



Robust assignment of customer orders with uncertain configurations in a production network for aircraft manufacturing

Jens Buergin, Philippe Blaettchen, Juri Kronenbitter, Katharina Molzahn, Yannick Schweizer, Caroline Strunz, Manuel Almagro, Frank Bitte, Stephan Ruehr, Marcello Urgo & Gisela Lanza

To cite this article: Jens Buergin, Philippe Blaettchen, Juri Kronenbitter, Katharina Molzahn, Yannick Schweizer, Caroline Strunz, Manuel Almagro, Frank Bitte, Stephan Ruehr, Marcello Urgo & Gisela Lanza (2019) Robust assignment of customer orders with uncertain configurations in a production network for aircraft manufacturing, International Journal of Production Research, 57:3, 749-763, DOI: [10.1080/00207543.2018.1482018](https://doi.org/10.1080/00207543.2018.1482018)

To link to this article: <https://doi.org/10.1080/00207543.2018.1482018>



© 2018 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 04 Jul 2018.



Submit your article to this journal [↗](#)



Article views: 1021



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 1 View citing articles [↗](#)

Robust assignment of customer orders with uncertain configurations in a production network for aircraft manufacturing

Jens Buergin^{a*}, Philippe Blaettchen^a, Juri Kronenbitter^{a,b}, Katharina Molzahn^{a,b}, Yannick Schweizer^a, Caroline Strunz^a, Manuel Almagro^a, Frank Bitte^b, Stephan Ruehr^b, Marcello Urgo^{ib}^c and Gisela Lanza^a

^awbk Institute of Production Science, Karlsruhe Institute of Technology, Karlsruhe, Germany; ^bAirbus Operations GmbH, Hamburg, Germany; ^cDepartment of Mechanical Engineering, Politecnico di Milano, Milan, Italy

(Received 19 December 2017; accepted 22 May 2018)

Production of multi-variant products in a network requires the assignment of customer orders to locations and periods. This is a highly complex planning task, as requirements of procurement, production, distribution, and sales have to be considered. Providing customers with the flexibility of configuring their ordered products after order assignment further increases the complexity of the planning task by taking uncertainty into account. Therefore, a robust optimisation model, using scenarios representing potential customer-specific order configurations, is introduced. By providing enough flexibility to handle maximum work overload caused by the potential order configurations at locations, a robust assignment of orders can be guaranteed in order to avoid undesirable situations causing delays and additional costs. Therefore, the mid-term adjustments of the flexibility limits are enabled by the changeability of workforce supply by making use of external workers. An industrial application of the model in manufacturing of the Airbus A320 Family of aircrafts is presented. The costs for offering configuration flexibility to customers are quantified by the expected value of perfect information. The explicit consideration of configuration uncertainty through the use of scenarios is discussed based on the value of the stochastic solution in comparison to the results attained by simplistically using the expected value.

Keywords: Robust optimisation; production planning; manufacturing networks; uncertainty

1. Introduction

Manufacturing companies need to be increasingly flexible, e.g. in terms of a responsive work organisation that enables to meet sophisticated customer demands and growing global competition (Palpacuer 2000). To react to the individual needs of customers by offering customisable products, making use of flexibility as well as economies of scale, the concept of mass customisation is applied by companies as a competitive strategy (Da Silveira, Borenstein, and Fogliatto 2001). Mass customisation implies that customers can configure their products by choosing options offered in a catalogue (Da Silveira, Borenstein, and Fogliatto 2001). Different product variants, defined by a basic product model and selected options, can be produced on the mixed-model assembly lines (MMALs) in intermixed sequences making use of efficient flow production (Boysen, Fliedner, and Scholl 2009b). Following the trend of globalisation, companies offer products to international markets by operating manufacturing networks (Rudberg and Olhager 2003). Thus, production planning for customisable products produced on MMALs at various locations of a manufacturing network, which is also referred to as a production network, is a complex task.

To increase the efficiency of production systems and overcome the growing complexity, it is necessary to use elaborate approaches to production planning (Hackstein 1989). Production planning tasks can be structured according to the Supply Chain Planning Matrix in the dimensions ‘planning horizon’, covering long-term, mid-term, and short-term planning tasks according to hierarchical planning, and ‘supply chain process’ of the intra-organisational supply chain, such as procurement, production, distribution, and sales (Fleischmann, Meyr, and Wagner 2015). Mid-term master planning with a planning horizon of 6–24 months integrates planning of procurement, e.g. material requirements planning, production, e.g. master production scheduling, and distribution based on sales planning, and allows for central coordination of multiple production locations (Fleischmann, Meyr, and Wagner 2015).

*Corresponding author. Email: jens.buergin@kit.edu

In the case of the Airbus single-aisle A320 Family, the order backlog equals the production quantity for more than the next eleven years according to the current production rate (Airbus 2017). Final assembly of A320 Family aircrafts is executed on final assembly lines and additional stations after the lines at the locations Hamburg (D), Toulouse (F), Tianjin (CN), and Mobile (USA). Thus, mid-term master planning has to assign customer orders to locations. Orders that have been promised for a specific quarter can simultaneously also be assigned to a delivery month within that quarter. As not all of the A320 Family basic product models, which are A318, A319, A320, and A321, can be produced at each of the production locations, the basic product model has already to be selected by the customers prior to order assignment. The latest possible time for conducting order assignment is determined by the lead time of location-specific material requirements planning, especially for structural parts related to the basic product model. Furthermore, it depends on the necessity to inform customers about the delivery month. Thus, the optimisation potential of assigning orders to months and not only to locations may be exploited.

However, options further defining order configurations, e.g. options related to cabin configuration, might be chosen by the customers after order assignment (Buergin et al. 2016). Offering customers the flexibility to choose each option at the latest possible point in time depending on its lead time is a service that has been elaborated for the Airbus A320 Family and is referred to as Just-In-Time Specification (Belkadi et al. 2016; Colledani et al. 2016; Buergin et al. 2018). Therefore, when offering the Just-In-Time Specification service, the uncertainty of order configurations has to be considered when conducting order assignment (Buergin et al. 2016, 2018). Potential option choices crucially affecting the workload accruing in the final assembly should not be neglected when assigning orders (Buergin et al. 2016, 2018). As the customers of orders to be assigned are already known, the probabilities of their potential configurations may be estimated based on historical data as well as on current trends, and thus be anticipated for order assignment in the production network.

The assignment of orders to lines and cycles as well as additional stations and time slots at the production location can be executed later on as short-term planning after option choices have been made (Buergin et al. 2016). In line with hierarchical planning, detailed, lower level plans are made with a shorter planning horizon, being restricted by the upper level plan (Fleischmann, Meyr, and Wagner 2015), which means, in this case, the assignment of orders to locations and months. Thus, short-term planning should be anticipated by mid-term planning (Fleischmann, Meyr, and Wagner 2015).

The paper is structured as follows: Within Section 2, the state of the art on the topics relevant to the approach presented here is examined. This is followed by a mathematical description of the robust model for the assignment of customer orders with uncertain configurations in the production network in Section 3. In Section 4, the results of applying the approach to the Airbus A320 Family are presented. The paper is concluded in Section 5 with a summary and an outlook on future research.

2. Literature review

In the context of MMALs, there are two commonly studied planning problems besides mid-term master planning (Boysen, Flidner, and Scholl 2009a): the long- to mid-term assignment of assembly tasks to stations on lines, called assembly line balancing (Boysen, Flidner, and Scholl 2009a; Ríos, Mas, and Menéndez 2012), as well as the short-term building of a sequence, in which orders are inserted into the MMALs (Boysen, Flidner, and Scholl 2009b). Assembly line balancing is assumed as given for mid-term master planning and thus not further regarded. In the following sub-sections, the focus lies on short-term sequencing to be anticipated by master planning as well as mid-term master planning itself. Moreover, as order configurations are uncertain for mid-term master planning, robust optimisation is also addressed.

2.1. Short-term sequencing

Regarding sequencing of MMALs, approaches following two alternative objectives can be found: workload-oriented approaches minimising work overload as well as material supply-oriented approaches smoothing material requirements depending on product options (Boysen, Flidner, and Scholl 2009b).

As an MMAL is defined by its ability to handle the assembly of a range of product variants in an arbitrary sequence, there are variants that require more than the average share of workload and others that require less (Boysen, Flidner, and Scholl 2009b). Conceptually, following a workload-oriented approach leads to alternations between variants with a high workload and others with a low workload in order to avoid overloading stations (Boysen, Flidner, and Scholl 2009b). With mixed-model sequencing (e.g. Okamura and Yamashina 1979; Bard, Dar-Elj, and Shtub 1992), each variant, i.e. model, and its impact on each station is considered in detail regarding its explicit schedule, while with car sequencing (e.g. Parrello, Kabat, and Vos 1986; Solnon et al. 2008) these impacts are aggregated to sequencing rules that indirectly lead to avoidance of undesired sequences, i.e. a maximum of H variants using a certain option are allowed in any sequence of N variants (Boysen, Flidner, and Scholl 2009b). Moreover, workload-oriented level scheduling is an indirect workload-oriented approach that smooths workload, ignoring capacity constraints (Boysen, Flidner, and Scholl 2009b).

Just-In-Time supply of material is enabled by a production sequence smoothing material requirements, (e.g. Miltenburg 1989; Kubiak 1993; Duplaga and Bragg 1998) directly or indirectly (Boysen, Fliedner, and Scholl 2009b). With part-oriented level scheduling, the target is to evenly distribute the demand for each part among the planning horizon according to a target rate (Boysen, Fliedner, and Scholl 2009b). Model-oriented level scheduling approximates part-oriented level scheduling by applying a target rate for each variant, i.e. model, instead of each part (Boysen, Fliedner, and Scholl 2009b). Therewith, complexity can be reduced by not considering a high number of different parts, but it requires that a single variant is produced more than once in the planning horizon (Boysen, Fliedner, and Scholl 2009b).

2.2. Mid-term master planning

Depending on the industry, orders are assumed not to be available at the time of mid-term master planning (Meyr 2004). Respective approaches determine assignments to periods and, in case of the production network, also to locations on the basis of quantities of aggregated product variants (Hax and Meal 1973; Wittek et al. 2011). In particular, aggregation in terms of quantities of the basic product models and also quantities of options might be applied (Meyr 2004; Wittek et al. 2011).

On the contrary, there are approaches for assigning individual customer orders instead of quantities to production periods and locations found in the literature. Boysen, Fliedner, and Scholl (2009a) suggest a comprehensive planning framework of which an important aspect is the anticipation of sequencing within master planning. As master planning, they consider the assignment of orders to periods, taking inventory costs for orders produced too early and costs for late deliveries into account, and suggest specific constraints for anticipating the sequencing approaches mixed-model sequencing, car sequencing, and part-oriented level scheduling (Boysen, Fliedner, and Scholl 2009a). Dörmer, Günther, and Gujjula (2015) also address the problem of assigning orders to periods and develop different approaches anticipating mixed-model sequencing. They further define an integrated procedure that they find to be superior to sequential planning, but by giving up hierarchical planning, sequencing has to be already conducted at the time of master planning (Dörmer, Günther, and Gujjula 2015). Both Boysen, Fliedner, and Scholl (2009a), as well as Dörmer, Günther, and Gujjula (2015) assume that order specifications in terms of option choices are given at the time of planning. However, as their approaches solely consider assignments to periods and not to locations, they may be applied between mid-term master planning and short-term sequencing after assignments to locations have been determined.

Furthermore, there also exist approaches for specifically assigning orders to locations. Such an approach is presented by Bruns and Sauer (1995). Their multi-site scheduling procedure handles global as well as local scheduling separately, trying to prevent the creation of bottlenecks by analysing capacities at the locations when conducting global scheduling (Bruns and Sauer 1995). Besides, Chan et al. (2006) develop an approach for handling the assignment of orders to plants and the local scheduling simultaneously. Chen and Hung (2014) consider material costs, production costs, delivery costs, and penalty costs for late deliveries as well as workload when assigning orders to locations. Guo, Wong, and Leung (2013) presented an approach for assignments to locations minimising the tardiness and the throughput time of orders as well as idle times. The introduced approaches for order assignment to locations consider workload in terms of production times at the locations and therefore require option choices inducing workload to be certain. Moreover, they do not specifically consider requirements for the sequencing of orders on the mixed-model assembly lines.

In summary, there are approaches either considering quantities of aggregated product variants or orders with specified configurations. The middle ground would be to consider order configurations as uncertain, including more information than only basic product models, but also not requiring that option choices have been fixed. To the best knowledge of the authors, option choices have not been considered as uncertain in any work for assignment of orders to periods and locations so far. Such an approach is introduced in this paper, especially being applicable if orders have been received at the time of mid-term planning, but not yet been configured completely.

2.3. Robust optimisation

Uncertainty in terms of option choices can be considered for the assignment of orders by taking the probabilities of order configurations into account. Potential realisations of uncertain values can be constructed by generating scenarios (Kall and Wallace 1994; Kaut and Wallace 2003). Thus, a stochastic problem in terms of a mathematical optimisation model with the uncertainty of some parameters can be solved under consideration of the generated scenarios (Kaut and Wallace 2003).

Instead of solving the stochastic problem, a much simpler, deterministic problem could be solved by replacing uncertain values with their expected values, which is called the expected value problem (Birge and Louveaux 2011). However, this would mean to ignore the existence of uncertainty and its consequences, i.e. its scenario-specific corrective actions (Birge and Louveaux 2011). The advantage of considering scenarios instead of expected values for order assignment is presented in this paper.

Compared to stochastic optimisation models, robust optimisation models also make use of scenarios, but reflect a risk aversion in decision-making by not only considering the expected value of the result regarding the scenarios, but also the variability of the result (Mulvey, Vanderbei, and Zenios 1995). Therefore, in the robust optimisation model presented in this paper, the expected value and the maximum value both are weighted and simultaneously minimised in the objective function, as suggested by Hodges and Lehmann (1952). Thus, robustness, meaning a high as well as a stable performance of the system to be planned, can be achieved (Stricker and Lanza 2014).

The robustness of the optimal solution of an optimisation model can be evaluated in terms of model robustness as well as solution robustness (Mulvey, Vanderbei, and Zenios 1995). Model robustness refers to the feasibility of the model regarding the scenarios according to the model constraints, whereas solution robustness refers to the optimality of the model regarding the objective function values of the scenario-specific solutions (Mulvey, Vanderbei, and Zenios 1995; Scholl 2001). In order to achieve model robustness, corrective actions, that are dependent on the degree of violation of the model constraints by the realised scenario and thus are implemented after information on the realised scenario has been revealed, are anticipated in the objective function of stochastic programmes with recourse (Scholl 2001; Birge and Louveaux 2011). Hence, violations of the model constraints are penalised in robust optimisation models (Mulvey, Vanderbei, and Zenios 1995). However, corrective actions could also be implemented proactively when making the planning decision under uncertainty in order to avoid such violations and respective penalties. In production planning, actions to adjust flexibility limits are referred to as changeability (Zaeh, Moeller, and Vogl 2005). Hence, in the context of mid-term planning presented in this paper, proactive corrective actions in terms of changeability could be taken mid-term under uncertainty and reactive corrective actions in terms of flexibility could be taken short-term based on the realised scenario.

With regard to production planning, robustness has been considered in production scheduling, making schedules less sensitive to uncertain events that potentially disrupt them (see e.g. Janak, Lin, and Floudas 2007; Tolio and Urgo 2007; Urgo and Váncza 2014). Regarding mid-term planning, a robust optimisation models in literature consider costs for surplus or shortage of products to achieve model robustness (see, Mirzapour Al-e-hashem, Malekly, and Aryanezhad 2011; Khakdaman et al. 2015) instead of applying costs for the implementation of proactive and reactive corrective actions to avoid the occurrence of such results. To the best knowledge of the authors, there is no robust optimisation approach that considers proactive and reactive corrective actions for mid-term production planning simultaneously.

3. The robust optimisation model for order assignment

In this section, the robust optimisation model for assigning customer orders with uncertain configurations in terms of option choices to locations and periods in the production network is introduced. Therefore, short-term sequencing on MMALs assigning orders to lines and cycles for a specific period at a certain location is anticipated. Moreover, uncertain option choices are anticipated through scenarios.

A customer order consists of the basic product model as well as a range of options to be specified by the customer. Customers have to choose one option from each option group. Each option group may additionally contain the default choice for cases where none of the options in the group have to necessarily be chosen. At the time of mid-term master planning, it is considered that the customer and the basic product model of each order are known, but option choices are not necessarily specified and thus explicitly considered as uncertain. Therefore, the probabilities of the potential configurations are estimated for each customer and the basic product model. Hence, probabilities of configurations and thus dependent option choices are considered instead of option choices themselves. If option choices were independently combined to configurations instead, this would lead to an increased number of scenarios due to configurations that have never been chosen and might not be chosen by the customers.

A scenario-based approach is considered for the modelling of uncertain option choices. The combination of one potential configuration for each order is considered as one scenario. As the total number of scenarios might be very large as it equals the multiplication of the number of potential configurations for each order, only a subset of scenarios can be considered as input for the optimisation model for order assignment. Therefore, a sampling approach for scenario generation which represents the overall scenarios as effectively as possible is necessary. As the workload of an order is induced by its potential option choices and thus is an aggregated view on option choices, the workload of each order can be considered representatively in the sampled scenarios. For model robustness of the optimisation model, the potential configuration with the maximum workload has to be contemplated for each order, resulting in a worst-case scenario regarding workload. Further scenarios are generated by stratified sampling (see e.g. Han, Kamber, and Pei 2012, 109–110) of configurations from clusters of a similar workload according to the cluster probabilities and the number of scenarios to be generated. For clustering, a *k*-means algorithm (see, e.g. Han, Kamber, and Pei 2012, 451–452) is applied to the workload distribution function of each customer order.

In order to handle all generated scenarios including the worst-case scenario, and thus all potential scenarios, avoiding any infeasibilities of the model and ensuring model robustness, corrective actions are considered in the objective function of the model instead of implementing hard constraints. In the following, a distinction is made between proactive corrective actions that directly have to be made mid-term, when orders are assigned under uncertainty, and reactive corrective actions that are made short-term, after information on the realised scenario has been received. This is necessary because the planning horizon of some actions is longer than for others, as will be shown below.

In the objective function, not only multiple scenarios but also multiple criteria are integrated for order assignment. For the sake of tangibility of the model results as well as due to the difficulty of evaluating criteria weights by the decision-maker, the criteria with respect to the scenarios are monetarised in the following objective function (see e.g. Keeney and Raiffa 1993, 66–67, 111, 125–127). The objective considered is thus

$$\min f(x) = C^{OR}(x) + C^{OS}(x) + C^{WLD}(x) + C^{LS}(x), \tag{1}$$

where x is the vector of binary decision variables x_{ilt} , which describe the assignments of orders to locations and periods. The notations used for the mathematical formulation of the optimisation model are presented in Table 1.

Order-related costs are costs that accrue for each order independently from other orders and only depend on its customer, option choices and assignment. Therefore, the expected value of each order assigned is calculated regarding the normalised scenario probabilities:

$$C^{OR}(x) = \sum_{s \in \{1, \dots, S\}} \left[p_s \times \sum_{t \in \{1, \dots, T\}} \sum_{l \in \{1, \dots, L\}} \sum_{i \in \{1, \dots, I\}} (C_{ilts} \times x_{ilt}) \right]. \tag{2}$$

Table 1. Notations.

x	Vector of binary decision variables x_{ilt}
$x_{ilt} \in \{0, 1\}$	Binary decision variable for assignment of customer order i to location l and period t
$i \in \{1, \dots, I\}$	Customer order
$l \in \{1, \dots, L\}$	Location
$t \in \{1, \dots, T\}$	Period
$C^{OR}(x)$	Order-related costs
$C^{OS}(x)$	Order spacing costs
$C^{WLD}(x)$	Workload deviation costs
$C^{LS}(x)$	Level scheduling costs
$s \in \{1, \dots, S\}$	Scenario
p_s	normalised probability of scenario s
$C_{ils}^{material}$	Material costs for order i at location l in scenario s
$C_{ilts}^{inventory}$	Inventory costs for order i at location l in period t and scenario s
$C_{ilt}^{penalty}$	Penalty costs for order i at location l in period t
$C_{il}^{distribution}$	Distribution costs for order i at location l
$\Delta_{ilts}(x)$	Workload deviation at location l in period t and scenario s
w_{is}	Workload of order i in scenario s
K_{lt}	Capacity at location l in period t
$C_{lts}^{flexibility}$	Flexibility costs at location l in period t and scenario s
$C_l^{changeability}$	Changeability costs at location l
β_{lt}	Flexibility limit for flexibility at no charge
K_{lt}^{max}	Flexibility limit of internal workers, i.e. maximum capacity, at location l in period t
$P_{lt}^{internal}$	Cost rate for overtime of internal workers at location l in period t
$P_{lt}^{external}$	Cost rate for working time of external workers at location l in period t
$K_l^{external}$	Capacity of one full-time external worker at location l
K_{ut}^{cycle}	Cycle capacity: the number of cycles available for production in period t on line u , on which the basic product model $m \in \{1, \dots, M\}$ or option can be produced (e.g. $u \in U_m$) at location l_u
$\Delta_{ml}^{LS,L}(x)$	Deviation from proportionate distribution among locations of product model $m \in \{1, \dots, M\}$ at location l
$\Delta_{mlt}^{LS,T}(x)$	Deviation from proportionate distribution among periods at locations of Product model $m \in \{1, \dots, M\}$ at location l in period t
H_{mlt}/N_{mlt}	Sequencing rule of product model $m \in \{1, \dots, M\}$ at location l in period t

Costs for investments in equipment and machines as well as for the regular workforce are not taken into account as they are considered as fixed for mid-term planning. Thus, the order-related costs cover material costs depending on the option-related materials and location-specific suppliers as well as inventory costs for orders assembled too early depending on the option-related tied capital and the amount of too early periods. Moreover, the order-related costs include customer-specific penalty costs for late deliveries depending on the amount of delayed periods, customer-specific penalty costs for assembly at another location than the one preferred by the customer, as well as distribution costs depending on the customer location and assembly location:

$$C_{ilts} = C_{ils}^{\text{material}} + C_{ilts}^{\text{inventory}} + C_{ilt}^{\text{penalty}} + C_{il}^{\text{distribution}} \quad (3)$$

$$\forall i \in \{1, \dots, I\}, \forall l \in \{1, \dots, L\}, \forall t \in \{1, \dots, T\}, \forall s \in \{1, \dots, S\}.$$

Order spacing costs reflect the fact that customers placing multiple orders may require sometime between the deliveries of sequential orders, resulting in a postponement of the deliveries of orders already produced. If more orders are assigned to a period than can be delivered within that period, respective costs for inventory and also penalty in case of late deliveries are considered additionally to the inventory and penalty costs that are mentioned above and that are independent of spacing requirements.

Workload deviation costs consider the workload deviations between scenario-dependent workloads of orders based on the basic product models as well as the selected options of the assigned orders, and the capacity at each location in each period:

$$\Delta_{lts}(x) = \left[\sum_{i=1}^I (w_{is} \times x_{ilt}) \right] - K_{lt} \quad \forall l \in \{1, \dots, L\}, \quad \forall t \in \{1, \dots, T\}, \quad \forall s \in \{1, \dots, S\}. \quad (4)$$

By respecting detailed workload and capacity explicitly, mixed-model sequencing is anticipated. In order to ensure model robustness and also consider solution robustness regarding workload deviations, the workload deviation costs cover flexibility costs and changeability costs, both representing corrective actions. The two cost terms reflect the combination of the expected value regarding the scenarios by the flexibility costs and the maximum value by the changeability costs in order to achieve robustness in terms of low and stable workload deviations:

$$C^{\text{WLD}}(x) = \left[\sum_{s \in \{1, \dots, S\}} p_s \times \sum_{t \in \{1, \dots, T\}} \sum_{l \in \{1, \dots, L\}} C_{lts}^{\text{flexibility}}(\Delta_{lts}(x)) \right] + \sum_{l \in \{1, \dots, L\}} C_l^{\text{changeability}} \left(\max_{s \in \{1, \dots, S\}, t \in \{1, \dots, T\}} \{(\Delta_{lts}(x) - K_{lt}^{\text{max}})/K_l^{\text{external}}\} \right). \quad (5)$$

Flexibility costs represent the expected value of scenario-dependent costs for using different degrees of flexibility, which can be modelled by a piecewise linear cost function reflecting short-term reactive corrective actions:

$$C_{lts}^{\text{flexibility}}(\Delta_{lts}(x)) = \begin{cases} 0, & \Delta_{lts}(x) \leq \beta_{lt} \\ P_{lt}^{\text{internal}} \times (K_{lt}^{\text{max}} - \beta_{lt}) + P_{lt}^{\text{external}} \times (\Delta_{lts}(x) - K_{lt}^{\text{max}}), & \beta_{lt} < \Delta_{lts}(x) \leq K_{lt}^{\text{max}} \\ P_{lt}^{\text{internal}} \times (K_{lt}^{\text{max}} - \beta_{lt}) + P_{lt}^{\text{external}} \times (\Delta_{lts}(x) - K_{lt}^{\text{max}}), & \Delta_{lts}(x) > K_{lt}^{\text{max}} \end{cases}$$

$$\forall l \in \{1, \dots, L\}, \forall t \in \{1, \dots, T\}, \forall s \in \{1, \dots, S\}. \quad (6)$$

Flexibility at no charge may be provided up to β_{lt} by documenting and balancing working hours in working hours accounts. Additional overtime of workers can be incurred up to their maximum capacity K_{lt}^{max} by paying for the overtime. At K_{lt}^{max} , the limit of the desired flexibility of internal workers is reached. Above this limit, work overload can be managed by external workers considering the respective cost rate. However, external workers have to be qualified and thus changeability costs for this proactive corrective action, i.e. the costs for allowing for flexibility beyond the maximum flexibility of internal workers, have to be considered at each location. According to (5), external workers are qualified at each location for all periods to handle the maximum work overload which is induced at least in one of the periods by the worst-case scenario representing the maximum workload of each customer order. By supplying the flexibility to also handle the worst-case scenario, model robustness is guaranteed. Regarding the number of workers to be qualified, the capacity of an external worker at a location is

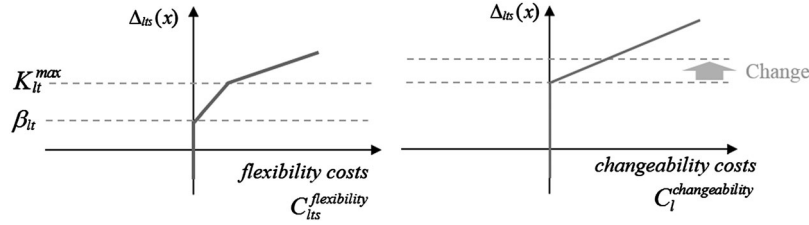


Figure 1. Cost functions depending on workload deviations for flexibility costs and changeability costs.

considered. The cost functions for flexibility costs and changeability costs are illustrated in Figure 1. By using cost functions, realistic costs for respective corrective actions resulting in robustness in terms of low and stable workload deviations can be applied instead of asking the decision-maker to express preferences. Moreover, a combination with other monetarised criteria in the objective function is possible without requiring further weightings.

Whereas a workload-oriented approach is anticipated by workload deviation costs, a material supply-oriented approach is anticipated by level scheduling costs. Therefore, option-oriented level scheduling as an intermediate approach, with a level of detail between the part-oriented level scheduling and the model-oriented level scheduling approaches introduced before is followed, in line with the modelling of orders with options. As orders are assigned to locations and periods, the basic product models, as well as scenario-dependent option choices, can be proportionately distributed between the locations and periods. In order to take model robustness as well as solution robustness into account, corrective actions are considered for deviations from proportionate distributions by piecewise linear cost functions. For uncertain option choices, the expected value of the costs of the scenarios is considered. The proportionate distribution depends on the cycle capacities. The formulas for calculating the deviation from the proportionate distribution are given in the following for the proportionate distribution of the basic product models among locations (7) as well as among periods (8):

$$\Delta_{ml}^{LS,L}(x) = \left(\sum_{i \in \{1, \dots, I\} | m_i = m} \sum_{t \in \{1, \dots, T\}} x_{ilt} \right) - \left(\frac{\sum_{t \in \{1, \dots, T\}} \sum_{u \in \{1, \dots, U\} | l_u = l \wedge u \in U_m} K_{ut}^{cycle}}{\sum_{l' \in \{1, \dots, L\}} \sum_{t \in \{1, \dots, T\}} \sum_{u \in \{1, \dots, U\} | l_u = l' \wedge u \in U_m} K_{ut}^{cycle}} \times \sum_{i \in \{1, \dots, I\} | m_i = m} \sum_{t \in \{1, \dots, T\}} \sum_{l' \in \{1, \dots, L\}} x_{il't} \right)$$

$\forall l \in \{1, \dots, L\}$,

(7)

$$\Delta_{mlt}^{LS,T}(x) = \left(\sum_{i \in \{1, \dots, I\} | m_i = m} x_{ilt} \right) - \left(\frac{\sum_{u \in \{1, \dots, U\} | l_u = l \wedge u \in U_m} K_{ut}^{cycle}}{\sum_{l' \in \{1, \dots, L\}} \sum_{u \in \{1, \dots, U\} | l_u = l' \wedge u \in U_m} K_{ut}^{cycle}} \times \sum_{i \in \{1, \dots, I\} | m_i = m} \sum_{t' \in \{1, \dots, T\}} x_{ilt'} \right)$$

$\forall l \in \{1, \dots, L\}, \forall t \in \{1, \dots, T\}$.

(8)

Requirements for level scheduling can be considered for each basic product model and each option individually. If material related to the basic product model or an option is supplied globally by one supplier or if the share among local suppliers does not matter, a proportionate distribution among periods may be sufficient. If several options of an option group are supplied by one supplier, the options may be considered in an aggregated form as will be illustrated in the application section.

Besides the objective function, constraints are part of the robust optimisation model and are shortly described in the following. Each order has to be assigned to one period at one location:

$$\sum_{l \in \{1, \dots, L\}} \sum_{t \in \{1, \dots, T\}} x_{ilt} = 1 \quad \forall i \in \{1, \dots, I\}.$$

(9)

In each period and at each location, the maximum amount of orders to be assigned equals the cycle capacity available at all lines of the location:

$$\sum_{i \in \{1, \dots, I\}} x_{ilt} \leq \sum_{u \in \{1, \dots, U\} | l_u = l} K_{ut}^{cycle} \quad \forall l \in \{1, \dots, L\}, \forall t \in \{1, \dots, T\}.$$

(10)

Furthermore, production restrictions regarding certain basic product models are considered by setting the respective decision variables to zero. If locations exclusively serve customers of specific markets or if specific customers are served from specific locations only, such delivery restrictions are also considered by setting decision variables for prohibited assignments to zero.

Any capacity constraints of suppliers besides level scheduling requirements can also be considered. If they are strict and related to certain basic product models, a consideration by model constraints is possible. For a supplier providing material for all the basic product models at all locations and applying a sequencing rule on one of the basic product models, car sequencing can be anticipated at the assembly locations by deducing respective sequencing rules for the locations and periods:

$$\sum_{i \in \{1, \dots, I | m_i = m\}} x_{ilt} \leq \frac{H_{mlt}}{N_{mlt}} \times \sum_{u \in \{1, \dots, U | l_u = l\}} K_{ut}^{cycle} \tag{11}$$

$$\forall m \in \{1, \dots, M | H_{mlt}/N_{mlt} < 1\}, \forall l \in \{1, \dots, L\}, \forall t \in \{1, \dots, T\}.$$

Hence, car sequencing can also be used as a workload-oriented approach at the suppliers and thus as the material supply-related approach from the master planning perspective, considering capacity constraints of suppliers.

Figure 2 provides an overview of all criteria considered in the objective function and the constraints in the robust optimisation model for order assignment, illustrating how they reflect requirements of the dimensions procurement, production, distribution, and sales of the intra-organisational supply chain process.

4. Industrial application and results

4.1 Industrial case description

The robust optimisation model for order assignment is applied to aircraft manufacturing of the Airbus A320 Family. The second quarter of 2015 with 128 customer orders is taken as a sample. It is assumed that there are contracts promising delivery quarters for all orders at the time of planning and that months for delivery are confirmed after order assignment. In this case, assignments to months as periods can neither cause inventory costs nor penalty costs for late deliveries. For each order, one of the basic product models A319, A320, and A321 is selected before the time of planning. Based on the basic product models and the respective average list prices (see Airbus 2014), the sales price of the 128 orders is approximately US-\$ 13.1 billion. The locations for final assembly in the considered quarter in 2015 are Hamburg with three assembly lines, Toulouse with two assembly lines, and Tianjin with one assembly line. After the taked assembly line stations, there are further non-taked stations including paint stations. There are production restrictions implying that in Toulouse, exclusively A320s can be assembled, and in Tianjin A319s and A320s. As A321s can solely be assembled in Hamburg and sequencing rules related to it have to be considered at the plants supplying the respective fuselage sections, car sequencing is anticipated at the location

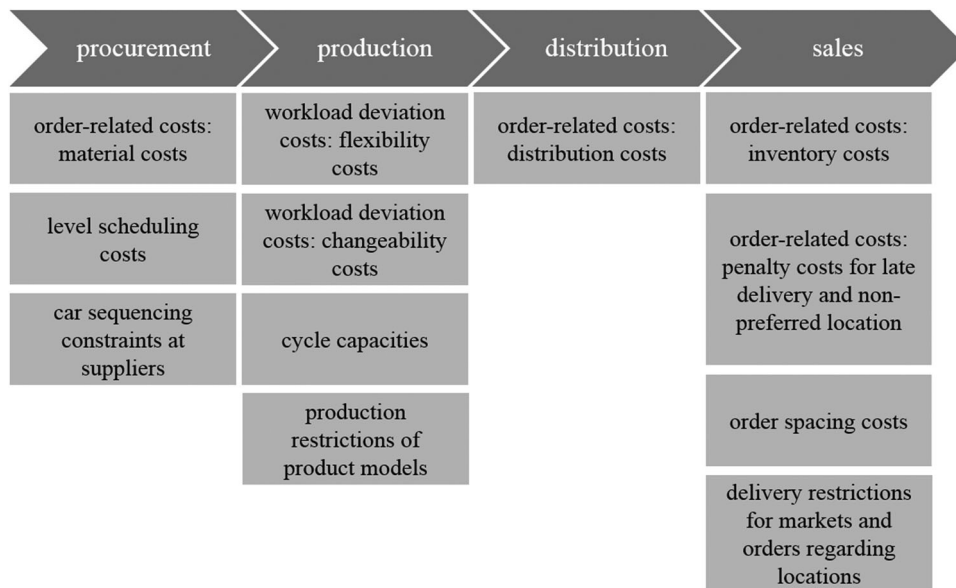


Figure 2. Overview on model objectives and constraints related to intra-organisational supply chain process.

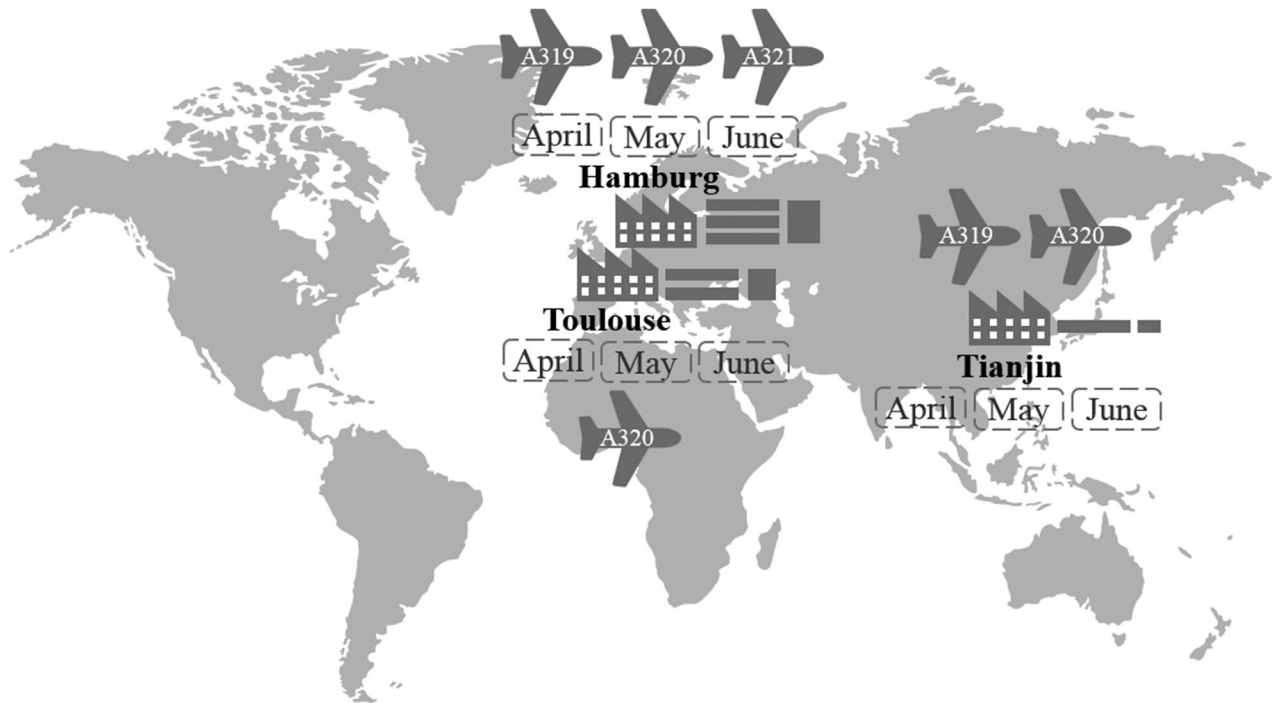


Figure 3. Production network with final assembly locations for Airbus A320 Family aircraft manufacturing for months of the second quarter 2015.

Hamburg. Moreover, contractually defined locations for individual orders are upheld in addition to the fact that the location Tianjin only delivers to Asian, primarily Chinese, customers. The respective production network with the final assembly locations is illustrated in Figure 3.

Ten option groups with a major dependency between their options and the respective impact on workload within the assembly lines are considered. They are namely the type of in-flight entertainment, the type of movable class divider, the number of additional galleys, the number of additional lavatories, the number of additional stowages, the number of additional centre fuel tanks as well as option groups indicating whether a global system for mobile communication, gaseous O₂, a cargo loading system, and SpaceFlex are selected or not. An additional eleventh option group represents the number of paint days for the paint stations which are the bottleneck of the non-takt stations. Moreover, an option group indicates whether an order is a head of version, which is a newly designed aircraft version for a customer, or a rebuild of a previous head of version. A rebuild may differ from its head of version regarding the other 11 option groups considered. Production of the head of versions is regarded as limited to Hamburg and Toulouse and thus the respective option choice has to be certain. The option choices for all other option groups are considered as uncertain, independent from the option choice regarding head of version or rebuild. As input for the optimisation model with regards to setting the solving time limit to 10 h, 200 scenarios are generated by sampling the potential option choices of the 128 customer orders. In terms of the data used for potential customer order configurations, 57% of the 128 orders are considered as deterministic with only one configuration available. For all other orders, up to 10 configurations are included. Paint days are deterministic in the case of the 128 orders.

Regarding workload deviation costs, β_{lt} are set to reflect workload deviations of 0.0% and K_{lt}^{\max} to reflect those of 0.5% for the locations and months with respect to the capacities K_{lt} . Thus, no flexibility (0.0%) is provided at no charge and the flexibility of internal workers is also kept low (0.5%), as flexibility already used up in mid-term planning is not available for short-term planning and production control anymore. Regarding short-term planning, flexibility is required for mixed-model sequencing as aircrafts have to be sequenced considering daily capacities resulting in daily workload deviations. For example, even if the monthly workload deviation is zero, there might be daily work underload or overload requiring flexibility. During execution, flexibility might also be required for handling disturbances.

Level scheduling is considered for the basic product models A319 and A321 due to each fuselage section supplied globally by the same internal plant. Thus, level scheduling is considered among the months at the respective final assembly locations. A320 is not explicitly regarded, but implicitly by pursuing a proportionate distribution of A319 and A321. For paint days and head of versions, level scheduling is pursued among locations and months. As these option groups are not

related to supply, level scheduling is applied in terms of workload-oriented level scheduling respecting workload not accruing on the the mixed-model assembly lines. Paint days are considered for scheduling of the non-takt stations and head of versions are taken into account due to the administrative work. As cycle capacities of the lines are considered for the proportionate distribution, level scheduling for them is sufficient if their capacities, which are not considered explicitly for level scheduling, resemble the cycle capacities at the locations.

4.2 Results of application

The model is solved for 200 scenarios with IBM ILOG CPLEX 12.7 using up the time limit achieving an optimality tolerance of the mixed-integer problem of at least 0.01%. First of all, the value for offering configuration flexibility to customers by offering the Just-In-Time Specification service is quantified. Therefore, each of the 200 scenarios is optimised individually, reflecting the situation that the scenario in terms of the option choices is known prior to optimisation. The expected value of these scenario-optimal solutions compared to the value of the optimal solution of the robust model considering the 200 scenarios is referred to as the expected value of perfect information (Birge and Louveaux 2011). In the application, the expected value of perfect information equals 0.0031% of the result of the scenario solution, implying that these costs are expected to be saved if requiring the customers to specify their option choices prior to the mid-term order assignment.

However, comparing the value of the scenario solution to the real planning of Airbus for the same orders under the assumptions made shows that the costs are 0.2816% higher for the real planning, as demonstrated in Figure 4. An important aspect for evaluating the real planning is that with a probability of 100% regarding the scenarios, the limit of the desired flexibility of internal workers K_{lt}^{max} is exceeded, meaning an infeasibility of the solution if the proactive corrective action of qualifying external workers is not taken. As assembly has to be conducted anyhow after mid-term planning, weekend shifts of internal workers would still be possible as reactive corrective actions instead of the proactive corrective actions to handle workload above the desired flexibility of internal workers. However, they are considered as undesired reactive corrective actions and thus are not included in the optimisation model, but evaluated in terms of follow-up costs. Follow-up costs reflect costs for additional working time on weekends, but also delays and thus inventory and penalty costs that accrue if assembly tasks usually conducted within the assembly lines are shifted to non-takt stations after the lines for some aircrafts. They apply depending on the workload deviation of each specific scenario and their expected value equals 0.1661% of the result of the scenario solution in the case of real planning.

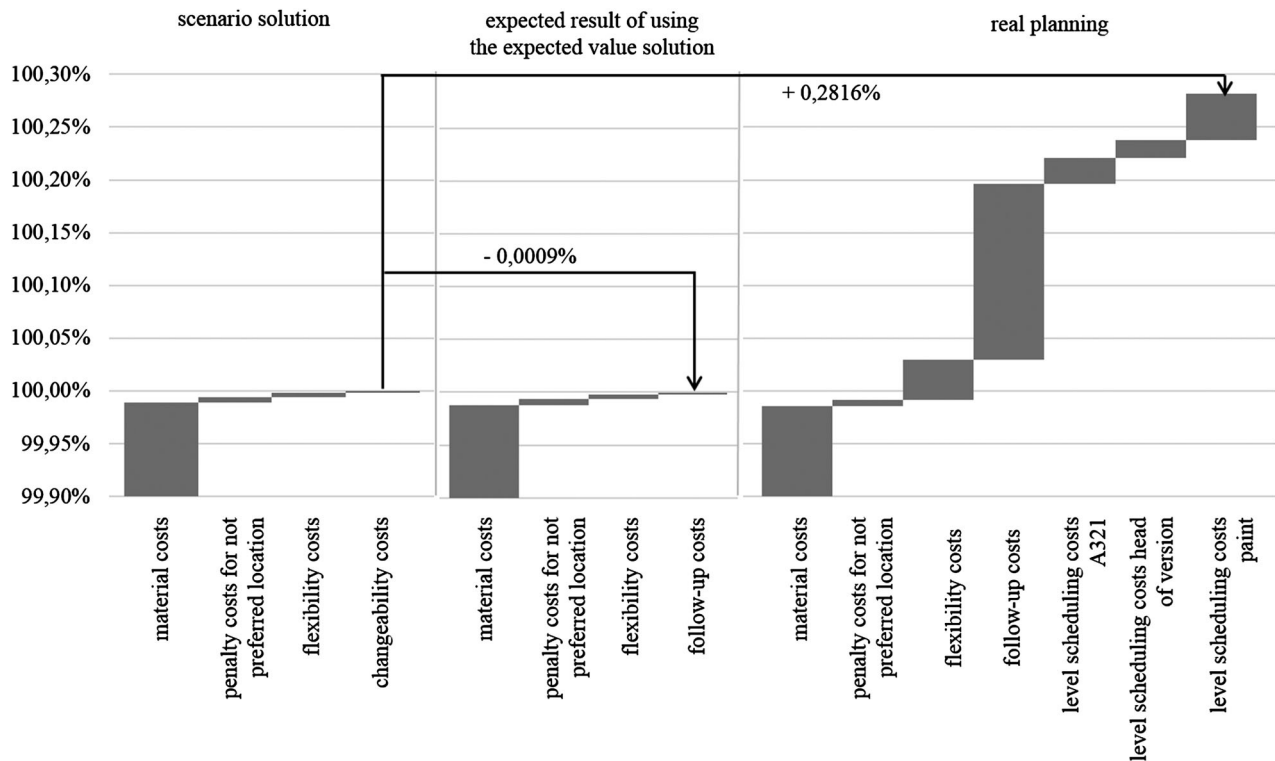


Figure 4. Objective function results of scenario model as well as expected value model and real planning regarding 200 scenarios.

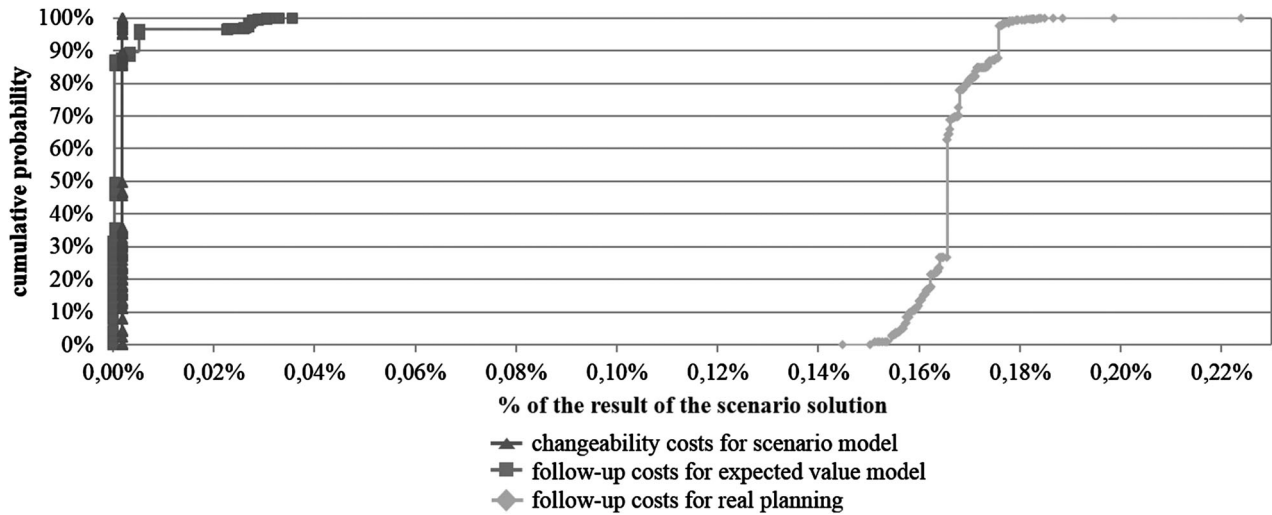


Figure 5. Distribution of changeability costs of scenario model and follow-up costs of expected value model and real planning.

Besides considering scenarios, the optimisation model can also be applied using the expected option choice for each option instead. As this resembles the consideration of one scenario, the model is solved within two seconds for an optimality tolerance of the mixed-integer problem of 0.0001%. The comparison of the expected result of using the expected value solution regarding the 200 scenarios compared to the scenario solution is referred to as the value of the stochastic solution (Birge and Louveaux 2011) which is 0.0013% of the result of the scenario solution. Therefore, changeability costs of 0.0038% of the result of the scenario solution would be necessary to handle workload deviations over the maximum internal capacity with a probability of about 68%, which are two times the changeability costs of 0.0019% of the result of the scenario solution. However, if planning is conducted using the expected value model not considering explicit option choices via scenarios, no actions would be taken to qualify external workers and thus follow-up costs are relevant instead of changeability costs. The expected result of using the expected value solution under consideration of follow-up costs is 0.0009% lower than the result of the scenario solution as demonstrated in Figure 4. This is the case because follow-up costs are undesired reactive corrective actions dependent on the realised scenario only applying if needed short-term, whereas changeability costs are considered as proactive corrective actions independent from the realised scenario based on a mid-term decision. The expected follow-up costs of the expected value solution are 0.0016% of the result of the scenario solution, but can amount up to 0.0357% in the worst case. Thus, depending on the realised scenario, they might be much higher than the changeability costs of the scenario solution which are 0.0019% of its result. Herewith, the risk aversion is reflected by the willingness to accept higher expected costs (0.0019% instead of 0.0016%), but avoiding the risk of having to pay much more (0.0357% in the worst case) as illustrated in Figure 5. Hence, the changeability costs resemble an insurance fee.

Taking a closer look at workload deviations reveals that the maximum workload deviation of the scenario solution is 0.84% whereas it is 1.19% for the expected value solution. The workload deviations of the respective location and

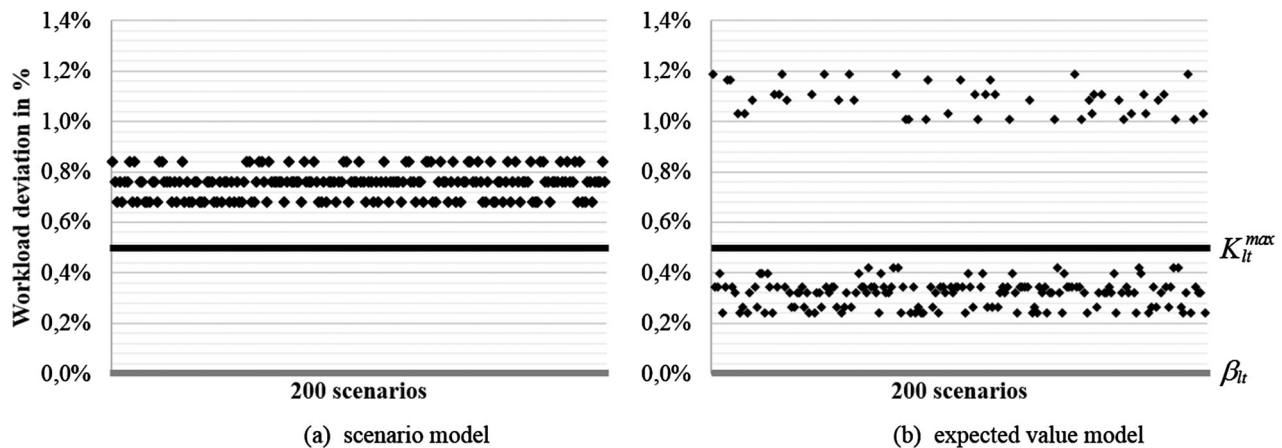


Figure 6. Workload deviations for 200 scenarios.

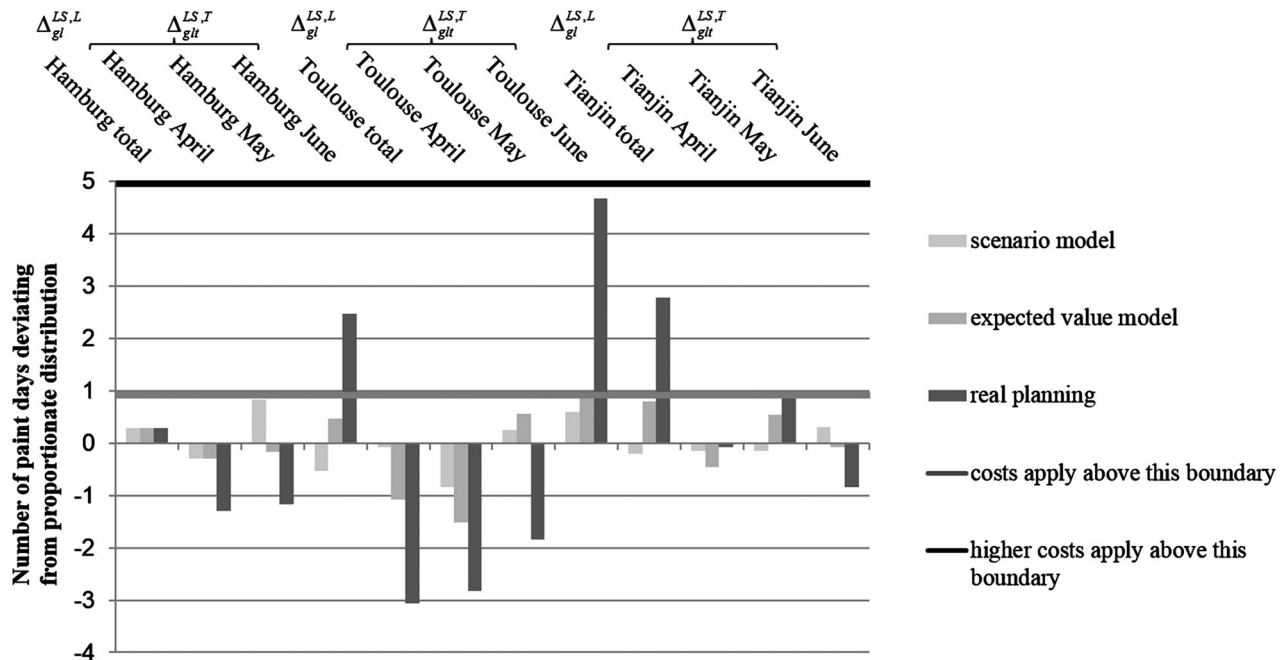


Figure 7. Deviations from the proportionate distribution of number of paint days at locations and for months of the considered sample quarter.

month with the maximum value are given in Figure 6 for the 200 scenarios demonstrating that lower maximum deviations and a higher stability can be achieved by applying the scenario model. In the scenario solution, workload deviations above the flexibility limit of 0.5% exclusively occur for any scenario at the one location for which changeability costs accrue. In the expected value solution, the expected workload deviations at all locations and months are lower than 0.5% so that no changeability costs are considered. Expected and maximum workload deviations above the flexibility limit of 0.0% cannot be avoided for all locations and months by any solution.

The advantage of considering proactive corrective actions in the robust scenario model described above is demonstrated by also applying the scenario model without including proactive corrective actions in terms of changeability costs, but including follow-up costs as part of the reactive corrective actions. The respective results show that the follow-up costs are 0.0005% of the result of the robust scenario solution and the maximum workload deviation is 0.89%, which is higher than that for the robust scenario model including changeability costs, but lower than that for the expected value model. The follow-up costs can amount up to 0.0173% in the worst case and thus be much higher than the changeability costs of the robust scenario solution of 0.0019% of its result. Thus, it can be concluded that the consideration of proactive corrective actions within the scenario model plays a crucial role to achieve a stable performance and thus solution robustness.

According to Figure 4, level scheduling costs are prevented both in the scenario model and in the expected value model, but not for the real planning. Particularly, level scheduling costs for paint days accrue for real planning. Figure 7 illustrates that the number of paint days (option group $g = 11$) for real planning deviate from their proportionate distribution among the locations as Tianjin is overloaded with respect to the first boundary of the piecewise linear cost function. Moreover, a proportionate distribution among the months at the locations Hamburg and Toulouse is not given for the real planning.

A further experiment has been conducted to validate a setting in which there are contracts promising not only delivery quarters but delivery months at the time of order assignment for all of the orders. The solution reveals that inventory costs and penalty costs for late deliveries apply and that penalty costs for assembly at another location, workload deviation costs and level scheduling costs and thus the overall costs are higher than in the case with quarterly contracts. As a managerial implication, it can be concluded that promising delivery months after order assignment is beneficial.

5. Conclusion

An optimisation model for robust assignment of customer orders with uncertain configurations has been presented and applied to the Airbus A320 Family aircraft manufacturing. It was demonstrated how corrective actions with regard to workload deviations can be implemented in terms of flexibility and changeability. Whereas flexibility is considered for short-term, reactive corrective actions dependent on the realised scenario, changeability reflects mid-term, proactive corrective actions

under uncertainty regarding the scenarios. For the latter, the worst-case scenario with the maximum workload is considered for ensuring model robustness by qualifying external workers to handle the workload. Therewith, the advantage of explicitly considering uncertain option choices in the scenario model, compared to applying the expected value model and neglecting uncertainty by only considering expected option choices, is demonstrated. Furthermore, it is validated that the consideration of changeability besides flexibility in the scenario model enhances solution robustness. To sum it up, the advantage of the robust optimisation model, i.e. the scenario model considering flexibility and changeability, is that a high and stable performance regarding the overall costs and workload deviations, in particular, can be achieved by making use of appropriate proactive and reactive corrective actions.

The costs of offering to customers the flexibility to choose options as late as possible in terms of the Just-In-Time Specification service is quantified by the expected value of perfect information. Although the service causes costs for production planning at the manufacturing company, it may enhance customer satisfaction. As demonstrated, the maximum costs for the high workload can at least be kept low by applying the scenario model compared to the expected value model.

As assigning orders based on the optimisation model may enhance the current planning of Airbus A320 Family, the model was also tested in a day-to-day business planning situation, in which delivery months were already specified for most of the orders. In such a context, the potential of the model to minimise inventory costs and penalty costs for late deliveries, while minimising the overall objective function, was demonstrated.

Future research could further elaborate the model inputs regarding potential configurations for customer orders and respective probabilities. They might be continuously updated based on specified order configurations and market trends related to the respective customer segment for each customer individually. It might also be necessary to generate forecasts for new customers and also new options that may be offered.

Furthermore, there is potential to further investigate the proportion of flexibility that should optimally be offered for workload deviations and level scheduling in mid-term planning, and not be reserved for short-term planning as well as production control to manage disturbances.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The results were conducted within the project ‘ProRegio – customer-driven design of product-services and production networks to adapt to regional market requirements’ financially supported by the European Union’s Horizon 2020 Framework Programme [grant number 636966] as well as within the project ‘Systematic decision support for mid-term order planning in global production networks for multi-variant series production under uncertainty of customer order configurations’ financially supported by the German Research Foundation (Deutsche Forschungsgemeinschaft) [grant number LA 2351/43-1].

ORCID

Marcello Urgo  <http://orcid.org/0000-0002-0341-9208>

References

- Airbus. 2014. “New Airbus Aircraft List Prices for 2015.” Accessed December 11, 2017. <http://www.airbus.com/newsroom/press-releases/en/2015/01/new-airbus-aircraft-list-prices-for-2015.html>.
- Airbus. 2017. “ODs Airbus Commercial Aircraft October 2017.” Accessed November 28, 2017. http://www.aircraft.airbus.com/market/orders-deliveries/?eID=maglisting_push&tx_maglisting_pi1%5BdocID%5D=240348.
- Bard, Jonathan F., Ezey M. Dar-Elj, and Avraham Shtub. 1992. “An Analytic Framework for Sequencing Mixed Model Assembly Lines.” *International Journal of Production Research* 30 (1): 35–48. doi:10.1080/00207549208942876.
- Belkadi, Farouk, Jens Buergin, Ravi K. Gupta, Yicha Zhang, Alain Bernard, Gisela Lanza, Marcello Colledani, and Marcello Urgo. 2016. “Co-Definition of Product Structure and Production Network for Frugal Innovation Perspectives: Towards a Modular-based Approach.” *Procedia CIRP* 50: 589–594.
- Birge, John R., and François Louveaux. 2011. *Introduction to Stochastic Programming*. 2nd ed. Springer Series in Operations Research and Financial Engineering. New York: Springer.
- Boysen, Nils, Malte Fließner, and Armin Scholl. 2009a. “Production Planning of Mixed-Model Assembly Lines: Overview and Extensions.” *Production Planning & Control* 20 (5): 455–471. doi:10.1080/09537280903011626.

- Boysen, Nils, Malte Fliedner, and Armin Scholl. 2009b. "Sequencing Mixed-Model Assembly Lines: Survey, Classification and Model Critique." *European Journal of Operational Research* 192: 349–373.
- Bruns, Ralf, and Jürgen Sauer. 1995. "Knowledge-based Multi-Site Coordination and Scheduling." In *Flexible Automation and Intelligent Manufacturing*, edited by R. D. Schraft, 115–123. Redding, CT: Begell House.
- Buergin, J., F. Belkadi, C. Hupays, R. K. Gupta, F. Bitte, G. Lanza, and A. Bernard. 2018. "A Modular-based Approach for Just-In-Time Specification of Customer Orders in the Aircraft Manufacturing Industry." *CIRP Journal of Manufacturing Science and Technology* 21: 61–74.
- Buergin, Jens, Philippe Blaettchen, Chuanqi Qu, and Gisela Lanza. 2016. "Assignment of Customer-Specific Orders to Plants with Mixed-Model Assembly Lines in Global Production Networks." *Procedia CIRP* 50: 330–335.
- Chan, Felix T. S., S. H. Chung, L. Y. Chan, G. Finke, and M. K. Tiwari. 2006. "Solving Distributed FMS Scheduling Problems Subject to Maintenance: Genetic Algorithms Approach." *Robotics and Computer-Integrated Manufacturing* 22: 493–504.
- Chen, Rong-Chang, and Pei-Hsuan Hung. 2014. "Multiobjective Order Assignment Optimization in a Global Multiple-Factory Environment." *Mathematical Problems in Engineering* 2014: 1–14.
- Colledani, M., L. Silipo, A. Yemane, G. Lanza, J. Buergin, J. Hochdörffer, K. Georgoulas, et al. 2016. "Technology-based Product-Services for Supporting Frugal Innovation." *Procedia CIRP* 47: 126–131.
- Da Silveira, Giovani, Denis Borenstein, and Flávio S. Fogliatto. 2001. "Mass Customization: Literature Review and Research Directions." *International Journal of Production Economics* 72: 1–13.
- Dörmer, Jan, Hans-Otto Günther, and Rico Gujjula. 2015. "Master Production Scheduling and Sequencing at Mixed-Model Assembly Lines in the Automotive Industry." *Flexible Services and Manufacturing Journal* 27: 1–29.
- Duplaga, E. A., and D. J. Bragg. 1998. "Mixed-model Assembly Line Sequencing Heuristics for Smoothing Component Parts Usage: A Comparative Analysis." *International Journal of Production Research* 36 (8): 2209–2224. doi:10.1080/002075498192850.
- Fleischmann, Bernhard, Herbert Meyr, and Michael Wagner. 2015. "Advanced Planning." In *Supply Chain Management and Advanced Planning: Concepts, Models, Software, and Case Studies*, edited by Hartmut Stadler, Christoph Kilger, and Herbert Meyr, 71–95. 5th ed. Berlin: Springer-Verlag.
- Guo, Z. X., W. K. Wong, and S. Y. S. Leung. 2013. "A Hybrid Intelligent Model for Order Allocation Planning in Make-to-Order Manufacturing." *Hybrid Evolutionary Systems for Manufacturing Processes* 13 (3): 1376–1390. doi:10.1016/j.asoc.2012.07.019.
- Hackstein, Rolf. 1989. *Produktionsplanung und -Steuerung (PPS): Ein Handbuch für die Betriebspraxis*. 2nd ed. Düsseldorf: VDI-Verlag GmbH.
- Han, Jiawei, Micheline Kamber, and Jian Pei. 2012. *Data Mining: Concepts and Techniques*. 3rd ed. The Morgan Kaufmann series in data management systems. Amsterdam: Elsevier/Morgan Kauffman.
- Hax, Arnoldo C., and Harlan C. Meal. 1973. "Hierarchical Integration of Production Planning and Scheduling." *Sloan Working Papers* 656–73.
- Hodges, J. L., and E. L. Lehmann. 1952. "The Use of Previous Experience in Reaching Statistical Decisions." *The Annals of Mathematical Statistics* 23 (3): 396–407. doi:10.1214/aoms/1177729384.
- Janak, Stacy L., Xiaoxia Lin, and Christodoulos A. Floudas. 2007. "A New Robust Optimization Approach for Scheduling Under Uncertainty." *Computers & Chemical Engineering* 31: 171–195.
- Kall, Peter, and Stein W. Wallace. 1994. *Stochastic Programming*. Wiley Interscience series in systems and optimization. Chichester: Wiley.
- Kaut, Michal, and Stein W. Wallace. 2003. "Evaluation of Scenario-generation Methods for Stochastic Programming." *Stochastic Programming E-Print Series*. Accessed February 21, 2016. <http://edoc.hu-berlin.de/docviews/abstract.php?id=26731>.
- Keeney, Ralph L., and Howard Raiffa. 1993. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge: Cambridge University Press.
- Khakdaman, Masoud, Kuan Y. Wong, Bahareh Zohoori, Manoj K. Tiwari, and Rico Merkert. 2015. "Tactical Production Planning in a Hybrid Make-to-Stock–Make-to-Order Environment Under Supply, Process and Demand Uncertainties: a Robust Optimisation Model." *International Journal of Production Research* 53 (5): 1358–1386. doi:10.1080/00207543.2014.935828.
- Kubiak, Wieslaw. 1993. "Minimizing Variation of Production Rates in Just-in-Time Systems: A Survey." *European Journal of Operational Research* 66 (3): 259–271. doi:10.1016/0377-2217(93)90215-9.
- Meyr, Herbert. 2004. "Supply Chain Planning in the German Automotive Industry." *OR Spectrum* 26 (4): 447–470. doi:10.1007/s00291-004-0168-4.
- Miltenburg, John. 1989. "Level Schedules for Mixed-Model Assembly Lines in Just-In-Time Production Systems." *Management Science* 35 (2): 192–207. doi:10.1287/mnsc.35.2.192.
- Mirzapour Al-e-hashem, S. M. J., H. Malekly, and M. B. Aryanezhad. 2011. "A Multi-Objective Robust Optimization Model for Multi-Product Multi-Site Aggregate Production Planning in a Supply Chain Under Uncertainty." *International Journal of Production Economics* 134: 28–42.
- Mulvey, John M., Robert J. Vanderbei, and Stavros A. Zenios. 1995. "Robust Optimization of Large-Scale Systems." *Operations Research* 43 (2): 264–281.
- Okamura, K., and H. Yamashina. 1979. "A Heuristic Algorithm for the Assembly Line Model-Mix Sequencing Problem to Minimize the Risk of Stopping the Conveyor." *International Journal of Production Research* 17 (3): 233–247.

- Palpacuer, Florence. 2000. "Competence-based Strategies and Global Production Networks: A Discussion of Current Changes and Their Implications for Employment." *Competition and Change* 4 (4): 353-400.
- Parrello, Bruce D., Waldo C. Kabat, and L. Vos. 1986. "Job-shop Scheduling Using Automated Reasoning: A Case Study of the Car-Sequencing Problem." *Journal of Automated Reasoning* 2 (1): 1-42. doi:10.1007/BF00246021.
- Ríos, J., F. Mas, and J. L. Menéndez. 2012. "Aircraft Final Assembly Line Balancing and Workload Smoothing: A Methodological Analysis." *Key Engineering Materials* 502: 19-24.
- Rudberg, Martin, and Jan Olhager. 2003. "Manufacturing Networks and Supply Chains: An Operations Strategy Perspective." *Omega* 31 (1): 29-39. doi:10.1016/S0305-0483(02)00063-4.
- Scholl, Armin. 2001. *Robuste Planung und Optimierung: Grundlagen, Konzepte und Methoden, Experimentelle Untersuchungen*. Heidelberg: Physica-Verlag.
- Solnon, Christine, Dat van Cung, Alain Nguyen, and Christian Artigues. 2008. "The Car Sequencing Problem: Overview of State-of-the-art Methods and Industrial Case-Study of the ROADEF&Curlyapos;2005 Challenge Problem." *European Journal of Operational Research* 191 (3): 912-927. doi:10.1016/j.ejor.2007.04.033.
- Stricker, Nicole, and Gisela Lanza. 2014. "An Approach Towards Improving the Robustness of Production Systems." In *WGP Congress 2014*. Vol. 1018, 461-468. Advanced Materials Research: Trans Tech.
- Tolio, T., and M. Urgo. 2007. "A Rolling Horizon Approach to Plan Outsourcing in Manufacturing-to-Order Environments Affected by Uncertainty." *CIRP Annals* 56 (1): 487-490.
- Urgo, Marcello, and József Váncza. 2014. "A Robust Scheduling Approach for a Single Machine to Optimize a Risk Measure." *Procedia CIRP* 19: 148-153.
- Wittek, Kai, Thomas Volling, Thomas S. Spengler, and Friedrich-Wilhelm Gundlach. 2011. "Tactical Planning in Flexible Production Networks in the Automotive Industry." In *Operations Research Proceedings 2010: Selected Papers of the Annual International Conference of the German Operations Research Society*, edited by Bo Hu, Karl Morasch, Stefan Pickl, and Markus Siegle, 429-434. Berlin: Springer. doi:10.1007/978-3-642-20009-0_68.
- Zach, M. F., N. Moeller, and W. Vogl. 2005. "Symbiosis of Changeable and Virtual Production – The Emperor's New Clothes or Key Factor for Future Success?" International Conference on Changeable, Agile, Reconfigurable and Virtual Production.