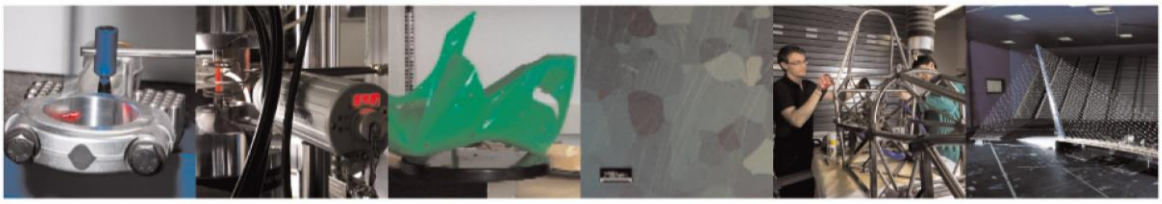

A risk based approach to support the supplying of components in a MTO assembly process

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A risk based approach to support the supplying of components in a *MTO* assembly process

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Product customization is becoming more and more an option required by the customers and, when referring to complex items, pursuing this path could have a strong impact on the way companies have to manage the products and the associated processes. In this context, a *Make To Order* (*MTO*) and *Engineer To Order* (*ETO*) paradigms are viable approaches. Using these paradigms, the coordination between supplying and manufacturing has a prominent importance. A missing component during the production phase can cause significant delays and disruptions in the plans and, consequently, delays respect to the due dates negotiated with the customers. Due to the intrinsic uncertainty associated to the selection of customization options by the user, the supplying of the components and the production/assembly process, company managers addressing this coordination problem have to ground on risk measures supporting the selection of the right supplying option, aiming at minimizing the probability of missing components. In this paper, we present an approach to support this selection in the production and assembling of complex products grounding on the definition and calculation of two indicators, the *Risk Index* and the *Criticality Index*. The first one addressing the risk associated to the supplying of a component through different supplying alternatives, the second one providing an assessment of the criticality of the coordination between the supplying and assembling phases together with the specific risk aversion. An application to a real *MTO* industrial case is also provided addressing the production of machine tools.

1. Introduction and motivation

Manufacturing has to cope more and more with product customization and, thus, higher variety. Manufacturing companies need to re-design their products and the related production processes to be easily customizable and move towards a different organization paradigm where every product has characteristics to be specifically designed and manufactured, causing the *Make-To-Stock* (*MTS*) paradigm to be not suitable anymore. The *Make-To-Order* (*MTO*) model, where a product is manufactured only if an order has been placed, is a widespread approach to cope with these cases, evolving towards *Engineering-To-Order* (*ETO*), if the customization also requires a specific design of the product, besides the manufacturing.

A shift towards the *MTO/ETO* production paradigm has a significant impact on the operation phase, specifically in relation to production planning and scheduling, where the variability of production requirements (machines, workers, tools, times, etc.) has to match the available resources and related capability. Also the availability of components has to be managed in a rather different way. Highly customized products are typically composed of a standard set of components plus some where customization applies. During the assembly phase, the coordination between the supplying of components and the associated assembling activities is fundamental for the lean management of resources, time and space. An additional complexity in the coordination of material supplying and production activities is incurred in the production of complex products, e.g., instrumental goods, turbines, valves, etc., where many assembling operations are executed by human workers, thus entailing a certain degree of variability and uncertainty.

This paper is focused on the coordination between material supplying and production activities in *MTO/ETO* systems producing complex products. Specifically, the proposed approach addresses the risk of stock-out for different components taking into account its potential impact on the production and assembly process, also considering the intrinsic uncertainty of manually executed activities. Grounding on these considerations, a level of *criticality* is assigned to components with the aim to identify those whose shortage is most likely to cause a delay in the production process and, consequently, a possible delay of the delivery date agreed with customer.

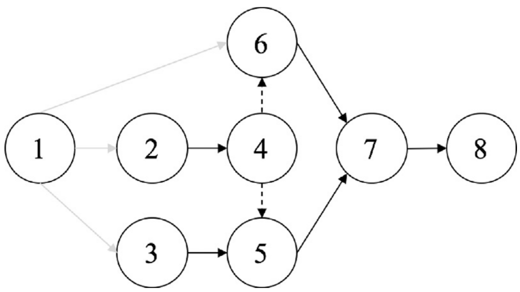


Fig. 1. *AoA* network representing an assembling process.

The calculation of components' criticality takes advantage of a project scheduling approach to estimate the time when specific components are expected to be needed to go on with the production process. This value is a stochastic variable due to the presence of the uncertainty affecting manually executed activities. The comparison with the corresponding supplier's lead-time provides a criterion to assess the level of criticality. *Criticality* is expressed in terms of two stochastic indicators that can be used by the company to reduce the risk of stock-out and optimizing the management of inventory and suppliers.

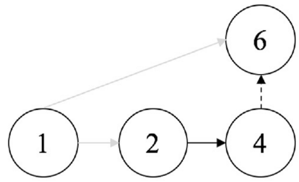
Section 2 provides an analysis of the related literature, while the complete problem statement is presented in Section 3 where the above-mentioned coordination problem is described with reference to the assembling of tailored machine tools. Section 4 and its sub-sections describe the proposed approach through five main steps. An application to a real industrial case is presented in Section 5. A final appendix reports detailed information on the products and processes addressed.

2. State of the art

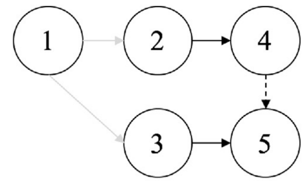
The coordination of production and material supplying is key factor in the management of a production process. A stock-outof materials or components needed by the production/assembly activities is likely to impact the production causing delays and/or non-efficiencies. In addition, being able of addressing the uncertainties in both the production and supplying are relevant aspects to be addressed.

Some approaches are focused on the impact of unavailability of components and their impact, using an inventory classification [29,31]. Stanford and Martin [29] provide an inventory classification to manage the stock turnover in a multi-item inventory system with constant demand. The approach organizes items in different classes and manages each class as a single entity. In Tsai and Yeh [31], the same problem is addressed through an algorithm providing an inventory classification without relying on a fixed number of groups. This class of approaches only look at the demand of components without addressing the inherent connection with the manufacturing process.

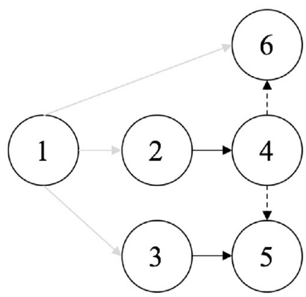
An example of coordination between activities and materials is presented in [12], where a production transfer process is addressed using a structured procedure for the material planning to avoid costly production stops or delayed deliveries to end customers. In this paper only the specific case of production transfer is considered through a qualitative evaluation. Capacity planning in manufacturing processes is considered in Carvalho et al. [8] and Jodlbauer and Altendorfer [18], where the relation between available item capacity and inventory is studied in a multi-item *MTO* production system with uncertain customer requests. In these cases, only a strategic analysis is used, without considering the real process but only its nominal capacity requests. This is a relevant lack in the available literature since, in the production/assembly of complex products, the scheduling of the activities and/or their execution can be different, thus, the time patterns of nominal requests are often rather different from the real ones. For these reasons we address the *dayby-day* coordination between the execution of production activities and the availability of components, taking into consideration the different process execution modalities through the estimation of the distribution of the start/completion times of the activities.



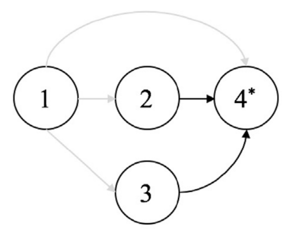
(a) Sub-network associated to the component supplied by arc $(1, 6)$.



(b) Sub-network related to the component supplied by arc $(1, 3)$.

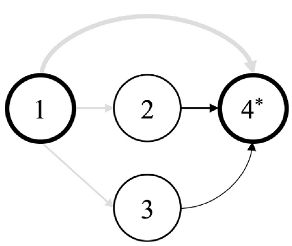


(c) Sub-network related to the supplying of component through arc $(1, 2)$.

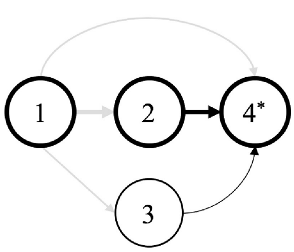


(d) Sub-network related to the supplying of component through arc $(1, 2)$ considering a single sink node instead of three.

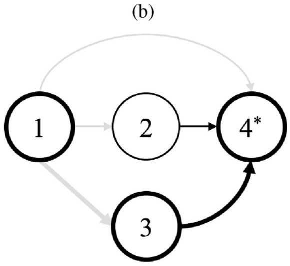
Fig. 2. An example of sub-networks identification for the three supplied components.



(a)

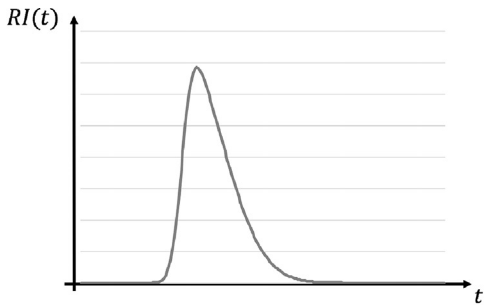


(b)

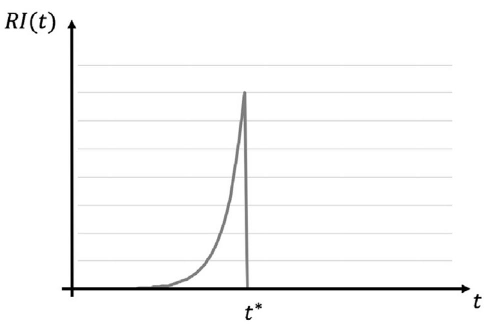


(c)

Fig. 3. *s-t paths* for the network, second component.



(a) *Risk Index* obtained for a component with stochastic supplying time.



(b) *Risk Index* obtained for a component with deterministic supplying time.

Fig. 4. *Risk Index* functions deriving from different supplying cases.

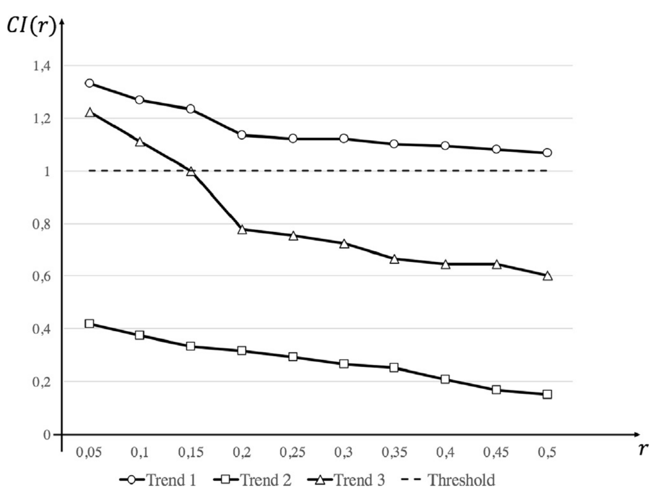


Fig. 5. Example of the *Criticality Index* trend for different components.

An additional consideration stems from the peculiar characteristics of the production/assembly of complex MTO products, where production activities are usually partitioned in phases, whose duration could add up to some days or weeks. Hence, a clear division between *strategic* supplying decisions and *tactical* production planning is not always sharp [4,14,19,22]. As a consequence the two decision levels have to be jointly considered due to their mutual influence. Examples of integration of these two aspects are given in hierarchical production planning and control frameworks [15,5,16]. This integration is highlighted also in [11,6,13] where specific manual assembly problems are considered.

We focus on a *MTO* process where a *one-of-a-kind* product is assembled, suitable to be considered as the execution of a project, considering both scheduling and supplying activities in a project scheduling approach [23,3,25].

This coordination problem has been previously addressed in Alfieri et al. [2] and [1], through a scheduling approach for *MTO* processes also considering material procurement, although risk assessment is not taken into consideration. Further extensions of these approaches takes uncertainty into consideration [30,17]. In Tolio et al. [30], a robust production control approach is presented able to handle uncertainties during the scheduling of local resources and ensure the completion of the process. Authors consider a single resource stochastic scheduling model that captures processing time uncertainties and aims at minimizing a risk measure of a scheduling performance indicator. Similarly, in [17], authors consider the problem of dynamically updating the manufacturing lead times used in a *MRP* in a multi-machine, multiproduct manufacturing environment. In theses works, the detailed knowledge of the production process is a key factor, but it is only used for production planning, not for the supplying of components. An example of the evaluation of the risk associated to a component in a *MTO* process is given in Radke and Tseng [27] and Radke et al. [26], where an aggregate risk level is estimated merging the stock out and tardiness risk of each component and the risk of tardiness of the associated assembling activities. The result achieved is the classification of inventory items into risk categories to support the inventory budget management.

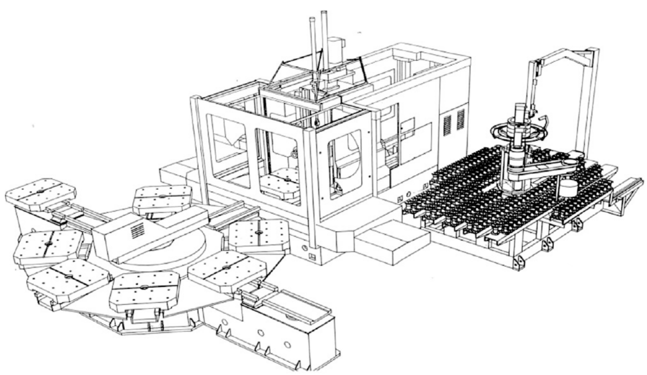


Fig. 6. The machine center *Tank 1330* with multi-pallet carousel and integrated tool rack.

The approach proposed in this paper considers the supplying of components as specific activities of the production process and addresses the coordination between supply and production. Grounding on the approaches in Radke and Tseng [27] and Radke et al. [26], two risk measures are proposed to support the identification of critical components exploiting a project network formalization for the production and supplying process [10,24,32,7].

3. Problem statement

We consider the assembly process of complex products with a high level of customization, a specific focus is provided for instrumental goods, e.g., machining centers, composed by a fixed standard structure onto which alternative sets of components are assembled according to the specific customer's requirements. Typical customizable elements are the size and type of the mandrel, depending on application sector and, thus, the materials to be machined, the number and type of axes of movement, ancillary elements as the tool rack and tool change devices, specific sensors and automation devices, in some cases the type of CNC, motors and drives, etc. According to the selected optional components, the assembly process could be rather different in terms of operations, precedence constraints, needed resources, number of workers involved and, obviously, components.

The specific focus of this paper is on assembly processes where most of the operations are executed by human operators with specific skills.

Manual assembly operations have uncertain duration by definition and together with the intrinsic complexity and variability of the assembling process, this entails the need of considering a variable duration of the operations and, thus, modeling processing times as stochastic variables.

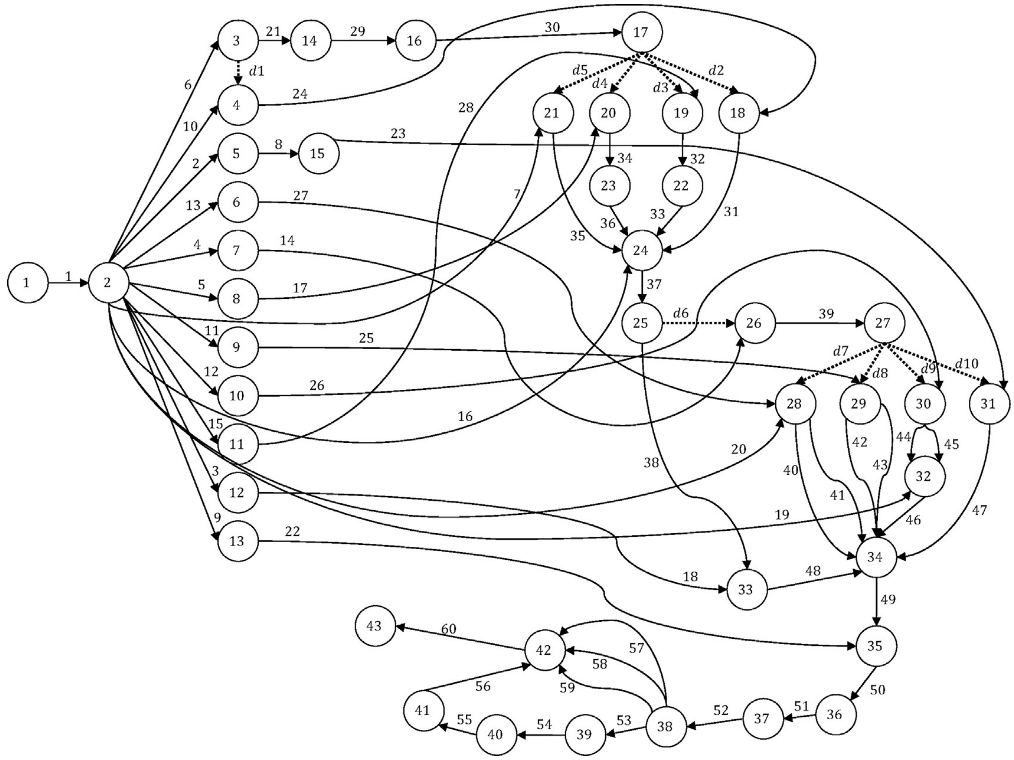


Fig. 7. *MCM S.p.A.* assembly process *AoA* net.

P estimated values for all components under study, using uniform distributions.

Element	P
Structures	2.1682
Mandrel	0.0054
Tank components	0.0000
Pallet components	0.0000
Table components	1.7854
Tool rack components	0.0000
Tool changer components	0.0000
Multi-pallet components	0.0000
Electric system components	0.0000
Pneumatic system components	0.5824
Protection components	0.0000
Machinery system components	0.0001
Perimetral enclosure	0.0000
Option group components	0.0000
Pallet stock components	0.0000

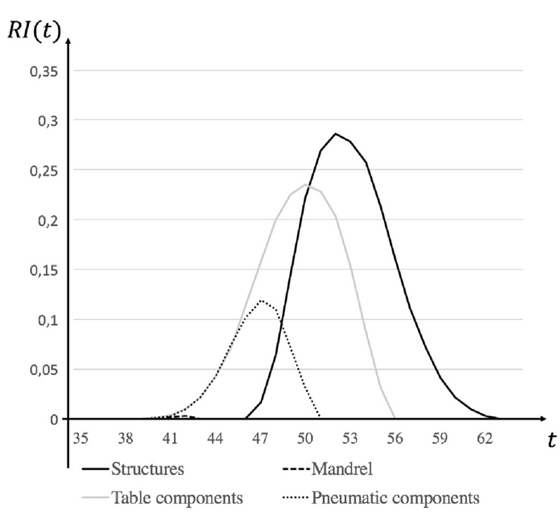


Fig. 8. *Risk Index* results in the uniform distributions case; only the function with not-null values are represented.

Another important aspect relevant for the considered sector is floor-space constraints. Machine centers are huge products whose dimension ranges from 20 m^2 for the smallest ones to some thousands for big machine-systems. As floor-space is occupied for the whole assembly process, space constraints are a serious concern, also taking into consideration that (i) available space is limited, thus it is not possible to have a lot of machines under assembly in the same moment, (ii) additional space is occupied by operators and process-related equipment and (iii) sub-assemblies are assembled in advance and before being incorporated into the machine. A typical example is tool racks, whose dimensions are usually large to host as much tools as possible. Thus, accurate planning is beneficial for floor-space management, besides being crucial for timely deliveries. Since the main activity this process focuses on is the assembly one, also the availability of components has to be considered in relation to the floor-space management. Indeed, the stock-out of a certain component while the floor-space is dedicated to its assembly operations can significantly delay the completion time of that process and the occupation of the space with consequences also on other orders.

Additional considerations are relevant referring to the different kind of components involved. Some of them are strategic pieces of knowledge for the manufacturer, e.g., the mandrel. These components are built in-house rather than being supplied, to guarantee the manufacturer a safe control on the core technologies. For these components, specific *pre-assembling* activities are modeled. On the other hand, components purchased from the suppliers are taken into consideration in terms of the associated supplying activities.

In this context, assembly and component supply operations mutually affect each other with strict precedence relations between their starting times. Indeed, there are some assembly activities that need the availability of a certain components and *vice versa*, components can be ordered only after certain operations (e.g., machine design and engineering). In addition to this, the uncertainty of manual operation durations makes this relation and activity completion times only partially predictable.

Hence, coordinating the availability of both purchased and self manufactured components with the assembly process of the products is a key factor to guarantee the smooth operation of the assembly shop and match the due dates agreed with the customers. Specifically stock-out of components is a very critical event, potentially causing important delays on the machine's completion time as well as perturbing the utilization of production resources and floor space.

The proposed approach addresses the assessment and mitigation of the stock-out risk for components together with their negative impact on the assembling phase taking advantage of the knowledge related to the assembly process as well as its intrinsic uncertainty.

It grounds on two indicators estimated through the *cumulative distribution function* (*cdf*) of the component's stock-out to provide support in the management of inventory and suppliers.

4. Solution approach

Coordinating production and material supplying activities consists in matching the availability of components with the assembly process. In this perspective, it could happen that a component is available but still not requested by the assembling process or, on the contrary, it is not available while the assembly process needs it. To model this, let us consider two events:

- Event A: the component is needed by the assembly process;
- Event B: the component is available.

Event A represents the case in which the assembly process is ready to use the component and requires it, while event B models the availability of the component at the assembling location or, in general, at the warehouse.

The associated probability density functions (*pdf)* are, respectively, $f_A(t)$ and $f_B(t)$:

$$f_A(t) = \begin{cases} 1 & \text{if the assembly process is surely ready to use the component} \\ 0 & \text{if the assembly process is surely not ready} \\ \in (0, 1) & \text{otherwise} \end{cases}$$

$$f_B(t) = \begin{cases} 1 & \text{if component is surely available} \\ 0 & \text{if component is surely not available} \\ \in (0, 1) & \text{otherwise} \end{cases}$$

We hypothesize that the assembly phase is the most important aspect and, hence, components are requested to be available at the earliest start time of the assembly operations not to delay the process. Thus, the coordination is successful if B occurs not later than A. Considering the stochastic nature of the described problem, the coordination works if $F_A(t) \leq_{st} F_B(t)$, where $F_i(t)$ is the cumulative distribution function (*cdf*) associated to the events $i = A$, B and $\leq_{st}$ provides a *stochastic dominance* (described in Shaked and Shanthikumar [28] and reported in Appendix A.1). Due to the difficulty to calculate the exact distributions, we propose a simplified approach where only a subset of the quantiles of these distributions is taken into consideration, to estimate the risk of not having the component available when needed.

The proposed approach is structured in five steps:

1. *Assembly modeling*: provides a formalization of the assembly process through a stochastic project network;
2. *Sub-network identification*: the assessment of the risk is performed considering a single component at a time, thus a sub-network is identified being the set of activities having dependencies with the considered component;
3. *Event cumulative distribution function estimations*: using on the isolated network, the *cdf*s associated to event A and event B are estimated;
4. *Risk Index estimation*: grounding on the estimated *cdf*s, a first risk indicator is calculated;
5. *Criticality Index estimation*: grounding on the estimated *cdf*s a second risk indicator is calculated.

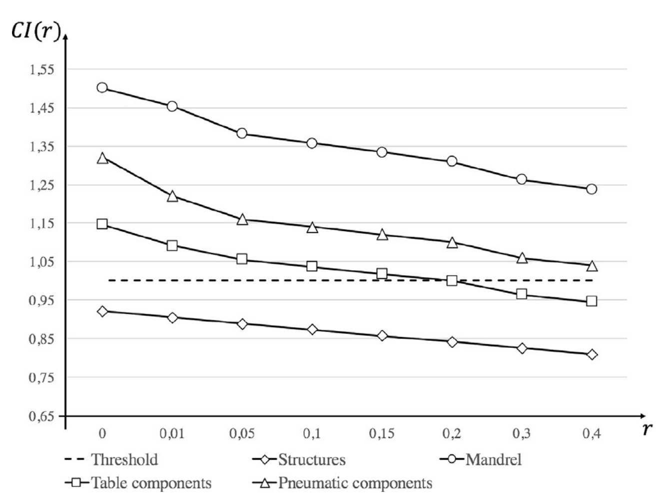


Fig. 9. *Criticality Index* results, in the uniform distributions case; only the components with significant values are represented.

Table 2
P estimated values for all components under study, using triangular distributions.

Element	P
Structures	0.8462
Mandrel	0.0000
Tank components	0.0000
Pallet components	0.0000
Table components	1.8465
Tool rack components	0.0000
Tool changer components	0.0000
Multi-pallet components	0.0000
Electric system components	0.0000
Pneumatic system components	0.2852
Protection components	0.0000
Machinery system components	0.0000
Perimetral enclosure components	0.0000
Option group components	0.0000
Pallet stock components	0.0000

4.1. *Assembly modeling*

Let us consider a stochastic *Activity on Arc* (*AoA*) network, modeled through a *Directed Acyclic Graph* (*DAG*) [9] $D = (N, A, p)$, where A is the set of arcs representing the assembly activities, N is the set of nodes and p is a vector of independent random variables modeling the activity durations. Hence, each activity $a \in A$ is modeled trough an arc with a stochastic duration $p_a \in p$.

In addition, different types of arcs are considered to model different types of activities:

- *supplying activities* (solid light gray arcs);
- *dummy activities* (whose duration is equal to 0, used to model additional precedence constraints, represented with dashed arcs);
- *generic activities* (all the other operations, e.g., design, assembly, etc., represented with solid black arcs).

An example is provided in Fig. 1, it represents the assembling of a product made up of three elements. Three material supplying activities are represented (arcs (1, 2), (1, 3) and (1, 6)), two pre-assembling operations on a single sub-assembly element (arcs (2, 4), (3, 5)), two dummy activities (arcs (4, 5) and (4, 6)), two assembling activities plus the final delivery (arcs (5, 7), (6, 7) and (7, 8) respectively). One of the pre-assembling operations (arc (2, 4)) constitutes a prerequisite for activities (5, 7) and (6, 7), hence, the two *dummy* activities ((4, 5) and (4, 6)) are used to add precedence relations not represented by any other activity.

Two types of supplying activities are considered. A first type is used to model the supplying of standard components managed by the warehouse. For these components, replenishment orders are placed according to the used stock management policies. We expect the supplying to occur according to a deterministic delivery date t^*, hence, a step *cdf* $F_{suppl}(t)$ is associated to the supplying.

$$F_{suppl}(t) = \begin{cases} 1 & \text{if } t \geq t^* \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

A different case is represented by the supplying of components whose production and/or assembling is outsourced to external companies. For these, a stochastic delivery time is used to model possible delays, whose distribution is defined considering the performance of the supplier. In case not enough data for this supplying are available, uniform or triangular distributions are used. For the other activities (production, assembling, etc.), due to intrinsic variability of the human behavior, a stochastic distribution is used.

4.2. *Sub-network identification*

The second step of the procedure addresses the identification the portion of the project network coupled with the supplying of a given component, i.e., the supplying itself and possible preassembling activities together with activities whose execution is concurrent with the supplying one. This sub-network has the following characteristics:

- the source node is the initial node of the whole network;
- the sink node is the one preceding the activity requiring the component under study.

In other words, the sub-network represents all the activities defining when the component will be used in the assembly process, they are fundamental to calculate the starting time of the assembly activity associated to the component under study.

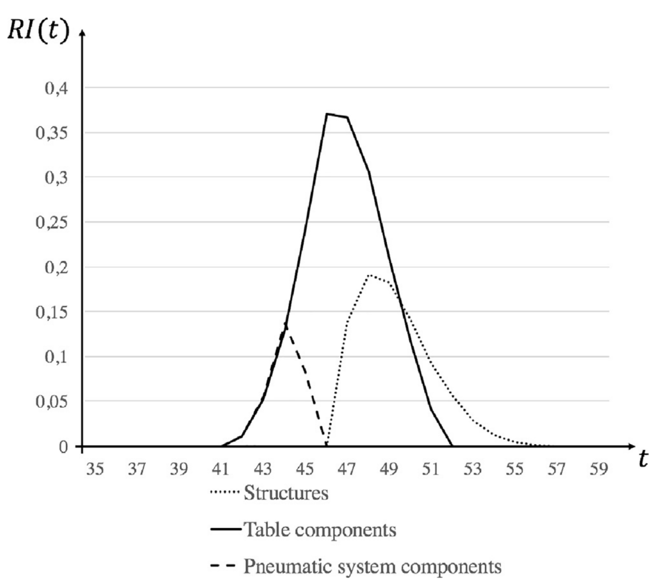


Fig. 10. *Risk Index* results in the triangular distributions case; only the function with not-null values are represented.

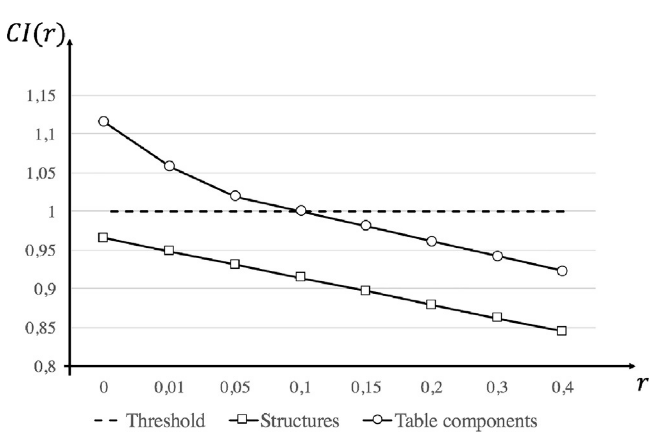


Fig. 11. *Criticality Index* results in the triangular distributions case; only the components with significant values are represented.

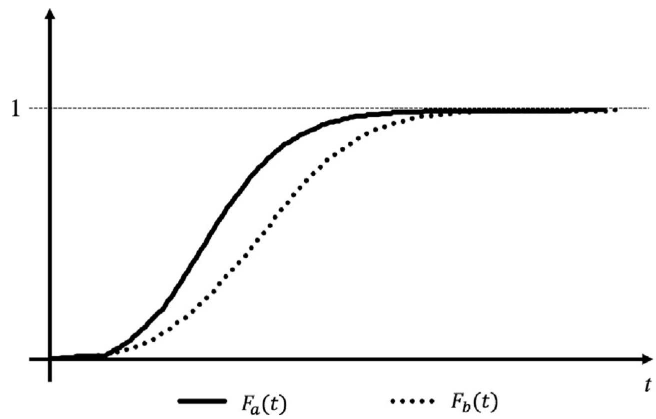


Fig. 12. Random variables *A* and *B* are depicted using their *cdf*s. In this case, variable *B* is *stochastically larger* than *A*.

Using the example in Fig. 1, it is possible to identify three different classes of sub-networks with the described characteristics.

A first case refers to the component supplied through activity (1, 6), needed to execute activity (6, 7). Fig. 2a shows the set of activities in the sub-network made up of all the activities from the initial node (node number 1) to the node before the activities requiring the component (node 6). In this set of arcs, there are the supplying activity for the first element (arc (1,6)) and some activities related to the second element (arcs (1,2) and (2,4)). In addition, there is also a *dummy activity* going from node 4 to node 6, representing a precedence relation between pre-assembly activity (2,4) and activity (6,7).

The second sub-network, the one in Fig. 2b, shows the activities related to the supplying of the component operated by the arc (1,3). Notice that, differently from the previous case, the supplying of the component under study is followed by activity (3,5), hence, the node *preceding the activity requiring the component to be available* is node 5, The activity requiring the component to be ready is arc (5,7) and, as a consequence, the activity (3,5) is included in the sub-network.

The last case is related to the supplying of the component through arc (1,2) (Fig. 2c). In this case, the activities requiring the component to be available are both (6,7) and (5,7). For this reason we have two nodes (5 and 6) preceding the activities requiring the component. Moreover, due to the presence of the dummy activities (4,5) and (4,6) also node 4 complies with the definition. Hence, nodes (4, 5 and 6) are sink nodes of the sub-network that needs to be furthermore reshaped to have a single sink node. This is done merging nodes 4, 5 and 6 in node 4^* (Fig. 2d).

4.3. *Event cumulative distribution function estimations*

The sub-networks identified in the previous step can be used to estimate $F_A(t)$ and $F_B(t)$, representing the time to the occurrence of events *A* and *B*. These distribution functions will be used for the calculation of the *Risk Index* and the *Criticality Index* in following two steps.

To estimate the time when the production process is going to require the component under study (event *A*), a variation of the *Monte Carlo Simulation* approach presented in Burt and Garman [7] is used, able to calculate the makespan of a *AoA* network by considering all the *s-t paths*. As defined in Lawler [21], given a network where *s* represents the source and *t* the sink, a *s-t path* is a sequence of arcs with the form $(s, i_1), (i_1, i_k), \ldots, (i_k, t)$, (i_1, i_2) represents an arc starting in node i_1 and ending in node i_2.

Nevertheless, our aim is to calculate the earliest time the component is going to be requested independently from its supplying. Hence, rather than considering all the *s-t* paths, we exclude those including the activity modeling the supplying of the component under study. The algorithm used for identify the *s-t* paths is an application of the *Depth First Search* on the *AoA* network, it grounds on the classic tree traversal problem also described by Knuth [20]. Using the sub-network presented in Fig. 2d, it is possible to identify the set of *s*-*t* paths for the estimation of $F_A(t)$. Three different *s*-*t* paths exists (Fig. 3): the first one (Fig. 3a) contains arc (1, 4*), the second one (Fig. 3b) arcs (1, 2) and (2, 4*), the third one (Fig. 3c) arcs (1, 3) and (3, 4*). Since the component under study is supplied through arc (1, 2) all the paths containing it are excluded from the set, hence, only the first and third paths are considered.

For the estimation of $F_B(t)$, we use the same approach with some differences. Since the event *B* depends on the supplying of the component under study, we will consider only the paths including this supplying activity. If, as described before, the supplying process is deterministic, then only the uncertainty coming from the other stochastic activities in the considered path (if any) are taken into consideration.

Given a single path, the distribution of its duration is calculated [32,24], in particular, a *convolution* operation is used for the *series reduction* of two or more activities. Given two activities α and β in series with stochastic durations described by $F_\alpha(t)$ and $F_\beta(t)$ respectively, the sum of the two duration is distributed as $F_\gamma(t)$ given by:

$$F_\gamma(t) = F_\alpha(t) * F_\beta(t) = \int_0^t F_\alpha(t-s)\, \mathrm{d}F_\beta(s)$$

where * is the *convolution* operator. By iteratively applying the *series reduction* on all the activities in a path, it is possible to obtain the stochastic duration of the whole path.

Table 3
Formal description of the three $CI(r)$ trends represented in Section 4.5.

Risk	Trend 1			Trend 2			Trend 3		
	$CI(r)$	t^*	$\hat{t}$	$CI(r)$	t^*	$\hat{t}$	$CI(r)$	t^*	$\hat{t}$
0.05	1.33	20	15	0.42	5	12	1.22	11	9
0.10	1.27	19	15	0.38	4.5	12	1.11	10	9
0.15	1.23	18.5	15	0.33	4	12	1.00	9	9
0.20	1.13	17	15	0.32	3.8	12	0.78	7	9
0.25	1.12	16.8	15	0.29	3.5	12	0.76	6.8	9
0.30	1.12	16.8	15	0.27	3.2	12	0.72	6.5	9
0.35	1.10	16.5	15	0.25	3	12	0.67	6	9
0.40	1.09	16.4	15	0.21	2.5	12	0.64	5.8	9
0.45	1.08	16.2	15	0.17	2	12	0.64	5.8	9
0.50	1.07	16	15	0.15	1.8	12	0.60	5.4	9

Instead, given more than one path containing the supplying activity under study, the estimation of event *B cdf* is approached with a Monte Carlo simulation as done for the calculations related to events *A*.

With this approach, the distributions of occurrence time of events *A* and *B* are estimated.

4.4. Risk index estimation

The first risk measure considered is the (*Risk Index*) $RI(t)$, measuring the probability of the joint occurrence of two events: *a component is requested by the assembly process* and *it is not available*. The probability of the intersection of these two events is the probability of having the process blocked because the component is missing. To this aim, we consider two events:

- *the component under study is requested by the assembly process*, represented by $F_A(t)$;
- *the component is not available*, represented by $[1 - F_B(t)]$.

The *Risk Index* can be defined as:

$$RI(t) = F_A(t)[1 - F_B(t)] \quad (2)$$

Table 4
Details of the use-case described in Fig. 7.

ID	Activity name	Nodes	Distribution	Range [*days*]
1	Engineering	1–2	Uniform	5–7
2	Cooling liquid tank design	2–5	Uniform	4–6
3	Perimetral enclosure design	2–12	Uniform	1–2
4	Electric system design	2–7	Uniform	2–3
5	Machinery system design	2–8	Uniform	2–3
6	Structures supplying	2–3	Step	5
7	Mandrel supplying	2–21	Step	35
8	Tank component supplying	5–15	Step	35
9	Pallet component supplying	2–13	Step	20
10	Table component supplying	2–4	Step	35
11	Tool rack component supplying	2–9	Step	15
12	Tool changer component supplying	2–10	Step	5
13	Multi-pallet component supplying	2–6	Step	15
14	Electric system component supplying	7–26	Step	5
15	Pneumatic system component supplying	2–11	Step	35
16	Protection component supplying	2–24	Step	20
17	Machinery system component supplying	8–20	Step	30
18	Perimetral enclosure component supplying	12–33	Step	15
19	Option group component supplying	2–32	Step	20
20	Pallet stock component supplying	2–28	Step	40
21	Structure preparation	3–14	Uniform	10–20
22	Pallet preparation	13–35	Uniform	5–10
23	Tank pre-assembly	15–31	Uniform	5–10
24	Table pre-assembly	4–18	Uniform	6–13
25	Tool rack pre-assembly	9–29	Uniform	5–10
26	Tool changer pre-assembly	10–30	Uniform	3–6
27	Multi-pallet pre-assembly	6–28	Uniform	7–15
28	Pneumatic system pre-assembly	11–19	Uniform	5–8
29	Structure painting	14–16	Uniform	5–10
30	Axes and carter assembly	16–17	Uniform	14–21
31	Table assembly	18–24	Uniform	2–5
32	Pneumatic system assembly	19–22	Uniform	2–5
33	Pneumatic system wiring	22–24	Uniform	29–34
34	Machinery system assembly	20–23	Uniform	0–1
35	Mandrel assembly	21–24	Uniform	8–15
36	Machinery system wiring	23–24	Uniform	2–4
37	Protection assembly part 1	24–25	Uniform	7–8
38	Protection assembly part 2	25–33	Uniform	0–1
39	Electric system wiring	26–27	Uniform	6–11
40	Multi-pallet assembly	28–34	Uniform	2–3
41	Multi-pallet wiring	28–34	Uniform	4–5
42	Tool rack assembly	29–34	Uniform	2–4
43	Tool rack wiring	29–34	Uniform	2–4

Table 5
Details of the use-case described in Fig. 7 (continued).

ID	Activity name	Nodes	Distribution	Range [*days*]
44	Tool changer assembly	30–32	Uniform	2–3
45	Tool changer wiring	30–32	Uniform	4–5
46	Option group assembly	32–34	Uniform	2–3
47	Cooling liquid tank assembly	31–34	Uniform	1–3
48	Perimetral enclosure assembly	33–34	Uniform	0–1
49	Functional test	34–35	Uniform	20–22
50	Geometric test	35–36	Uniform	2–4
51	Metrology test	36–37	Uniform	2–3
52	Customer foundation availability	37–38	Uniform	1–2
53	Disassembly	38–39	Uniform	2–3
54	Delivery	39–40	Uniform	2–3
55	Installation	40–41	Uniform	20–40
56	Acceptance	41–42	Uniform	10–15
57	Programming course	38–42	Uniform	10–12
58	Machine management course	38–42	Uniform	5–6
59	Maintenance course	38–42	Uniform	5–6
60	Machine ready for production	42–43	Uniform	1–2
$d1$	Dummy 1	3–4	Deterministic	0
$d2$	Dummy 2	17–18	Deterministic	0
$d3$	Dummy 3	17–19	Deterministic	0
$d4$	Dummy 4	17–20	Deterministic	0
$d5$	Dummy 5	17–21	Deterministic	0
$d6$	Dummy 6	25–26	Deterministic	0
$d7$	Dummy 7	27–28	Deterministic	0
$d8$	Dummy 8	27–29	Deterministic	0
$d9$	Dummy 9	27–30	Deterministic	0
$d10$	Dummy 10	27–31	Deterministic	0

This expression only considers the occurrence probability of both events, hence it evaluate the occurrence probability without being influenced by the aversion to risk of the manager. The *Risk Index* can be used in two different ways. A first utilization mode is to compare the risk associated to two different components at a given time $\hat{t}$. Let us consider two components α and β and their risk indexes $RI_\alpha(t)$ and $RI_\beta(t)$ at a given time $\hat{t}$, the following cases are possible:

- $RI_\alpha(\hat{t}) > RI_\beta(\hat{t})$, the supplying of component α has a risk higher than β;
- $RI_\beta(\hat{t}) > RI_\alpha(\hat{t})$, the supplying of component β has a risk higher than α;
- $RI_\alpha(\hat{t}) = RI_\beta(\hat{t})$, the two components have comparable supplying risks.

The component with the higher value for the indicator is more likely to delay the assembly process and, if possible, actions can be taken to mitigate this eventuality. As an example, if this analysis is operated *ex ante*, i.e., before the assembling process has started, it could support the selection among different suppliers.

A second modality addresses the occurrence probability of a delay due to the unavailability of a component. This can be calculate integrating $RI(t)$ over the whole time horizon:

$$\mathbb{P} = \int_0^\infty RI(t)\,\mathrm{d}t = \int_0^{\inf} F_A(t)[1 - F_B(t)]\,\mathrm{d}t \quad (3)$$

The greater this probability, the higher the risk associated to the component. Let us consider Fig. 4. The first graph (Fig. 4a) is obtained considering a component whose supplying time is modeled with a general stochastic distribution. The obtained risk index function is a new stochastic distribution whose integral is equal to 1. The second case (Fig. 4b) refers to a component whose supplying is deterministic, i.e., modeled through the *cdf* in Eq. (1). In this case, the integral of the risk index function can be less than 1.

These integrals can be used to compare the risk associated to the supplying of different components or to create a rating system for the suppliers (or for the associated ordering procedure).

4.5. *Criticality index estimation*

The second index is the *Criticality Index* ($CI(r)$). Let us consider the occurrence probability of event A ($F_A(t)$) and define t^* the quantile of this distribution associated to the probability $(1-r)$, i.e., $t^* \mid F_A(t^*) = (1-r)$. In practical terms, t^* is the time when the probability for the component to be required for the assembling process is equal to $1-r$, where r is the risk associated to the evaluation of $F_A(t)$. In a similar way, let us consider the probability distribution associated to event B ($F_B(t)$) and define $\hat{t}$ the quantile of this distribution associated to the probability 1, i.e., $\hat{t} \mid F_B(\hat{t}) = 1 \wedge F_B(\hat{t}-1) < 1$. In practical terms, this is the time where the probability of having the component delivered is equal to 1.

Let us now define the *Criticality Index* as:

$$CI(r) = \frac{t^*}{\hat{t}} \tag{4}$$

The *Criticality Index* index can be used to assess the criticality of the components and of the assembling process. Let us consider a single component and a risk level r, three cases can occur:

- $CI(r) > 1$, the component is expected to be available before the occurrence of its need considering a risk r;
- $CI(r) = 1$, the component is expected to be available exactly when its need occurs considering a risk r;
- $CI(r) < 1$, the component is expected to be needed before it will be available considering a risk r.

In other words, if the index is greater or equal than 1 there is no criticality for the supplying activity. On the contrary, for values lower than 1 there could be problems in the coordination between supplying and assembling the component. This value can be also used to compare different supplying solutions.

Consider two different suppliers ˛ and ˇ providing the same component with different delivery times (in days), $\hat{t}_{˛} = 15$ and $\hat{t}_{ˇ} = 10$. Hypothesizing $r = 0$, we have $t^* = 12$. The indexes related to the two suppliers are $CI(0)_{˛} = 12/15 = 0.8$ and $CI(0)_{ˇ} = 12/10 = 1.2$ respectively. Grounding on this, relying on supplier ˛ is more risky than referring to supplier ˇ because the index associated with $r = 0$ is lower.

The use of this index is affected by the selection of the risk level r. If the manager has a low aversion to risk, he would like to consider the extreme case in which the assembly process will definitely require the component without compromises. He will choose $r = 0$, thus, $t^* \mid F_A(t^*) = 1$. Instead, if he wants to be cautious, he will consider the assembly process needing the component before the very last time instant (given by the 100th percentile of $F_A(t)$) choosing $0 < r < 1$, thus, $t^* \mid F_A(t^*) = (1-r)$.

To make the dependence of the index from the value of r explicit, it is possible to evaluate its value for different risk levels, i.e., fordifferent quantiles of the function $F_A(t)$. The result is a criticality function for a component in terms of r. This function can provide a wider set of information as shown in Fig. 5 (and further described in Table 3 in Appendix A.2). Specifically, the following cases apply:

1. The index is always greater than 1: the supplying of the component is not critical, hence, it is expected to be available whenever it is needed for the assembling.
2. The index is always lower than 1: the supplying of the component is always critical and it will unavailable when needed. A specific action is needed to manage these cases.
3. The index is greater than 1 only for $r \le r^*$: this case depends on the value of r^*. If it is low, then the probability to incur a critical situation is low, otherwise proper actions should be taken into consideration e.g., remove resources from a certain task in order to delay t^*.

Additional considerations can be provided in terms of the behavior of the index with respect to r since it impacts the value of CI. Its elasticity is a way of evaluating this impact.

$$\varepsilon_{CI(r)} = \frac{\%\Delta CI(r)}{\%\Delta r} \qquad (5)$$

With $\varepsilon CI(r) < 0$ the criticality depends on the risk level considered; on the contrary, if the elasticity is close to 0, the criticality only depends on the supplying process or the schedule of the assembling operations.

In the first case ($\varepsilon CI(r) \leq 0$), a $\varepsilon CI(r)$ with small absolute value indicates that the slope of the curve is small and the risk does not impact the supply criticality of the component too much; this means that, independently from the risk aversion of the manager, the criticality remains the same. On the contrary, a $\varepsilon CI(r)$ with large absolute value entails a larger slope and a stronger impact of r on the criticality index as well. Hence, the assessment of the criticality associated to a component strongly depends on the risk aversion of the manger. In the second case, if the criticality is greater than 1, then the supply process is always feasible; on the contrary, if the index is constant and lower than 1, it is important to find an alternative
supplier or supplying procedure to mitigate the criticality.

As an example, let us consider the first and last curves (Trend 1 and Trend 3) of the graph in Fig. 5 with $r \in [0.05, 0.10]$. The elasticity can be calculated as follows:

$$\varepsilon_{CI_1(0.05)} = \frac{\%\Delta CI^1}{\%\Delta r} = \frac{(1.33 - 1.23)/1.33}{(0.05 - 0.10)/0.05} = -0.076$$

$$\varepsilon_{CI_3(0.05)} = \frac{\%\Delta CI^3}{\%\Delta r} = \frac{(1.22 - 1.00)/1.22}{(0.05 - 0.10)/0.05} = -0.18$$

The elasticity of the third trend is bigger in modulus than the first one (both negative), it means that manger's risk aversion could impact more on the assessment of the risk of this component. Nevertheless, in this case, the different elasticity do not cause the two trends to intersects and, hence, a manager would always decide to address the component with the lowest CI or, if the two trends represent two alternative suppliers, select the one with the highest CI. On the contrary, referring only to the third trend, for different values of r, the component has a CI above or below threshold value
1. A manager with low aversion to risk would consider a low value of r, resulting in the component to have a CI greater than 1 and, hence, not being considered risky. On the contrary, a manager with high aversion to risk, would use a higher value of r, resulting in a CI lower than 1 and, consequently, putting this component among those needing attention or a proper action.

The elasticity also provides a measure of manager action's impact on the *criticality index*. In other words, considering the supplying processes of two different components, the mitigation action the manager could take will be more effective on the one with the steepest slope (bigger elasticity in module), since a shift of the trend upwards is most likely to intersect the value 1 for the steepest curve. Thus, the manager could decide to take a corrective action for this component because the action could be more effective.

5. Industrial application

The proposed approach is tested and validated on an industrial. The sector considered is the production and assembling of instrumental goods, specifically machine tools. The case under study has been provided by *MCM S.p.A.*, an Italian manufacturing company that designs and produces machining centers and flexible manufacturing systems. *MCM* provides its customers a wide range of customization options for their machines and, in many cases, the customizations are so relevant that it has to partially reshape the associated production and assembling process. The organizational paradigm used is, obviously, the *MTO*.

Both the production and purchasing phases are very important for the company because, due to the customization, each machine tool or system requires specific components that must be properly supplied. Moreover, due to the high customization ranges of its products, *MCM* does not retain a stock for all of the components but rather place an order for the supplying of some of them as soon as a new machine requires them. As an example, mandrels are supplied upon specific request but, for ancillary component (wires, common drives, etc.), an inventory is available. As a consequence, some components are more critical in terms of supplying activities and coordination with the assembling process.

5.1. *Formalization*

The use case refers to the assembling process of a machine tool model equipped with additional optional elements. The machine under study (Fig. 6) has a turning table and uses 800 × 800 mm pallets. It also comprehends a tool rack with 40 positions. In addition, the customer asked for a specific mandrel, a multi-pallet carousel and a cooling fluid tank different from the standard one. Hence, the company had to redesign some portions of the machine accordingly.

The production process for the machine is reported in Fig. 7. It is composed by 70 activities, starting from the *overall design and negotiation and supplying of components,* to the final delivery to the customer. The assembly process also contains 15 activities related to the supplying of key components. If a component is avail- able at the assembling line, it is possible to execute the assembly and/or pre-assembly operations. It is the case of the tool rack that needs a pre-assembly operation before being assembled onto the machine structure. A key phase is the preparation of the structure, entailing the scraping of motion guides and the main elements of the machine body. After the complete assembling of the machine, three tests phases are executed and, finally, the machine is ready to be partially disassembled and delivered to the customer. The final installation is executed at the customer's premises together with the initial training.

Each activity in the process has a stochastic duration modeled with a discrete distribution. We assume a deterministic delivery date for the supplying of the components, thus using the step function (Eq. (1)) where t^* represents the delivery date. For all the other activities, we model the durations with a distribution fitting the real data (uniform in Section 5.2.1 and triangular in Section 5.2.2
respectively). The distributions have been estimated grounding on historical data of similar assembly processes executed by *MCM* in the past. The uniform distributions are modeled considering the minimum and maximum values observed. For the triangular distributions, due to the small number of data, the minimum value is both the minimum and mode duration and the maximum one is the worst-case duration the human operator can run into. Dummy activities, having duration equal to 0, are deterministic by definition. In the whole analysis, a single day is used as time unit. A schematic description of all the activities in the process is included in Tables 4 and 5 in Appendix A.3.

5.2. *Results*

The proposed approach is applied to the process described above and provides interesting information in relation to the execution of the assembly process but also in relation to its structural properties. The results have been obtained through 10,000 replicates using a code implemented on *Matlab* and executed on a 2.4 GHz *Intel Core i5* with 8 GB memory.

5.2.1. *Uniform distributions*

According to the results in Table 1, the only components with a positive probability to impact on the execution of the process are the structures, table components, pneumatic system components and the mandrel, where P is an indication of the risk level associated to the supplying of each component under study, useful only for a comparison. Notice that, the structures have the most relevant value.

The *Risk Indicators* depicted in Fig. 8 tell us that only four supplying activities are considered *risky*. The P values for each component are included in Table 1.

An additional analysis can be obtained through the $RI(t)$ function, reported in Fig. 8. The higher the peak of the function, the higher the total probability of incurring a delay due to the missing item. Possible actions, e.g., the anticipation or solicitation of some deliveries, can be taken to mitigate the probability of incurring these problems. The criticality index $CI(r)$ has been calculated with r varying from 1% to 40%. The $CI(r)$ index gives us a comparison between the expected time when the component will be needed and its supplying. The values are plotted in Fig. 9 where the threshold value is 1. It is possible to see the behavior of the same components addressed in terms of the $CI(r)$. Indeed, if the structure supplying is still considered a critical activity (the function assumes value less than 1 for the whole range of r), the mandrel and the pneumatic components are not that critical, having all the values above the threshold. In addition, the $CI(r)$ related to the table has values greater than 1 if $r < 20\%$ and lower in the other cases. It means that the assessment of its criticality strongly depends on the risk aversion of the manager or the company.

Since the supplying of the structures is critical, together with other components, specific actions could be taken to mitigate the associated its risk. We suppose that these reactive actions are taken after the scheduling of assembly activities, thus, without the possibility to anticipate them or allocate additional resources. Under this hypothesis, only the supplying activities could be subject of a mitigation action. For example, it is possible to (i) solicit structures supplier in order to shorten their due date from 5 to 2 days, or (ii) solicit the table component supplier shortening the delivery time to 20 days, instead of 35. The contemporary application of these actions would impact on the process with a reduction of the P value for both the structures (0.9571) and table components (<0.0001). Another option could be having a stock of one or more of these critical components with the obvious consequence of getting rid of the risk but increasing the inventory. Nevertheless, since the structure is also the largest component of the machine, managing a stock for them is not reasonable anyway. On the contrary, since all the other components are not critical, the current supplying procedure is consistent with the assembling process.

5.2.2. *Triangular distributions*

A similar analysis has been executed using triangular distributed activities. The aggregated results for the *Risk index* are reported in Table 2. As for the previous case, only some components have a risk level different from zero, namely the structures, table components and pneumatic system components, in which the second one has the greatest value (1.8465). The risk trends for the supplying of the components are represented in Fig. 10.

Differently from the previous case, the component with the highest value is the table, whose $RI(t)$ is caused by the delivery time of 35 days. Also the $CI(r)$ values for the structures and table components suggest a critical situation for both the supply activities for certain values of r, as depicted in Fig. 11.

A possible reaction to this situation could be to push the suppliers to deliver faster or find another supplying solution with a shorter delivery time, under the same hypothesis used for the uniform distribution case. Indeed, by reducing the delivery time for the table components to 30 days, we will reduce the related P value to 0.1253, without affecting other components, thus obtaining a better situation than before. Another option could be the joint reduction of the delivery time for the table components (30 days) and the structures (3 days). The result is the mitigation of both the criticalities with new P values equal to 0.3187 and 0.1270 for structures and table components respectively. The considerations made about the stock management of the structures and other components are valid also in this case.

6. **Conclusion**

In this paper, we addressed the importance of the coordination between the need of a component on the assembly line of a manufacturing *MTO* process and its availability. The need of this coordination increases when every activity is executed by human operator and thus suffers from uncertain duration. In this case, the coordination cannot be easily identified but it requires a proper modeling and estimation process. For these reasons, we presented the *Risk Index* and the *Criticality Index* as two different modalities for analyzing the coordination problem. The first one allows to estimate the risk of lack of coordination and compare different solution on a point-wise base and on its whole domain. The second one is able to give an absolute evaluation, considering also the evolution of the index.

We also applied the approach on a real industrial case represented by Italian company *MCM S.p.A.* that designs, produces and sells machining centers. The results coming from the use-case give important information about the supply situation but also about the process, indeed some critical component has been identified.

As a conclusion, the use of the proposed approach could be helpful to give the manager an estimation of the impact of planning decisions taking into consideration the interrelation between production and supplying activities. Grounding on this analysis, proper actions can be taken to reduce the risk of delaying the delivery time of products due to the stock out of components. This approach specifically addressed MTO and ETO systems producing complex products, hence, where keeping inventory of these components is not a viable strategy.

Future developments will address assembly processes for multiple items, where cannibalization of missing components could happen in real industrial environment.

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Appendix A. Stochastic ordering

A.1 *Stochastic ordering*

The approach described in this document grounds on the definition of *dominance* between random variables. In particular, it is possible to define four different dominance categories.

1. The random variable X_1 is said to be *larger in expectation* than the random variable X_2, if $E(X_1) \geq E(X_2)$.
2. The random variable X_1 is said to be *stochastically larger* than the random variable X_2, if $P(X_1 > t) \geq P(X_2 > t)$ or $1 - F_1(t) \geq 1 - F_2(t)$ for all t, where F_i represent the *cdf* of X_i. The stochastic ordering is denoted by $X_1 \geq_{st} X_2$. An example is given in Fig. 12.
3. The random variable X_1 is said to be *larger in the likelihood sense* than the random variable X_2 (both continuous), if $f_1(t)/f_2(t)$ is nondecreasing in $t \geq 0$, where f_i represents the *pdf* of X_i. The random variable X_1 is said to be *larger in the likelihood sense* than the random variable X_2 (both discrete), if $P(X_1 = t)/P(X_2 = t)$ is nondecreasing in $t \geq 0$. This relation is denoted by $X_1 \geq_{lr} X_2$.
4. The random variable X_1 is *almost surely larger* than or equal to
5. the random variable X_2 if $P(X_1 \geq X_2) = 1$. This ordering implies that the *pdf*s f_1 and f_2 may overlap at most on one point and is denoted by $X_1 \geq_{as} X_2$.

A.2 *Critical index example data*

The three trends depicted in Fig. 5 grounds on the data in Table 3.

A.3 *Process activity descriptions*

Process activity descriptions are included in Table 4 and Table 5.

References

[1] Alfieri A, Tolio T, Urgo M. A project scheduling approach to production and material requirement planning in manufacturing-to-order environments. J Intell Manuf 2012;23:575–85.

[2] Alfieri A, Tolio T, Urgo M. A two-stage stochastic programming project scheduling approach to production planning. Int J Adv Manuf Technol 2012;62:279–90.

[3] Alfieri A, Urgo M. Project scheduling for aggregate production scheduling in make-to-order environments. In: Schwindt C, Zimmermann J, editors. Handbook on project management and scheduling, vol. 2. Springer International Publishing; 2015. p. 1249–66. Ch. 56.

[4] Anthony RN. Planning and control systems: a framework for analysis. Harvard University; 1965.
[5] Bitran GR, Tirupati D. Hierarchical production planning. In: Graves SC, Rinnooy Kan AHG, Zipkin PH, editors. Logistics of production and inventory. Handbooks in operations research and management science, vol. 4. Amsterdam: Elsevier; 1993. p. 523–68.
[6] Bortolini M, Faccio M, Gamberi M, Pilati F. Including material exposure and part attributes in the manual assembly line balancing problem. IFAC-PapersOnLine 2016;49(12):926–31.
[7] Burt JM, Garman MB. Monte carlo techniques for stochastic network analysis. ACM – winter simulation conference 1970.
[8] Carvalho AN, Oliveira F, Scavarda LF. Tactical capacity planning in a real-world ETO industry case: an action research. Int J Prod Econ 2015;167:187–203.
[9] Demeulemeester EL, Herroelen WS. Project scheduling: a research handbook. Springer; 2002.
[10] Elmaghraby SE. Activity networks – project planning and control by networks models. John Wiley and Sons; 1977.
[11] Faccio M, Gamberi M, Pilati F, Bortolini M. Packaging strategy definition for sales kits within an assembly system. Int J Prod Res 2015;53(11): 3288–305.
[12] Fredriksson A, Wänström C, Johansson MI, Medbo L. A structured procedure for materials planning during production transfer. Prod Plan Control 2015;26(9):738–52.
[13] Hanson R, Medbo L. Aspects influencing man-hour efficiency of kit preparation for mixed-model assembly. Proc CIRP 2016;44:353–8.
[14] Harris B, Lewis F, Cook DJ. A matrix formulation for integrating assembly trees and manufacturing resource planning with capacity constraints. J Intell Manuf 2002;13(4):239–52.
[15] Hax AC, Meal HC. Hierarchical integration of production planning and scheduling. In: Logistics. Studies in the management sciences, vol. 1. Amsterdam: North-Holland; 1975.
[16] Hopp WJ, Spearman ML. Factory physics: foundations of manufacturing management. Irwin: McGraw-Hill; 2000.
[17] Ioannou G, Dimitriou S. Lead time estimation in MRP/ERP for make-to-order manufacturing systems. Int J Prod Econ 2012;2(139):551–63.
[18] Jodlbauer H, Altendorfer K. Trade-off between capacity invested and inventory needed. Eur J Op Res 2010;1(203):118–33.
[19] Jodlbauer H, Altendorfer K. Trade-off between capacity invested and inventory needed. Eur J Op Res 2010;203(1):118–33.
[20] Knuth DE. The art of computer programming, vol. 2. Addison-Wesley; 1989. [21] Lawler EL. Combinatorial optimization: network and matroids. Holt: Rinehart and Winston; 1976.
[22] Lödding H, Lohmann S. Incap – applying short-term flexibility to control inventories. Int J Prod Res 2011;50(3):909–19.
[23] Márkus A, Váncza J, Kis T, Kovács A. Project scheduling approach for production planning. CIRP – Annu Manuf Technol 2003.
[24] Martin JJ. Distribution of the time through a direct, acyclic network. J Op Res 1965;13(1):46–66.
[25] Neumann K, Schwindt C. A capacitated hierarchical approach to make-to-order production. Eur J Autom 1998.
[26] Radke AM, Tolio T, Tseng MM, Urgo M. A risk management-based evaluation of inventory allocations for make-to-order production. CIRP Ann – Manuf Technol 2013;1(62):459–62.
[27] Radke AM, Tseng MM. A risk management-based approach for inventory planning of engineering-to-order production. CIRP Ann – Manuf Technol 2012;61:387–90.
[28] Shaked M, Shanthikumar JG. Stochastic orders and their applications. Springer; 2007.
[29] Stanford RE, Martin W. Towards a normative model for inventory cost management in a generalized ABC classification system. J Op Res Soc 2007;7(58):922–8.
[30] Tolio T, Urgo M, Váncza J. Robust production control against propagation of disruptions. CIRP Ann – Manuf Technol 2011;1(60):489–92.
[31] Tsai C-Y, Yeh S-W. A multiple objective particle swarm optimization approach for inventory classification. Int J Prod Econ 2008;2(114):656–66.
[32] Valdes J, Tarjan RE, Lawler EL. The recognition of series parallel digraphs. ACM – Symposium on Theory of Computing 1979:1–12.