. The uncertainty affecting the availability of resources is modelled through a finite set of scenarios Ω, each of them with an occurrence probability π_ω. Each scenario defines the resource availability in all the cycles within the planning horizon. As described in the previous section, only a subset Ω' of Ω is considered, obtained through sampling.

If the availability of resources is not enough to satisfy the workload, the operations that cannot be executed are processed after the paced line, in an additional station. The objective of the local order sequencing approach is to minimize the *rwc*, i.e., the quantity of equivalent man hours not completed in the assembly stations. In the current formulation, we give up in differentiating the *rwc* per assembly line, station and job. We rather consider the sequencing of three different assembly lines having the same cycle time. For each cycle, we compute the difference between the assigned workload and the (uncertain) availability of resources for all the scenarios. This is done for the three assembly lines together, since they are sharing the same set of workers and summing up the *rwc* over the whole planning horizon. The process is modelled as a single resource problem (considering the workers as a unique type of resource) to mitigate the computational complexity. Explicitly considering different skills entails an exponential increase of the scenarios, since different uncertainty affects the different classes of workers. Nevertheless, since the aircrafts mostly differ in terms of cabin fittings, not requiring specific skills to be assembled, this does not result in an oversimplification.

To address robustness in sequencing, the aim is at minimizing the *CVaR* of the *rwc*, i.e., the expected value of the *rwc* falling in the worst α-% of the cases. Minimizing this risk measure allows to mitigate the overall impact of the worst cases in relation to the cost of overtime and/or additional working hours.

Grounding on the approach described in [13], the minimization of the *CVaR* can be defined as a MIP model to minimize (3),

$$R(\boldsymbol{y}) = \beta + \frac{1}{1-\alpha} \sum_{\omega \in \Omega'} (\lceil rwc_\omega - \beta \rceil \cdot \pi_\omega) \quad (3)$$

where rwc_ω is the residual work content in scenario ω, π_ω is the occurrence probability of the scenario, α is the level of risk selected and β, at the end of the optimization, assumes the value of the *CVaR* and is, thus, minimized. The objective function is optimized over $\boldsymbol{y}$, a decision variable representing the sequence of aircrafts entering the assembly lines.

5. Industrial Application

5.1. Global order allocation

The scenario model for global order allocation is applied to the assignments of orders for the Airbus A320 family for one quarter in 2015. More than one hundred customer orders, summing up to a sales price of about 13 bn. US dollars, have to be allocated to the production sites for final assembly in Hamburg, Toulouse and Tianjin (Figure 2). A pool of 200 scenarios have been defined, representing potential configurations of the customers of the orders and used to sample the reduced set to be utilized for the decision model, including the worst-case scenario with the maximum workload for each order.

Figure 2. The final assembly line in Tianjin (courtesy of AIRBUS).

The order assignment has been carried out using both the scenario model and the expected value one using IBM ILOG CPLEX. Notice that, for non-disclosure reasons, the results have been normalized. The normalization process has been carried out taking the costs obtained and considering the values as a fraction of the value of the overall costs of the objective function of the solution of the scenario model.

The optimal solution of the scenario model yields to workload deviation costs of 0.0057%. 0.0038% are flexibility costs and 0.0019% are changeability costs. Therefore, costs for internal over hours are applied to workload deviations from 0.0% to 0.5%. It is assumed that 0.5% is the flexibility limit of the permanent staff. For the workload exceeding this limit, changeability costs are incurred. Flexibility limits are set quite low in order to preserve flexibility for sequencing considering uncertainty of the availability of production resources.

These results have been compared with the ones obtained using expected values for workloads instead of scenarios. The comparison shows that, using the expected values, flexibility costs amount to 0.0042% and changeability costs to 0.0038%. Thus, both are higher than the ones obtained through the scenario model. The benefits of using the stochastic approach in place of the expected value one are measured by this difference, called *value of the stochastic solution* [6], whose value is 0.0013%. Thus, the solution provided by the scenario approach pursues robustness, as further detailed through the workload deviations given in Table 1, last row, showing the mean of the sum of the positive workload deviations over all sites and months (columns *average value*). The results indicate that the scenario approach leads to a lower value compared to the expected value one. The same applies for the sum of the maximum workload deviations (columns *max*).

For both the approaches, the workload deviations exceed the 0.5% flexibility limit for two months at the Tianjin site, but the maximum value reached with the scenario-based approach (0.84%) is lower than the maximum of the expected value one (1.19%), resulting in lower changeability costs.

However, further considerations must be done. In the case the assignment is planned through the expected value approach, a smaller number of temporary workers would be qualified, leading to infeasibilities in some of the scenarios (with a probability of about 68%), requiring late and usually costly corrective actions, e.g., extra shifts on week-ends. This reflects the benefits of the robust approach in protecting the decisions against extreme unfavourable events to minimize the risk for additional manufacturing costs.

Table 1. Workload deviations $\Delta_{lts}(x)$ for global order allocation.

site	month	scenario solution		expected value solution	
		average value	**max**	**average value**	**max**
Hamburg	**1**	-0.01%	0.32%	-0.10%	0.10%
	2	-0.03%	-0.01%	-0.01%	0.05%
	3	-0.08%	-0.01%	-0.02%	0.13%
Toulouse	**1**	-0.05%	0.45%	-0.01%	0.31%
	2	-0.01%	-0.01%	-0.01%	0.36%
	3	0.00%	0.16%	-0.03%	0.02%
Tianjin	**1**	0.75%	**0.84%**	0.22%	0.29%
	2	0.21%	0.35%	0.35%	**1.19%**
	3	-0.08%	**0.57%**	0.49%	**0.60%**
sum of pos. values		0.96%	2.69%	1.06%	3.03%

Both the scenario model and the expected value model have been solved with a ten hours solution limit, resulting in a sufficient optimality tolerance of the MIP problem in case of 200 scenarios. Due to the remarkable solving time, with regard to industrial applicability, not more scenarios are considered to represent the 7.3×10^{18} potential scenarios regarding the considered configurations, although a higher number of scenarios can be useful to improve the reliability of the solution.

5.2. Local order sequencing

For the local order sequencing, the experiments have been carried out over a test set defined with reference to the Airbus A320 family for the same quarter of 2015 as considered for global order allocation, but for the Hamburg's production site only. Three different pools of orders are used aimed at sequencing one, two or three months of production. The objective function to minimize is the *CVaR* (α=0.05) and, in order to identify possible dependence of the results from the sampling of the scenarios we consider three different cases with 100, 500 and 2000 sampled scenarios and three replicates for each of the cases.

The general performances of the algorithm are reported in Table 2, reporting the time needed to solve the test instances with IBM ILOG CPLEX. The average solution time is about 96 seconds, ranging from a minimum of about 9 seconds to a maximum of 470 seconds. The results show a clear dependence of the solution time from the number of scenarios and it is the largest number of scenarios (2000) determining the worst solution time, i.e., about nine minutes to find the optimal solution.

Table 2. Local order sequencing solution times.

Sequenced production	Number of scenarios	Average solution time (s)
1 month	100	9.25
	500	14.41
	2000	47.86
2 months	100	9.95
	500	30.73
	2000	207.11
3 months	100	14.20
	500	64.45
	2000	470.34
		96.48

In relation to the quality of the solution obtained, with reference to other planning approaches, the schedule minimizing the *CVaR* of the residual work content is compared against the one obtained through an expected value approach, i.e., an approach aiming at minimizing the expected value of the residual work content over the considered scenarios.

Notice that, for non-disclosure reasons, the results have been normalized. The normalization process has been carried out taking the ranges for the *rwc* obtained in the experiments and considering the values as a fraction of the whole range. As an example, the average minimum level of the *rwc* obtained through the expected value approach is 19%, i.e., it is at the 19% of the range between the minimum and maximum values of the *rwc* obtained on all the experiments. If the minimum value is 0 and the maximum is 100, then the real value should be 19 hours.

Table 3. Local order sequencing results.

	EV	CVaR
Min. *rwc*	0.19	0.19
Avg. *rwc*	0.47	0.47
Max. *rwc*	0.92	0.91
0.05-VaR *rwc*	0.67	0.66
0.05-CVaR *rwc*	0.72	0.71

The results of this comparison are reported in Table 3 showing that, in terms of minimum and average value of the *rwc*, the two approaches are comparable. On the contrary, the most consistent advantage of the CVaR method (implying a higher computational effort) lies in the reduction of the impact of the worst cases, i.e. in the lowering of 0.05-VaR, 0.05-CVaR and maximum value of the distribution (66% against 67%, 71% against 72% and 91% against 92%) as shown in Table 3.

6. Conclusions

We presented a novel framework for production planning in the aeronautical sector structured in two decision steps: one for order allocation and one for production sequencing, taking into consideration the uncertainty associated to both the characteristics of the product configurations and the availability of resources. The two steps address the prominent sources of uncertainty through a scenario model while the remaining uncertainty is addressed in an aggregate way.

The approach has been tested and validated at Airbus showing promising results. The benefits of using scenarios compared to neglecting uncertainty by applying the expected value model are demonstrated. The novel framework thus gives guidance regarding the explicit modelling of specific sources of uncertainty.

The future development of the approach will address the capability of using different models for the uncertainty, i.e., analytical models, with the aim at reducing the dependency of the performance from the need of sampling a high number of scenarios.

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