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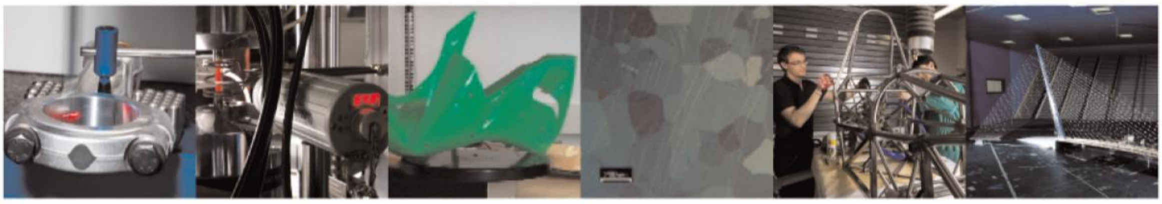

An approach for the robust design of a reconfigurable assembly cell with 7-axis robot

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An approach for the robust design of a reconfigurable assembly cell

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ABSTRACT

The increasing variety of products and the variability of the demand is pushing manufacturing companies in a challenging competing environment. These trends affect many industrial sectors, including the automotive sector, and propagate within the supply chain impacting all the related businesses, including the production of *spare parts*. The automotive *spare part*'s market requires a very high number of different products to support the need for replacing parts during the whole life cycle of cars. As the design of cars becomes more and more sophisticated, producing *spare parts* requires complex production processes, the use of different technologies and different materials. In this context, the design of assembly systems to produce them and proper management policies has a considerable importance for the competitiveness of *spare parts* suppliers. In this paper, the authors propose an approach to provide a robust solution for a reconfigurable assembly cell. An initial configuration together with a proper reconfiguration plan is selected for a reconfigurable assembly cell with the aim at coping with the intrinsic uncertainty of the *spare part* market. An innovative reconfigurable assembly cell architecture is exploited while robustness is pursued *robust* by minimizing a function of the risk associated to the cost, both fixed and operational, of the assembly cell. The viability of the proposed approach is demonstrated through the application to an industrial case.

KEYWORDS

reconfigurable assembly cell; design; robustness

1. Introduction and motivation

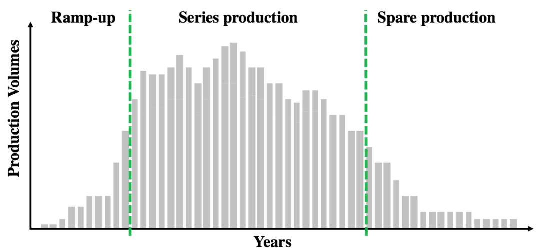
Throughout the last decade, the European and worldwide manufacturing sector is moving from mass production-oriented to personalized production (Abele et al. 2006), (Chryssolouris 2005). Due to this trend, companies are put under pressure due to shorter time to market, increased level of customization and, thus, high variety of products with smaller volumes to be produced (Wiendahl et al. 2007).

Although competitive, these challenges could also be beneficial for a company, because they offers the possibility to enter new markets, increase the production volumes and revenues. However, these positive effects can be achievable only if the company is able to manage the product's variety (ElMaraghy et al. 2013). In order to do this, factories have to evolve from *functional factory* with high resource flexibility but long delivery time, to a factory with a stronger market orientation, quick responsiveness and high innovation ability (Wiendahl and Hernández 2001).

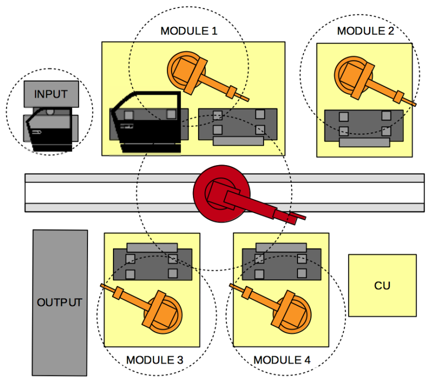
From a production point of view, this high variety entails the need to cope with different products, production processes and small batches in a continuously changing environment. Manufacturing systems must be able to manage these factors with the introduction of adaptation enablers, both at the hardware and organizational level, that allow the system to smoothly and rapidly change and adapt to the dynamics of the market (Monostori et al. 2016). Hardware enablers are linked to concepts like *flexibility* and *reconfigurability* (Terkaj et al. 2009b), i.e., the ability of a system to adapt to variable processes or production volumes, within pre-defined boundaries (H. and Wiendahl 2009), (Hallgren and Olhager 2009), and to be arranged and rearranged by physically change components and pieces of equipment (Koren et al. 1999), (El-Maraghy 2005).

Organizational enablers are methods or approaches able to manage the production resources in a profitable way. The purpose of organizational enablers has been defined as *co-evolution* in Tolio et al. (2010), that is the ability to manage strategically and operationally the propagation of engineering changes to gain a competitive advantage from the market and regulatory dynamics. In this context, the design of manufacturing systems is a key phase, to be addressed in a strategically way and with a long-term vision, with the need to predict market behaviour and its uncertain dynamics (Terkaj et al. 2009a).

One of the sectors affected by these trends is the assembly of car-body components, characterized by variable customers' demand, technological evolution and, thus, a high degree of uncertainty all over the car life-cycle. In particular, the life-cycle of cars can



(a) Car production volumes during the whole life-cycle.



(b) Example of *reconfigurable* cell layout.

Figure 1.: Car life-cycle and *reconfigurable* cell layout.

be divided in three main phases (Figure 1a), (i) the *ramp-up* phase occurring when *original equipment manufacturers* (*OEM*s) introduce a new product in the market, (ii) the *series production* phase and (iii) the *spare production* phase wherein the *OEM*s have to guarantee replacement parts for at least 10 - 15 years. During this last phase, the demand for spare parts is fragmented in a wide range of different products with very low volumes and unpredictable evolution over the time. In addition to this, *OEM*s are moving towards an increasing variety of models and a continuous technological evolution in term of materials and processes. *OEM*s typically rely on *tier-1* suppliers of car-body components for the after market, and focus their internal production capacity on the *series production* and *ramp-up* phases. In order to remain competitive in this segment, *tier-1* suppliers have to match market evolution in a *co-evolution* way of thinking by acting proactively and providing the capability to integrate new technologies into the assembly system.

The set of components considered are usually produced in two main steps, deep drawing and assembly operations. The first one considers operations to form metal sheets. The second one considers the joining of the structure with additional elements, e.g., hinges or reinforcement bars on a door, using different assembly technologies. Focusing only on the assembly process, related technologies are clustered through the definition of *Functional Assembly Groups* (*FAG*s). A *FAG* represents a technology group, that is a cluster of similar joining technologies. Indeed, each *FAG* identifies a specific set of pieces of equipment required by the assembly process. For each *FAG*, different solutions for the same technology are available. The following set of *FAG*s is considered: laser joining, hemming, adhesive joining, resistance joining, mechanical joining and manual operation. Each product requires multiple *FAG*s for its assembly process, with very specific configurations and equipment entailing the need of configuration approaches able to handle the requirements in terms of different technologies and assembly processes.

In this context, several manufacturing paradigms have been developed to satisfy changes affecting products, processes and volumes (ElMaraghy et al. 2013). *Tier-1* suppliers typically rely on cellular manufacturing systems by pursuing two alternative solutions. The first one considers a *dedicated assembly cell* for each product in the portfolio. It allows to have high productivity but a low utilization factor and a high consumption in terms space in the shop floor. The second one relies on *universal assembly cells* dedicated to a specific (or a group) of technology, thus, a product has to visit different cells in order to complete its assembly process. This means having a higher saturation for the equipment but the routing of part through the plant could represent an issue.

The aim of this paper is the development of a reconfigurable assembly cell concept where a set of modular pieces of equipment (e.g., robots, fixtures, machine tools) can be easily rearranged to match the evolution of the manufacturing requirements (Figure 1b). This assembly cell is based on a standardized layout that considers a turntable as the input gate and a conveyor as the output. Inside the cell, a set of modular devices (*modules* in Figure 1b) are arranged around a *7-axis robot*, they can host a set of pieces of equipment able to provide alternative assembly technologies with alternative implementing solutions. The *7-axis robot* moves parts and components through the cell and, in some cases, it can take part to the execution of assembly operations.

The reconfigurable assembly cell can be easily reconfigured with a substitution of a modular device with another one and, thus, a quick action that allows to change the set of assembly processes the cell can handle without changing its architecture. Although conceptually simple, the use of such an assembly cell paradigm entails a higher degree of complexity in its design and management considering all the characteristics of both the technology and the environment in which it operates.

For these reasons, the industrial motivation of this paper lies on developing an approach able to support the decision-maker during the design and the management of a reconfigurable assembly cell in the automotive sector and operating in an uncertain context.

Outline Section 2 provides an analysis of the literature, while the problem statement is presented in Section 3. In Section 4, the solution approach is described and then applied on a real industrial case in Section 5. Finally, conclusions and future development directions are provided in Section 6. Additional tables and information are included in Appendix.

2. State of the art

The approach presented in this paper addresses the design of a *reconfigurable* assembly system operating in an uncertain environment over a medium-long time horizon. Many approaches and methods able to tackle this configuration problem have been developed. In the following, some concepts and approaches for the system configuration are introduced and discussed, with an emphasis on the ones more appropriate for the assembly systems.

2.1. *Cell formalization and design*

The problem of the design of an assembly cell belongs to the family of the system design problems, for which a classification according to the different system types considered has been developed. Considering the structure of the system and its capability to change, we have *dedicated* (*DMS*), *flexible* (*FMS*), and *reconfigurable* manufacturing systems (*RMS*) (ElMaraghy 2005). The same classification can be applied also to assembly systems (Lotter and Wiendahl 2009).

In particular, *reconfigurable* assembly systems are able to undergo a modification of the pieces of equipment to cope with new requirements. After these changes, the system is able to reach the performance level of a *dedicated* system. This class of systems requires technological enablers to quickly change the pieces of equipment (e.g., machines and fixtures) to switch from a product type to another. In the assembly system under study, the main technological enabler is a modular interface that allows the pieces of equipment in the system to be quickly swapped, but still requiring more time than a simple set-up on a flexible system. This new class of equipment are referred as *plug and produce modules* (Onori et al. 2012), (Wiendahl et al. 2007).

Regarding the problem formalization, it is possible to mention three theoretical studies. The first one is presented in Rheault et al. (1996), it introduces the concept of *Dynamical Cellular Manufacturing System* (*DCMS*) defining a specific type of manufacturing system organized as a production cell with modular components and representing the technological enabler for the *reconfigurable* systems. In Rheault et al. (1995), a modular framework for the *DCMS* is presented, it exploits the concept of *Virtual Cellular Manufacturing Systems* (*VCMS*), developed in McLean et al. (1982). The *VCMS* is a logical grouping of processors that are not necessary transposed into physical proximity. In Venkatadri et al. (1997), authors use a *Fractal Layout* framework, instead of the *Group Technology* one for designing an entire production system. In this case, authors define a *fractal cell* as a set of contiguous workstations on the shop floor that are capable to process most, if not all products that enter the system. These works provide some interesting theories about the formalization and the design process of manufacturing (and assembly) systems, but, in doing this, they do not provide any link with the real production process and its characteristics.

This link is usually pursued by considering the throughput of the system as the one of the bottleneck operation (or station), as in Li et al. (2011), without actually taking into account the whole system but only a part of it. Instead, this link is well discussed in Chan et al. (2006), that takes into account the allocation order of elements inside the cell during the performance evaluation. In other words, for a different choice of resource allocation, we have a different production process. Another example is proposed in Ceglarek et al. (2015), where authors address the configuration of a *remote laser welding* assembly line considering its production process and task sequencing.

An important topic is the choice of the *KPI* to be measured on the system under study. Many authors figured out that the main differential factor in a cellular manufacturing system is represented by the handling system and its behaviour. Indeed, for a different set of resources and, thus, a different layout, the system has a different handling/routing path and different handling/routing times. Many works in the literature agree on the importance of handling; some of them address this problem in terms of time-related performance (Wesolowski 1973), (Massoud 1999), others as a cost function for the design and management of the cell, like in Ahkioon et al. (2009), where a complete cost formulation is provided, or in (Kia et al. 2012), where the alternative process routings are used.

In order to develop an effective approach for the configuration of the assembly cell under study, it is needed to have a formal representation of the assembly process and the assembly cell, supporting a tailored performance evaluation method.

An example of contribution that addresses this lack is presented in Renna and Ambrico (2015). Instead, in Manzini et al. (2018b), the same *reconfigurable* assembly cell presented in this paper is considered. Authors proposed a formal representation for this class of systems and address its configuration.

2.2. *Cell reconfiguration*

The class of assembly systems considered in this paper is able to undergo a reconfiguration with limited cost and time effort (Napoleone et al. 2018; Bi et al. 2008). The need of considering the reconfiguration during the design of a reconfigurable system is discussed in Goldengorin et al. (2013), Hu et al. (2011), Koren and Shpitalni (2010) and in Shabaka and Elmaraghy (2007). The authors of these papers claim that, since the customers' demand changes over time, also the assembly cell layout has to change accordingly. For this reason and since the economical impact of a reconfiguration could be relevant, reconfiguration actions have to be considered during the design phase of the system.

Contributions addressing system design also take into account a multi-period environment (Wesolowski 1973) and (Rosenblatt 1986). In particular, in Rosenblatt (1986), the author addresses the arrangement of physical facilities within a production system by optimizing a cost function on a multi-period time horison. The author also defines the *Dynamic Plant Layout Problem* (*DPLP*) and claims that the major aspect is selecting the best layout for each period, also entailing the decision on the pieces of equipment that should change in the system.

Concerning the cost for reconfiguration, the literature is less prolific and it is addressed as a generic relocation cost (Ahkioon et al. 2009). The reconfiguration approach has to be connected to the type of assembly cell considered during the design phase, as discussed in Nazarian et al. (2010), Boysen et al. (2007) and Battini et al. (2011). In the case under study, it is possible to change the layout of the assembly cell with different actions with a different impact on the cell layout (as discussed in Section 3). The proposed approach selects the type of actions to be operated in order to match the production requirements while minimizing the associated cost and down time of the system.

2.3. *Robustness and risk*

Due to the uncertainty affecting the market, proactive actions have to be implemented during the design and the reconfiguration process. This concept is generally addressed in terms of the robustness of the solution with respect to the variable environmental conditions.

A *scenario tree* is a common approach to formalize the uncertain evolution of the production requirements, like in Montreuil and Laforge (1992) and Cao and Chen (2005). Tavakkoli-Moghaddam et al. (2007) and Süer et al. (2010) address the uncertainty on a multi-period with a variable demand in terms of its expected value and standard deviation.

Urban (1992), Kouvelis and Kiran (1991) and Batta (1987) address this problem by developing a *lower bound* for the function to be optimized. Instead, in Palekar et al. (1992) and in Rosenblatt and Lee (1987) the uncertainty dimension is faced by considering three different levels of demand: an optimistic, a pessimistic and the most likely ones.

The main drawback of these studies is that the uncertainty is always faced by approaches optimizing an expected value, or providing alternative solutions for extreme scenarios. In this way, extreme scenarios are not specifically addressed and mitigated. In a manufacturing context, these extreme situations can be due to requested volumes for a product. In the case the company is not able to address this request, it can incur in penalties or additional costs.

A possible approach to mitigate the impact of these extreme scenarios is exploiting risk-based approaches as discussed in Szegö (2005) for financial applications. This class of methodologies will be developed and applied to the manufacturing context.

3. Problem statement

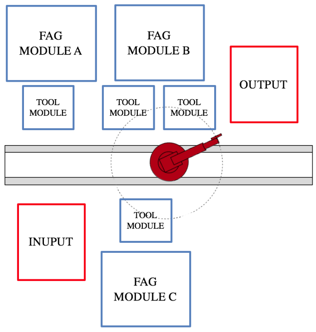
The described problem has been modelled as a multi-stage stochastic configuration problem in which the initial configuration and future reconfiguration plan for a reconfigurable assembly cell have to be decided.

The reconfigurable assembly cells are implemented as a set of modular devices, namely FAG modules, together with an input and an output stations arranged around a 7-axis robot. In front of every FAG module there is a set of tool modules able to host moulds, fixtures or tools needed for the execution of the process.

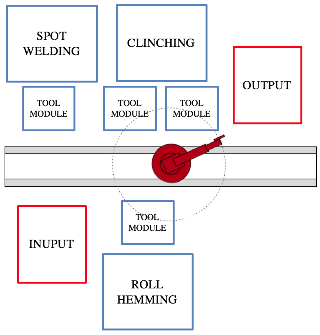
This modular approach allows to fast change the equipment in the cell by modifying the FAGs included and, thus, change the set of assembly processes the cell can operate. In order to successfully exploit this modular technology, different decision levels for the cell layout are considered, the configuration, the *equipment selection and allocation* and the *tool set-up*.

The configuration is defined as the set of pieces of equipment and their arrangement around the 7-axis robot and its track. The configuration in Figure 2a includes three FAG modules, an input and an output station and the 7-axis robot. Each FAG module has one or more associated tool modules. The installation of a new configuration requires the preparation of the basement for each station installed, the installation of the track, the design and the installation of the fences and the gates. For this reason, the moving from a configuration to another, namely a reconfiguration action, is operated on a one- or two-year basis.

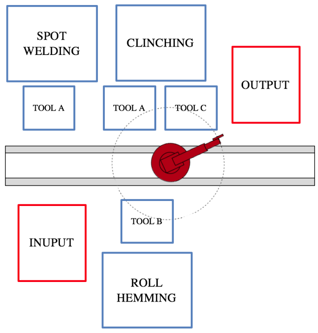
The *equipment selection and allocation* is defined as the set of pieces of equipment



(a) Configuration, a set of equipment and their positions around the *7-axis robot* and its track.



(b) *Equipment selection and allocation*, a set of *FAG* equipment and their allocation in the cell, considering a given configuration.



(c) *Tool set-up*, a set of tools and molds selected and their allocation in the cell, considering a given *equipment selection and allocation*.

Figure 2.: Reconfigurable assembly cell's layout description.

selected and their allocation in the cell, within a given configuration. Indeed, by exploiting the modular devices that have been described, it is possible to select the pieces of equipment associated to a *FAG*, and arrange them in the configuration, as depicted in Figure 2b. An *equipment selection and allocation* represents the collection of *FAG*s included in the cell. Changing from an *equipment selection and allocation* to another means changing the set of modules included in the cell and, thus, the set of assembly processes the cell can operate. Such a change is called *changeover*, that is a very fast and tactical action executed every time the set of products under work changes, typically on a three- or six-month basis.

The *tool set-up* is defined as the selection of the set of tools and fixtures and their positioning in the cell, given the *equipment selection and allocation* decision, as depicted in Figure 2c. Once the *equipment selection and allocation* is decided, it is possible to change the tools or molds needed by a *FAG* included in the layout with a simple *set-up*. Every time a new product has to be processed in the cell, it could be possible that its assembly process needs a *FAG* already included in the *equipment selection and allocation*, and a fixture that is specific for that product. In this case, the cell has to undergo a *set-up* to change the fixture. This action is operated every time the product to be assembled changes, i.e., almost every week.

It is straightforward that several *equipment selection and allocation* solutions can be arranged in the same configuration using different *FAG*s or arranging them differently, and that several *tool set-up* solutions can fit into an *equipment selection and allocation* by simply changing the set of moulds and fixtures. During the design of the cell, these three decision levels have to be addressed as well as the constraints and cost (time and money) for changing them. In addition, it is also needed to consider the alternative *execution modes* that can be implemented for the different *FAG*s.

An *execution mode* is the sequencing of a set of operations to be executed, given a specific arrangement of the pieces of equipment and the associated capability. A given operation can be processed according to different *execution modes* depending on the different characteristics of the equipment. To this aim all the possible *execution modes* have been identified and characterized (see Table 1):

(1) *Part processed inside the FAG module.* The *FAG* is implemented using a dedicated piece of equipment containing a working area. The part is moved into the

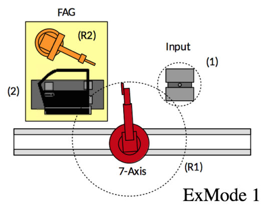
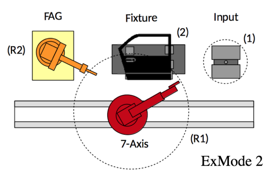
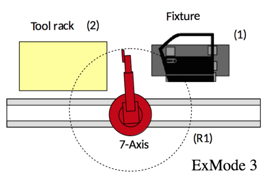
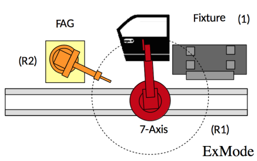
working area by a 7-axis robot with a proper handling tool. Once the part is inside the working area, it is processed.

(2) *Part held in the fixture while the FAG module processes it.* The dedicated piece of equipment takes advantage of an external fixture to work on the part. The 7-axis robot is used to move the part to and from the fixture. The fixture uses to be shared among different *FAG* module.

(3) *Part held in the fixture while the 7-axis robot works on it.* The 7-axis robot operates the process on a part while it is in the fixture. The 7-axis robot has to load a specific end-effector from a tool rack (e.g., glue gun for adhesive joining) to execute the operations.

(4) *Part handled by the 7-axis robot while the dedicated piece of equipment works on it.* In this case, the 7-axis robot handles the part while a dedicated piece of equipment executes the process.

Table 1.: *Execution modes* description: for each one, an example of configuration and task sequencing is given.

 ExMode 1	R1 loads the part from the turn table (1) R1 moves to the *FAG* module R1 releases the part in the fixture (2) R2 joins the sub-assemblies R1 loads the part R1 moves to the turn table (1) R1 releases the part in the fixture
 ExMode 2	R1 loads the part from turn table (1) R1 moves to the fixture (2) R1 releases the part in the fixture R2 joins the sub-assemblies R1 loads the part R1 moves to the turn table (1) R1 releases the part in the turn table
 ExMode 3	R1 loads sub-assemblies on the fixture (1) R1 moves to the machine tool rack (2) R1 loads the needed machine tool R1 moves to the fixture (1) R1 joins the parts R1 moves to the machine tool rack (2) R1 releases the tool and loads the clamp
 ExMode 4	R1 loads the part from fixture (1) R1 moves to the *FAG* module R2 joins the sub-assemblies while R1 holds it R1 moves to the fixture (1) R1 releases the part in fixture (1)

The specific *execution mode* implemented for each *FAG* determines the processing time of the operations and, consequently, has an impact on the performance of the whole cell.

In *execution modes* number 1 and 2, each *FAG* takes care of the execution of a specific assembly operation, while in *execution modes* number 3 and 4, the 7-axis robot is also involved. Due to this, the first two *execution modes* entail a higher cost in terms of equipment but guarantee better performance (i.e., shorter processing times). On the other side, the third and the fourth *execution modes* entail lower equipment cost but possibly worst performance, since the 7-axis robot must be used for both the execution of the process and the handling operations.

Formally, a configuration is defined as $z = (E, -, -, -) \in Z$, where E defines the number and position of the pieces of equipment in the layout (e.g., *FAG* modules, input station). Using this configuration, *equipment selection and allocation* decisions select the pieces of equipment J to be included in the cell and their *execution modes* V. The result of these two decision steps is modeled as $z = (E, J, V, -) \in Z$. Grounding on this, a *tool set-up* is identified by selecting the set of tools F, e.g., fixtures, to be arranged in the cell. The final configuration, including the *tool set-up*, is modeled as $z = (E, J, V, F) \in Z$.

The described reconfigurable assembly cell works in an environment where the production requirements are uncertain, indeed, the demand for *spare parts* cannot be completely forecast as in *series production*, although some information in terms of volumes and mix of products are provided by the *OEM*s. Typically, the demand for *spare parts* starts when the car model goes out of the production phase and undergoes a reduction of about 15% every year. *OEM*s update the forecast on the expected mix and volumes for the upcoming year on a 3-month basis, together with a range bounded by an optimistic and a pessimistic value. Grounding on this information, the supplier can aggregate the demand coming from all its customers and determine (i) the exact production volume for the upcoming 3 months, (ii) the expectation for the upcoming year and (iii) different optimistic and pessimistic scenarios for the considered 1-year time horizon. Hence, it is possible to define a set of possible evolutions of the mix of products and the associated volumes, namely *scenarios*, with an associated occurrence probability.

This is modeled through a *scenario tree* composed by a set of nodes and arcs, like the one in Figure 3. Each node of the tree, namely a *scenario node*, is characterized by specific requirements in terms of volume and product mix. A root *scenario node* represents the current requirements. The *scenario tree* defines a set of *scenarios* $\omega \in \Omega$

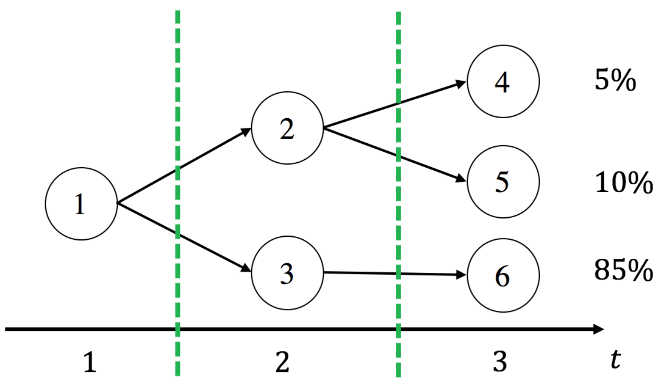


Figure 3.: Example of *scenario tree* containing three *scenarios* and six *scenario nodes* through three time periods.

composed by a sequence of *scenario nodes* $\omega(t)$, with $t \in [1, \ldots, T]$, one for each time period considered within the time horizon T. Each *scenario node* is characterized by a set of products to be processed $D^{\omega(t)} \subseteq P$ and the associated volume in terms of a batch dimension $B^{\omega(t)}$. Each *scenario* has an associated occurrence probability π_ω.

The sequence of *configurations* associated to each time period is represented as $x = \{z_1, z_2, \ldots, z_T\} \in X$. For each sequence of *configurations*, a cost function $ct_\omega(x)$, $\forall \omega \in \Omega$ and its distribution $CT(x)$ are considered. A risk-based function Φ exploiting the concept of $CVaR$ (Szegö 2005) is calculated by identifying the *scenarios* whose cost function assumes values in the rightmost tail of the distribution of the cost function $CT(x)$, specifically those values greater than the *Value at Risk*, and then calculating their expected value.

The whole approach grounds on a formal description of the problem reported in Table 2.

4. Solution framework

The described problem is solved through a sequential approach that (i) generates the set of candidate cell layouts Z over a given time horizon, (ii) evaluates the associated performance and (iii) select the optimal configuration sequence $x^* \in X$ to minimize a risk-based objective function Φ. The approach is organized in three steps (see Figure 4). These steps are briefly described in the following list.

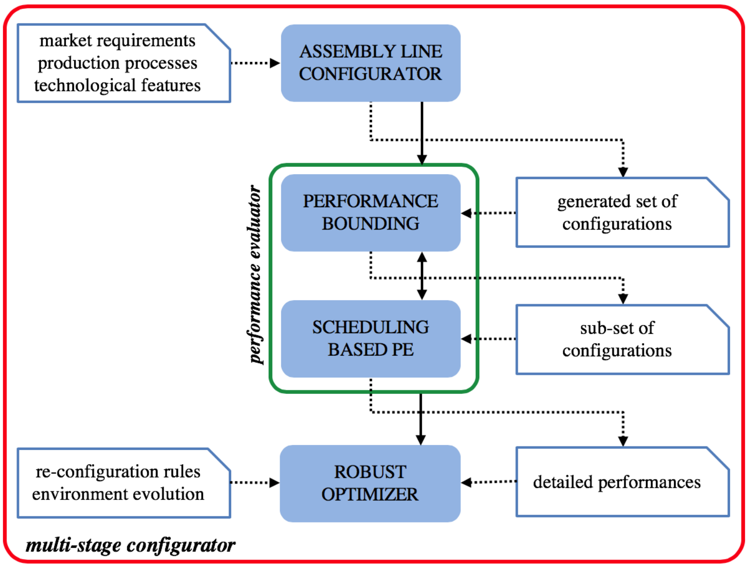


Figure 4.: Solution framework.

(1) The *assembly cell configurator* considers the requirements associated to a scenario node $\omega(t)$ in terms of assembly processes, technologies and related equipment, and generates a set of candidate layout solutions.
(2) The *performance evaluator* estimates the performances of a candidate solution through two approaches:
   - the *performance bounding* step uses an analytical approach for a fast estimation of the boundary performances of each candidate solution for slimming down the candidate list;
   - the *scheduling-based performance evaluator* estimates the exact performances of the candidate layouts using a scheduling-based approach.

Table 2.: Notation for data and variables.

	Sets
T	set of time periods
P	set of products
Ω	set of *scenarios*
Z	set of cell *configurations*
X	set of configuration evolutions
K	set of *execution modes*
$D^{\omega(t)}$	demand set in the *scenario node* $\omega(t)$
$B^{\omega(t)}$	batch set in the *scenario node* $\omega(t)$
A	set of assembly processes
	Variables
E	number and position of the set of equipment in a configuration
J	set of *FAG*s included in *equipment selection and allocation*
V	set of *execution modes* chosen for each *FAG*
F	set of machine tools chosen in *tool set-up*
x^*	optimal configuration sequence
	Parameters
π_ω	occurrence probability of *scenario* ω
$\omega(t)$	*scenario node* of *scenario* ω at time period t
$ct_\omega(x)$	cost function for configuration sequence x in scenario ω
$CT(x)$	distribution function of the cost of configuration sequence x
$C^{inv}(z_t)$	investment cost for configuration z_t
$C^{op}(z_t, D^{\omega(t)}, B^{\omega(t)})$	operational cost for configuration z_t
$C^{h,equip}(z_t \mid z_{t-1})$	equipment storage cost for configuration z_t
$C^{h,tool}(z_t \mid z_{t-1})$	tool storage cost for configuration z_t
$C^{rec}(z_t \mid z_{t-1})$	reconfiguration cost for configuration z_t
$C^{h,equip}$	unitary storage cost for the equipment
$C^{h,tool}$	tool storage cost
$C^{purch}(e)$	purchasing cost for each element $e \in E$
$C^{purch}(j, v)$	purchasing cost of piece of equipment j with *execution mode* v
$C^{tool}(f, v)$	purchasing cost of tool f with *execution mode* v
$Time_{comp}(z_t, p)$	expected completion time for configuration z_t processing product p
$d_p^{\omega(t)}$	demanded volume of product p in *scenario node* $\omega(t)$
$b_p^{\omega(t)}$	batch size of product p in *scenario node* $\omega(t)$
C^{hour}	hourly operational cost
$T_{changeover}$	overall *changeover* time
T_{set-up}	overall *set-up* time
c^{rec}	unitary reconfiguration cost
$\mathbb{1}^{rec}(z_t, z_{t-1})$	indication of equality between z_t and z_{t-1}
$c_u^{h,equip}$	space occupation cost for a piece of equipment
$u_{j,t}^{equip}$	indication of use of equipment j at time t
$c_u^{h,tool}$	space occupation cost for a tool
$u_{f,t}^{tool}$	indication of use of tool f at time t
k	discount rate
Φ	risk-based function
α	confidence level for the risk-based function

(3) The *robust optimizer* identifies the sequence of *configurations* to optimize the risk-based objective function considering the total cost (CT) of the cell over the considered time horizon.

In the representation in Figure 4, the flow of information is represented with dotted arrows, while the execution sequence for the steps is represented with solid arrows.

When the number of alternative pieces of equipment to be arranged in the cell is large, many candidate configurations could be available and the computational effort for the performance evaluation phase could be considerable. In addition, the need to cope with uncertain duration of the manual executed operations contribute to increase the complexity of the performance evaluation, precluding the possibility of addressing large problems. To this aim, two performance evaluation approaches are used. A first one able to fast process the set Z with an approximate evaluation of the performance (e.g., through a bounding approach) allowing to slim down the set of candidate solution identifying a promising subset. This subset only is further analysed using a second, more detailed performance evaluator, able to take the impact of scheduling rules into consideration. Finally, the cost of the selected solutions is estimated taking into account the occurrence probability of each scenario $\omega \in \Omega$ and, hence, the optimal cell configuration sequence x^* identified with the aim at minimizing a risk-based function of the associated cost.

4.1. *Assembly cell configurator*

The *assembly cell configurator* generates a set of candidate *configurations* matching the production requirements.

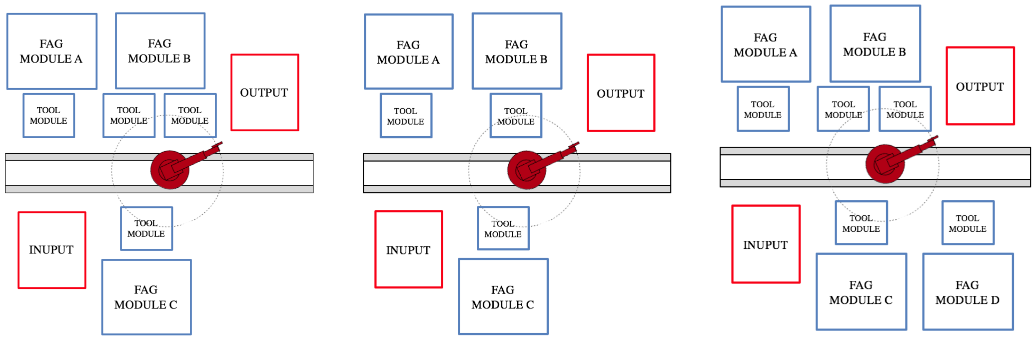
It considers a single scenario node $\omega(t)$ and identifies the technological requirements needed for processing the products in the set $D^{\omega(t)}$. Each product $p \in D^{\omega(t)}$ is characterized by an assembly process $a_p \in A$ and a set of requirement in terms of *FAG*s and tools from the sets J and F, respectively. In addition, a 7-axis robot as well as an input and an output stations and a control unit are included.

Grounding on the selected pieces of equipment, the *assembly cell configurator* also considers the alternative possible *execution modes* in the set K for each *FAG*, and the three different levels (see Section 3): configuration, *equipment selection and allocation* and *tool set-up*. The set of *configurations* is defined by arranging a set of *FAG* modules and associated tool modules together with the input and output stations and the control unit on both sides of the 7-axis robot. In this way, the length of the 7-axis robot track is defined together with the position of the *FAG* and tool modules in E.

Starting from a single configuration $z = (E, -, -, -) \in Z$, different alternative *equipment selection and allocation*s are generated by selecting the set of *FAG*s J and the associated *execution modes* V, i.e., $z = (E, J, V, -)$. Then, for each *equipment selection and allocation* alternative, different *tool set-up* solutions are also generated by selecting the set of tools F (e.g., moulds, fixtures, machine tools) to be arranged in the available tool modules, i.e., $z = (E, J, V, F)$.

An example of different alternative *configurations* is shown in Figure 5. In the first two examples, Figures 5a and 5b, three *FAG* modules are included in the assembly cell with the only difference that the *FAG module B* is equipped with one or two tool modules, respectively. The two configurations differ in terms of the number of fixtures that can be hosted in the *FAG module B* and, thus, in terms of the set of assembly operations it can handle and the associated size of the cell . The third example (Figure 5c) shows a different configuration for the cell with an additional *FAG* module.

Two examples of different *equipment selection and allocation* solutions are reported in Figure 6, both starting from the configuration in Figure 5a. The first solution (Figure 6a) considers the spot welding, clinching and roll hemming *FAG*s, while the second one (Figure 6b) substitutes the spot welding with the adhesive joining, and the roll hemming with the nut pressing. By changing the modules in a configuration it is possible to radically change the technological capability of the cell and, consequently, the set of assembly processes that can be handled. Due to the modular architecture, the change between alternative *equipment selection and allocation* solutions (*changeover*) is easy and can be done in a rather fast way.

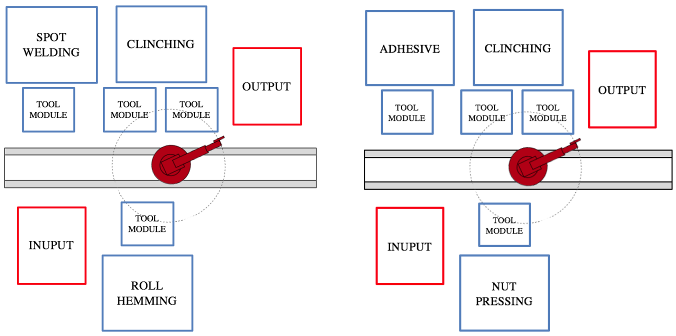


(a) configuration example with three *FAG* modules and four tool modules.

(b) configuration example with three *FAG* modules and three tool modules.

(c) configuration example with four *FAG* modules and five tool modules.

Figure 5.: Three different examples of configuration: by changing the number of *FAG* modules and associated tool modules, the size of the cell changes accordingly.



(a) *Equipment selection and allocation* example with spot welding, clinching and roll hemming *FAG*s.

(b) *Equipment selection and allocation* example with adhesive, clinching and nut pressing *FAG*s.

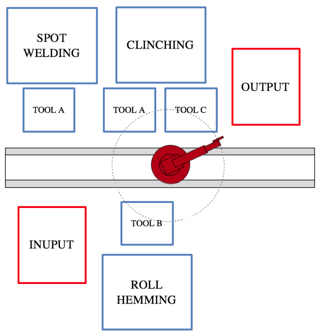
Figure 6.: Two different examples of *equipment selection and allocation* on the same configuration: by changing the set of *FAG*s allocated, the set of assembly processes handled changes accordingly.

Finally, two examples of *tool set-up* solutions are shown in Figure 7, both grounding on the *equipment selection and allocation* solution in Figure 6a. In particular, the two *tool set-up* solutions differ in terms of the tool included in the spot welding tool module and in the roll hemming one. By simply changing the fixture contained in a tool module it is possible to enable the cell to process a different product using the same class of processes.

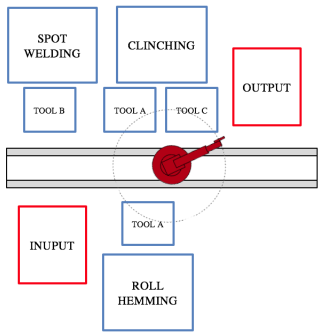
The described approach generates a set Z of candidate solutions in terms of *configurations*, *equipment selection and allocation* and *tool set-up*, also covering different *execution modes* for the same *FAG*.

4.2. *Performance evaluator*

As previously declared, the robot in the assembly cell is devoted to handle and transport the parts and, in some *execution modes*, it also takes part to assembly operations.



(a) *Tool set-up* example on an *equipment selection and allocation* solution with spot welding, clinching and roll hemming *FAGs*.



(b) *Tool set-up* example on an *equipment selection and allocation* solution with spot welding, clinching and roll hemming *FAGs*.

Figure 7.: Two different examples of *tool set-up* on the same *equipment selection and allocation*: by changing the set of tools and fixture arranged, the set of products to be assembled changes accordingly.

Hence, the robot is a shared resource whose control policy has a significant impact on the performance of the cell. Some of the operations (typically loading and unloading) are executed by human workers. Thus, the uncertainty associated to the execution of these operations has to be considered. The assembly process is modeled as a *flow-shop* with the possibility for some of the resources to be shared and the operations can have a random processing time.

Every time a different product has to be assembled, a *changeover* or a *set-up* is needed, thus, the assembly cell processes a sequence of batches of a single product type at time. Assuming the dimension of the batches as given, the evaluation of the performance of the cell can be done for the different batches independently by modelling the system as a *single product flow-shop* where scheduling decisions do not address the sequence of parts entering the system but only the resolution of conflicts for the shared resource(s).

This scheduling problem can be formalized as a *Stochastic Resource-Constrained Project Scheduling Problem* (*Stochastic RCPSP*) whose main aim is to cope with the uncertainty and optimize the utilization of the equipment, i.e., minimizing the makespan to produce the entire batch. In a context where the use of human operators is considered, the expected makespan (e.g., (Möhring et al. 2000) and (Radermacher 1985)) could not be the best choice in terms of target performance, because it does not protect against rare but very extreme scenarios (see (Tolio et al. 2011) and (Urgo et al. 2018) for a generic production plan, (Urgo and Váncza 2014) for the single scheduling problem and (Alfieri et al. 2012) and (Manzini and Urgo 2015) with regards to *Make-to-Order* processes). To overcome these limitations, a *proactive-reactive* scheme (*PR*) grounding on the approach presented in Manzini et al. (2018a) has been consider. It consists of two steps: first an initial schedule is identified taking uncertainty into consideration to limited extent while, during the second step, the schedule can be modified in case the actual durations of the operations deviates from those considered in the first stage. This *PR* approach is used for both the performance evaluation steps.

4.2.1. Bounding approach

The first performance evaluation (see Figure 4) aims at estimating an upper and a lower bound of the performance, i.e., the makespan of a candidate configuration $z \in Z$ by exploiting the *proactive* step of the approach presented in Manzini et al. (2018a).

In particular, it hypothesizes the duration of all the operations as the maximum possible value according to their stochastic distribution. As a consequence, the makespan obtained is an *upper bound* of the actual one. To obtain a lower bound, the last stage of the flow-shop is considered, i.e., the output station only and the duration of all the operations set to their minimum value. As a consequence, the value of the makespan obtained is a *lower bound* of the actual one.

The estimation of the performance obtained through this approach is exploited for slimming down the candidate set Z. Specifically, assuming two *configurations* $z_1 = (E_1, -, -, -)$ and $z_2 = (E_2, -, -, -)$, with $z_1, z_2 \in Z$ and the performance of the first configuration is better than the second one, considering all the feasible *equipment selection and allocation* solutions as well as *tool set-ups*, then configuration z_2 can be discarded because it is dominated by other solutions in the set Z. More formally:

$$MS_{UB}((E_1, -, -, -), p) \leq MS_{UB}((E_2, -, -, -), p) \tag{1}$$

$$MS_{LB}((E_1, -, -, -), p) \leq MS_{LB}((E_2, -, -, -), p) \tag{2}$$

$$\forall p,\ \forall J, F, V \in (E_1, -, -, -),\ \forall J, F, V \in (E_2, -, -, -) \tag{3}$$

where $MS_{LB}((E_i, -, -, -), p)$ and $MS_{UB}((E_i, -, -, -), p)$ are the *lower bound* and the *upper bound* of the makespan associated to the configuration $z_i = (E_i, -, -, -)$ processing product p. It means that, if z_1 dominates z_2 in terms of both the *upper bound* (Equation (1)) and *lower bound* (Equation (2)) in all the considered cases (Equation (3)), then z_2 can be discarded.

The remaining *configurations* $z \in Z$ will undergo the second performance evaluation step.

4.2.2. Scheduling-based performance evaluation

The second performance evaluation step (see Figure 4) grounds on the complete *proactive-reactive* scheme (Manzini et al. 2018a) to estimate the detailed performance of a candidate solution $z = (E, J, V, F)$ also considering the impact of the scheduling of the 7-axis robot missions.

The *proactive* step is executed considering the expected durations of the operations to identify a *baseline* schedule. The second step of the *PR* approach simulates the application of the *reactive* step during the execution of the assembly process, in order to modify the *baseline* schedule considering the deviations respect to the expected durations. The application of the *reactive* step is aimed to obtain a better estimation of the performance rather than providing an optimal schedule. To this aim, the *reactive* step is applied considering different samples for the stochastic processing times. Grounding on these experiments, the estimation of the makespan of each configuration $z \in Z$ is done by considering the average batch completion time (Equation (4)).

$$\mathbb{E}[Time_{comp}(z,p)] = \sum_{n \in N} \frac{Time_{comp}(z,p,n)}{N}, \forall z \in Z, \forall p \in P \tag{4}$$

Where $Time_{comp}(z,p,n)$ is the completion time obtained with the *scheduling-based performance evaluator* on configuration $z \in Z$ processing product $p \in P$ and considering sampling $n \in N$.

4.3. *Robust optimizer*

The last step of the approach, the *robust optimizer*, exploits the results of the previous steps in order to identify a final solution in terms of the initial configuration plus the reconfiguration plan of the cell in a given time horizon partitioned in periods.

First of all, a set of possible initial configuration and reconfiguration plans are generated by selecting the *configurations* from the set Z. Each sequence $x \in X$ is mapped against the time periods $t \in T$, i.e., $x = \{z_1, \ldots, z_t, \ldots, z_T\}$. Notice that each configuration can support alternative *equipment selection and allocation* as well as *tool set-up* solutions. Thus, a sequence x includes a wide range of cell's layouts that can be actually implemented throughout the time horizon.

The aim of the *robust optimizer* is to identify the configuration sequence x^* that minimizes a function of the risk associated to the cost related to the selected solution. The choice to adopt a measure of the risk is driven by the need of consider the impact of extreme unfavourable situations (e.g., not being able to fulfil an order) whose occurrence probability is low. To cover these cases, a *scenario tree* modelling the evolution of the production requirements (see Figure 3) has been considered. Each node in the tree is characterized by a set of requirements (products and volumes) and is linked to a specific set of time periods. The *scenario tree* defines a set of scenarios Ω , i.e., all the paths from the root to the leaves, whose occurrence probability is π_ω, $\forall \omega \in \Omega$, with $\sum_{\omega \in \Omega} \pi_\omega = 1$.

A solution to the described problem is a set of *configuration* sequences x, one for each scenario in the *scenario tree*. A cost function $ct_\omega(x)$, $\forall x \in X$, $\forall \omega \in \Omega$ is used to calculate the total cost of a solution x in a particular scenario ω.

The first part of the cost function $ct_\omega(x)$ (Equation (5)) considers an investment cost $C^{inv}(z_t)$ (Equation (6)) representing the acquisition cost of FAG modules, tool modules, 7-axis robot and the other equipment needed by z_t ($C^{purch}(e)$), the FAGs' equipment ($C^{purch}(j,v)$), and their tools ($C^{tool}(f,v)$). An operational cost $C^{op}(z_t, D^{\omega(t)}, B^{\omega(t)})$ (Equation (8)) is also considered, as the cost associated to the operation time of the cell, i.e., the time to assemble the required batches of products ($Time_{comp}(z_t,p) \cdot \lceil d_p^{\omega(t)} / b_p^{\omega(t)} \rceil$), the *changeover* ($T_{changeover}$) and the *set-up* ($T_{set-up}$).

A reconfiguration cost $C^{rec}(z_t)$ (Equation (9)) is added, it is the fixed cost for passing from a configuration z_{t-1} to z_t. Its value is different from zero only if they are different, i.e., if $\mathbb{1}^{rec}(z_t, z_{t-1}) \neq 1$ (Equation (10)). This cost considers the effort needed for installing new FAG modules or moving pieces of equipment in general. Finally, also a storage cost $C^h(z_t)$ is included in relation to both the FAGs (Equation (11)) and the tools (Equation (12)) that are available but not in use. In both the cases, the storage cost is modeled in terms of a space occupation cost ($c_u^{h,equip}$ and $c_u^{h,tool}$) for the equipment not in use at time t, i.e., if $u_{j,t}^{equip} = 1$ and if $u_{f,t}^{tool} = 1$. A discount rate k is used for the whole cost function.

$$ct_\omega(x) = \sum_{t \in T} \frac{C^{inv}(z_t) + \mathbb{E}[C^{op}(z_t, D^{\omega(t)}, B^{\omega(t)})]}{(1+k)^t} + \\ + \frac{C^{h,equip}(z_t \mid z_{t-1}) + C^{h,tool}(z_t \mid z_{t-1}) + C^{rec}(z_t \mid z_{t-1})}{(1+k)^t} \tag{5}$$

where

$$C^{inv}(z_t) = \sum_{e \in E} C^{purch}(e) + \sum_{j \in J} C^{purch}(j, v) + \sum_{f \in F} C^{tool}(f, v) \tag{6}$$

$$C^{op}(z_t, D^{\omega(t)}, B^{\omega(t)}) = \left[\left(\sum_{p \in P} \mathbb{E}[Time_{comp}(z,p)] \cdot \lceil d_p^{\omega(t)} / b_p^{\omega(t)} \rceil \right) \right] \cdot C^{hour} + \tag{7}$$

$$+ [T_{changeover} + T_{set-up}] \cdot C^{hour} \tag{8}$$

$$C^{rec}(z_t \mid z_{t-1}) = c^{rec} \cdot \mathbb{1}^{rec}(z_t, z_{t-1}) \tag{9}$$

$$\mathbb{1}^{rec}(z_t, z_{t-1}) = \begin{cases} 1 & \text{if } z_t = z_{t-1} \\ 0 & \text{if } z_t \neq z_{t-1} \end{cases} \tag{10}$$

$$C^{h,equip}(z_t \mid z_{t-1}) = \sum_{t \in T} \sum_{j \in J} c_u^{h,equip} \cdot u_{j,t}^{equip} \tag{11}$$

$$C^{h,tool}(z_t \mid z_{t-1}) = \sum_{t \in T} \sum_{f \in F} c_u^{h,tool} \cdot u_{f,t}^{tool} \tag{12}$$

The complete list of sets, variables and parameters is reported in Table 2 in Section 3.

Grounding on $ct_\omega(x)$, the *robust optimizer* looks for the best configuration and reconfiguration sequences associated to each scenario. In order to pursue the robustness of the proposed solution, the distribution of the cost function $CT(X)$, $\forall x \in X$ is estimated considering the occurrence probability of the scenarios. A risk-based function Φ is used as robustness indicator, hence, selecting the solution with the minimum possible value of the risk-based function is intended as selecting the most robust solution as well. The *Conditional Value at Risk* ($CVaR$) is the risk-based function used. Assuming the probability distribution function associated with a solution $CT(x)$, $\forall x \in X$ as in Figure 8, the $\Phi = CVaR_\alpha$ of $CT(x)$ is the expected value of the costs exceeding the *Value at Risk* (VaR_α), i.e., the cost exceeding the quantile $1 - \alpha$ with $\alpha \in (0, 1)$. In other words, VaR_α identifies the right $\alpha-$tail of the distribution of the cost and the $CVaR_\alpha$ is the expected value of this tail, as depicted in Figure 8.

5. Industrial case

The proposed methodology has been tested on an industrial case taken from a *tier-1* automotive supplier specialized in the production of parts of the car bodywork, e.g.,

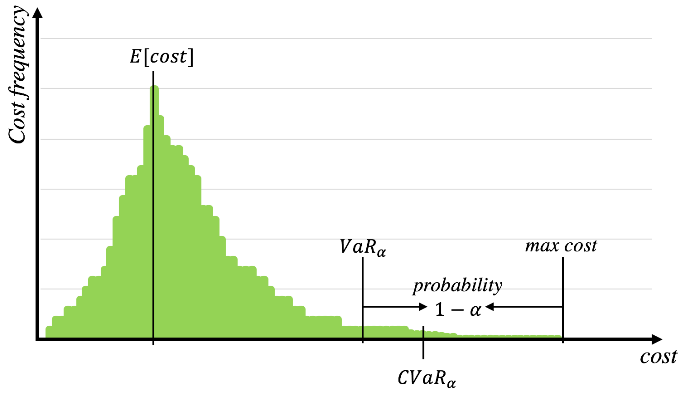


Figure 8.: Cost function with the indication of the VaR_α and the $CVaR_\alpha$ quantile.

hoods, tailgates, fenders, with a special focus on *spare parts*. The partner company is specialized in the *spare parts* production of a wide range of products for different OEMs with different materials and production technologies. Specifically, the company has increased its portfolio of spare parts offering from 48 different car models and 500 product types in 2013 to 60 models and more than 600 product types in 2017, with an increase of the total number of parts produced from $250,000$ to more than $450,000$ during the same years. Also the materials used for the production of these components is rapidly switching from steel to aluminium (European Aluminium 2016).

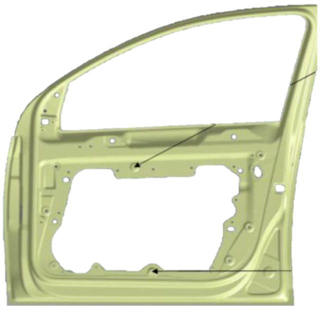
For these reasons, the company is willing to move towards multiple reconfigurable assembly cells able to completely process a set of multiple products, in order to reduce the movement of parts within the plant and, at the same time, support the management of a wide range of products with low volumes. The design concept stemming from this is described in the following subsection.

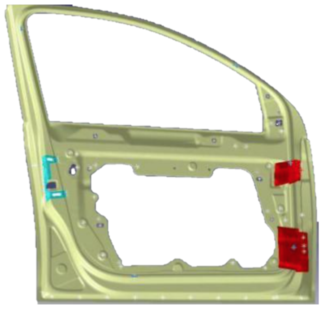
5.1. *Description of the industrial context*

A set of five car doors has been considered, for which a reconfigurable assembly cell has to be designed. The related assembly operations are shown in Figure 9. First, the door bodywork is assembled through nut pressing operations (Figure 9a), the process continues with the addition of components through adhesive joining operations (Figure 9b). The assembling of the hinges and a reinforcement bar is done through spot welding operations (Figures 9c and 9d) while the final joining of the inner part of the door (Figure 9e) with the outer part (Figure 9f) is operated through roll hemming.

Since these products come from different OEMs, each of them does not necessarily require all of these assembly steps, as described in Table 10, in Appendix. For example, the product A does not require the initial nut pressing but only products C, D and E need the reinforcement bar. This assembly step can be operated by the same spot welding equipment using a second fixture (e.g., T3 for product C and T4 for product D). This means that the cell needs, at least, a FAG module associated to spot welding including two tool modules, in order to process the product C.

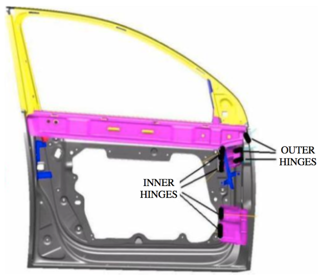
For each operation and for each product, the needed tools, e.g., the fixture, are reported in Table 10 together with the average processing times. The first three products (A, B and C) do not need any hemming operation because the company decided to complete their assembly in another cell. On the contrary, the products D and E also need a final hemming operation. In particular, product E needs two process steps

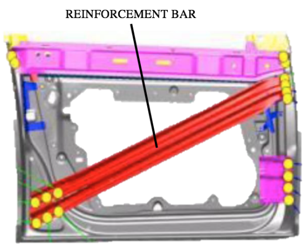




(a) The assembly of the bodywork through a nut pressing operation.

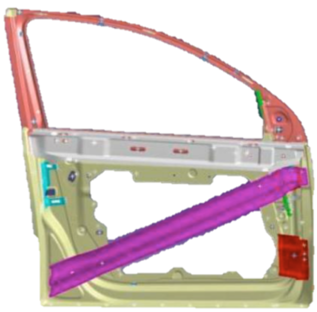
(b) The assembly of closing elements through adhesive operations.





(c) The assembly of hinges through spot welding operations.

(d) The assembly of reinforcement bar through spot welding operations.



(e) The resulting inner part of the door.

(f) The outer and inner parts of the door are joined through a roll hemming operation.

Figure 9.: The assembly process for a door of a car (courtesy of *Voestalpine Polynorm BV*).

using different fixtures for handling the door in different positions.

For each *FAG* listed in Table 10, the requirements for *execution modes* number 1 and 3 are reported. *Execution modes* number 2 and 4 are not considered because not feasible with the considered technologies. For the same reason, the spot welding and roll hemming operations are always executed according to the *execution mode* number 1 only.

Operations processed with *execution mode* number 3 have a longer processing time, on average, due to the need of the 7-axis robot, with a lower investment cost for the *FAG*s' equipment and tools (see Table 11). Additional data are included in Table 12 in Appendix.

These five products are the target product mix for a use-cases ($P = 5$) over a time horizon of 18 months divided in six time periods ($T = 6$), whose *scenario tree* is depicted in Figure 10. It models the evolution of the production requirements through a set Ω of 22 *scenario nodes*, organized in 6 *scenarios* as follows:

(1) *scenario* S1, $\omega_1 \to \omega_2 \to \omega_4 \to \omega_7 \to \omega_{11} \to \omega_{17}$ with an occurrence probability $\pi_1 = 0.5$;
(2) *scenario* S2, $\omega_1 \to \omega_2 \to \omega_5 \to \omega_8 \to \omega_{12} \to \omega_{18}$ with an occurrence probability $\pi_2 = 0.2$;
(3) *scenario* S3, $\omega_1 \to \omega_2 \to \omega_5 \to \omega_8 \to \omega_{13} \to \omega_{19}$ with an occurrence probability $\pi_3 = 0.1$;
(4) *scenario* S4, $\omega_1 \to \omega_3 \to \omega_6 \to \omega_9 \to \omega_{14} \to \omega_{20}$ with an occurrence probability $\pi_4 = 0.1$;
(5) *scenario* S5, $\omega_1 \to \omega_3 \to \omega_6 \to \omega_9 \to \omega_{15} \to \omega_{21}$ with an occurrence probability $\pi_5 = 0.05$;
(6) *scenario* S6, $\omega_1 \to \omega_3 \to \omega_6 \to \omega_{10} \to \omega_{16} \to \omega_{22}$ with an occurrence probability $\pi_6 = 0.05$.

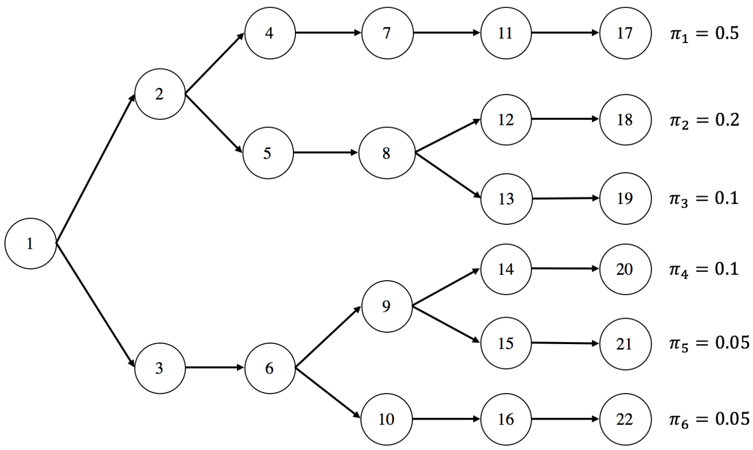


Figure 10.: *Scenario evolution tree* for the industrial case.

The requirements for each *scenario node* in terms of product mix, volumes and batch sizes are reported in Table 9, in Appendix.

In the *scenario* S1, only the products A, B and C have to be produced; this *scenario* is also the most probable one, with an occurrence probability of 50%. *Scenario* S2 and S3 consider the need to produce product D from the fifth time period on (*scenario nodes* 12 and 13), with occurrence probabilities 20% and 10% respectively. In the *scenario* S4, the product D has to be produced in advance, starting from the fourth time period (*scenario node* 9) with an occurrence probability of 10%. The *scenario* S5 introduces the request for product E during the last time period (*scenario node* 21) with a lower occurrence probability, equal to 5%. The *scenario* S6 presents the more demanding situation, in which all the five products are requested from the fourth time period on (*scenario node* 10) with a low occurrence probability, equal to 5%.

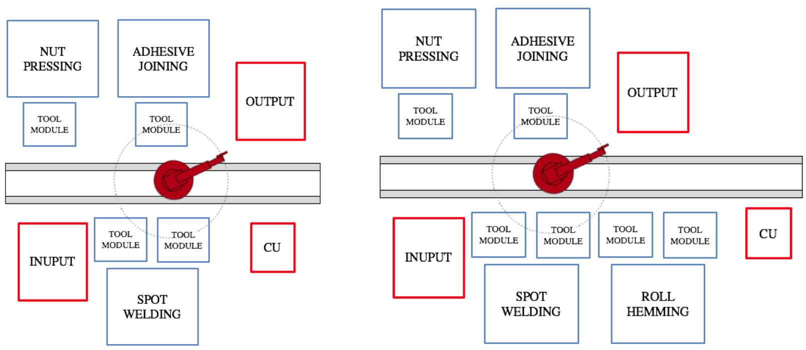
As already described, products D and E need, at least, four *FAG* modules and six tool modules. The aim of the approach is to devise a configuration of the cell, together with proper alternative reconfiguration plans, able to cope with all the possible evolution of the requirements, including the last two *scenarios*.

5.2. *Testing*

Considering the described industrial case, the *assembly cell configurator* generates a set Z consisting of 4 *configurations*, with 483 *equipment selection and allocation* solutions and $129,774$ *tool set-up* solutions to be evaluated. The set Z is then evaluated using the first-level *performance evaluator* that is able to discard $129,228$ *tool set-up* solutions, corresponding to about 99% of the total solution space. The 546 residual candidates are then evaluated through the second-level *performance evaluator*.

A *uniform* distribution is used for the processing times, whose expected values are reported in Table 10 while the upper and lower limits are obtained through a deviation of 10%. A total of 1.000 simulation runs have been carried out. Finally, the set of configuration sequences is generated and evaluated using the *robust optimizer*. This last step identifies the configuration sequence x^* that optimize the $CVaR_\alpha$ on the cost function $CT(x)$ with $\alpha = 0.9$.

200 feasible configuration sequences have been obtained, with the optimal one chosen by the *robust optimizer* has a *CVaR* cost of $611,595$ €. The selected configuration sequence $x^* = \{z_1, z_2, z_3, z_4, z_5, z_6\}$ suggests the use of an initial configuration in the first half of the time horizon (first three time periods) and a second one in the second half (second three time periods). The two *configurations* are depicted in Figure 11.



(a) configuration used in the first three time periods.

(b) configuration used in the fourth, fifth and sixth time periods.

Figure 11.: Optimal configuration evolution for the industrial case.

The initial configuration is the one in Figure 11a, whose details are reported in Table 3. This configuration includes two *FAG* modules with a single tool module and a third *FAG* module with two tool modules. Hence, it is possible to arrange the pieces of equipment requested for processing product A, B and C, i.e., the nut pressing and adhesive joining (with one tool module) and the spot welding (with two tool modules). This solution considers the implementation of nut pressing and spot welding with *execution mode* number 1 and adhesive joining with *execution mode* number 3. In addition, this solution considers the acquisition of the set of tools required for processing product A, B and C, namely T1 and T2 for the nut pressing, T1 and T2 for the adhesive joining, T1 and T3 for the spot welding. This configuration entails the following batch completion times: 5.97 hours for product A, 6.53 hours for product B and 9.52 hours for product C.

At the beginning of the fourth time period, the *Robust approach* suggests to *reconfigure* the cell with the addition of a *FAG* module with two tool modules aimed to host the roll hemming (Figure 11b). Some details about it are included in Table 3. In addition to the previous one, this configuration needs the acquisition of a series of tools: T3 for the nut pressing, T4 and T5 for the spot welding, and T1, T2, T3 for the roll hemming. The reconfiguration action costs $158,000$ € due to the fixed reconfiguration cost ($20,000$ €), the acquisition of roll hemming equipment ($75,000$ €) and associated tool modules ($18,000$ €), and the new tools ($45,000$ €). This configuration entails the following batch completion times: 6.06 hours for product A, 6.88 hours for product B, 10.07 hours for product C, 11.68 hours for product D and 9.95 hours for product E.

This strategy proposes to acquire all the pieces of equipment needed for *scenario* S1, at the beginning of the first time period. This behavior allows to have no *reconfigurations* of the cell in case of the occurrence of *scenario* S1. Then, during the fourth time period, i.e. when the request for product D or E could occurs (*scenarios* S4, S5 and S6), the cell is *reconfigured* by adding the pieces of equipment needed for processing these products. In this way, the devised configuration is also able to cope with the occurrence of the last two *scenarios* entailing the production of product E, but also with the occurrence of *scenarios* S2, S3 and S4 requiring the processing of product D in the last time periods.

The solution identified by the *Robust approach* is driven by the value α to be used in the optimization of the $CVaR_\alpha$. By using $\alpha = 0.8$, the configuration and reconfiguration plan is the same as the one for $\alpha = 0.9$ (Figure 11), but both adhesive joining and nut pressing are implemented with *execution mode* number 3. The resulting *CVaR* cost is $552,409$ €. Instead, using $\alpha = 0.7$ a solution that does not consider any reconfiguration action during the whole time horizon has been identified. It implements the configuration in Figure 11b from the first time period. Also this solution implements both adhesive joining and nut pressing with *execution mode* number 3 and guarantees a *CVaR* cost of $543,362$ €.

It is possible to see that, by using smaller values of α, a solution with a smaller *CVaR* cost is identified. This solution is able to minimize the risk associated to the cost function over a wider tail of the distribution but, on the other side, it considers higher investment cost for the installation of the cell for pieces of equipment that could be needed 5 time periods later or also never.

In order to evaluate the approach, two classes of analysis have been provided: the *single scenario optimum approach* and the *initial node optimum approach*. The first alternative approach takes into consideration a single *scenario* and implements the best configuration for each time period, i.e., the configuration that guarantees the minimum operational cost in each time period. The second one considers the best solution for the first time period only, without the possibility to reconfigure the cell.

Hypothesize to apply the solution of the *Robust approach* on a specific *scenario* and evaluate the associated expected cost. This cost is then compared with the ones associated to the two alternative approaches applied on the same *scenario*. The analysis for *scenarios* S5 and S6 are included in Tables 4 and 5. It considers investment, operational, storage and reconfiguration costs, over the whole time horizon, where t_τ stays for the time period $\tau - 1$.

Table 3.: Description of the first and the second *configurations* for the industrial case.

First configuration			
Number of *FAG* modules	3	Investment cost	456,040 €
Number of tool modules	4	Operational cost	15,320 €
Number of input stations	1	Storage cost	-
Number of output stations	1		

FAG type	*Execution mode*	tool modules	Tool type
Nut pressing	1	1	T1, T2
Adhesive joining	3	1	T1, T2
Spot welding	1	2	T1, T3

Product	Batch completion time
A	5.97 hours
B	6.53 hours
C	9.52 hours
D	-
E	-

Second configuration			
Number of *FAG* modules	4	Investment cost	138,000 €
Number of tool modules	6	Operational cost	16,001 €
Number of input stations	1	Storage cost	-
Number of output stations	1		

FAG type	*Execution mode*	tool modules	Tool type
Nut pressing	1	1	T1, T2, T3
Adhesive joining	3	1	T1, T2
Spot welding	1	2	T1, T3, T4, T5
Roll hemming	1	2	T1, T2, T3

Product	Batch completion time
A	6.06 hours
B	6.88 hours
C	10.07 hours
D	11.68 hours
E	9.95 hours

Table 4.: Comparison in terms of costs (in €) between the solution obtained with the *Robust approach* and two alternative approaches, the *single scenario optimum approach* and the *initial node optimum approach*, considering only *scenario* S5.

	Cost Type	t_0	t_1	t_2	t_3	t_4	t_5	**Total**
	Investment	456,040	-	-	108,000	-	30,000	594,040
	Operational	5,270	4,635	5,522	7,333	5,427	6,677	34,864
Robust	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	-	20,000	-	-	20,000
	Total (disc.)	461,310	4,332	4,823	110,472	4,140	26,150	**611,227**
	Investment	451,040	-	21,000	99,000	-	39,000	610,040
	Operational	4,433	3,953	3,210	4,086	3,199	2,453	21,334
Single	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	20,000	20,000	-	20,000	60,000
	Total (disc.)	455,473	3,694	38,615	100,475	2,441	43,815	**644,513**
	Investment	451,040	-					451,040
	Operational	4,433	3,953					8,386
Initial	Storage	-	-	unfeasible	unfeasible	unfeasible	unfeasible	0
	Reconfig.	-	-					0
	Total (disc.)	455,473	3,694					**459,426**

Table 5.: Comparison in terms of costs (in €) between the solution obtained with the *Robust approach* and two alternative approaches, the *single scenario optimum approach* and the *initial node optimum approach*, considering only *scenario* S6.

	Cost Type	t_0	t_1	t_2	t_3	t_4	t_5	**Total**
	Investment	456,040	-	-	138,000	-	-	594,040
	Operational	5,270	4,635	5,522	7,141	6,483	5,266	34,317
Robust	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	-	20,000	-	-	20,000
	Total (disc.)	461,310	4,332	4,823	134,804	4,946	3,755	**613,970**
	Investment	451,040	-	21,000	138,000	-	-	610,040
	Operational	4,433	3,953	3,210	6,742	6,049	4,909	29,296
Single	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	20,000	20,000	-	-	40,000
	Total (disc.)	455,473	3,694	38,615	134,479	4,615	3,500	**640,375**
	Investment	451,040	-					451,040
	Operational	4,433	3,953					8,386
Initial	Storage	-	-	unfeasible	unfeasible	unfeasible	unfeasible	0
	Reconfig.	-	-					0
	Total (disc.)	455,473	3,694					**459,167**

The solution provided by the *initial node optimum approach* becomes unfeasible from the third time period on for both the *scenarios*, i.e., when the product mix changes and products D and E are requested. The impossibility to *reconfigure* the cell makes the initial solution unfeasible.

On the other side, the *single scenario optimum approach* suggests to *reconfigure* the cell every time a new configuration is needed, in order to pursue the local optimum in terms of operational costs for every single *scenario node*. To this aim, it chooses to implement *execution mode* number 1 in every *FAG*, since it guarantees the best performance. With regards to *scenario* S5, a reconfiguration is foreseen in the third, fourth and sixth time periods due to the requests for product C, D and E entailing a change in the equipment needed. On the contrary, for *scenario* S6, a reconfiguration is foreseen in the third time period, due to the need to cope with product C, and in the fourth one, due to the requirements of products D and E. In both the cases, the solution obtained through this alternative approach has a smaller operational cost for each time period compared to the solution provided by the *Robust approach*, but also a higher total discounted cost.

This first comparison demonstrates how a myopic approach does not allow to obtain the minimum cost but only to optimize a local situation and, thus, how a long-vision and multi-*scenario* approach can be beneficial for the company.

The second analysis aims at assessing the quality of the solution proposed in terms of robustness. Consider the solution obtained using the *most probable scenario approach* and the associated reconfiguration plan that minimize the average cost associated for the most probable *scenario* only, i.e. S1 with $\pi_1 = 0.5$. This solution is then evaluated against the occurrence of *scenario* S5 with $\pi_3 = 0.05$. The *most probable scenario approach* suggests to implement the configuration in Figure 11a using the *execution mode* number 1 for every *FAG*. Furthermore, no *reconfigurations* are foreseen when considering the first three products only. When evaluating this solution in the *scenario* S5, it results unfeasible from time period number 4 on (*scenario node* 9) in which product D has to be processed. Grounding on this, the company could decide to react

Table 6.: Comparison in terms of costs (in €) between the solution obtained with the *Robust approach* and the *most probable scenario approach*, considering only the scenario S5.

	Cost Type	t_0	t_1	t_2	t_3	t_4	t_5	**Total**
Robust	Investment	456,040	-	-	108,000	-	30,000	594,040
	Operational	5,270	4,635	5,522	7,333	5,427	6,677	34,864
	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	-	20,000	-	-	20,000
	Total (disc.)	461,310	4,332	4,823	110,472	4,140	26,150	**611,227**
Most	Investment	472,040	-	-	99,000	-	39,000	610,040
	Operational	4,433	3,953	3,210	4,086	3,199	2,453	21,334
	Storage	-	-	-	-	-	-	0
	Reconfig.	-	-	-	20,000	-	20,000	40,000
	Total (disc.)	476,473	3,694	2,804	100,475	2,441	43,815	**629,702**

with a reconfiguration during the fourth time period, in order to add the needed pieces of equipment, and further react in the last time period to cope with the production of product E (Table 6).

It is straightforward to see that the *most probable scenario approach* does not protect against all the possible *scenarios* entailing the need of unexpected *reconfigurations* of the cell entailing a higher total cost than the one guaranteed by the *Robust approach.*

5.3. *Sensitivity analysis*

The cost function used in the *Robust approach* grounds on a set of parameters having an impact on the results. In this section, the influence of some of the parameters is investigated. The focus is on the analysis of the reconfiguration and operational costs. The variation of these parameters will be measured on the optimal solution identified for the use-case. The new optimal solution will be discussed as well.

In the previous analysis, the reconfiguration cost has been fixed to $20,000$ €. This value models the cost incurred for changing from a configuration to another, including the stop of the production for two weeks (80 hours). Assume different values for the reconfiguration cost considering which the new optimal *CVaR* cost is reported in Table 7.

Table 7.: Sensitivity analysis of the reconfiguration and operational costs.

Reconfiguration cost	**Optimal *CVaR* cost**	**Optimal solution**
0 €	592, 611 €	Two reconfiguration actions
20, 000 €	611, 595 €	One reconfiguration action
100, 000 €	620, 620 €	No reconfiguration action
***Operational* cost**	**Optimal *CVaR* cost**	**% of operational cost**
0 €/h	585, 015 €	0%
50 €/h	611, 595 €	4.35%
100 €/h	638, 175 €	8.33%
200 €/h	691, 335 €	15.38%
400 €/h	797, 411 €	24.63%

If this cost equals 0 €, the reconfiguration actions are not penalized and, thus, the optimal solution will change more often. Hence, the identification of the optimal solution will be driven by the investment and operational costs only, pursuing a totally reactive strategy.

The new optimal solution considers an initial configuration with three *FAG* modules and one tool module each (Figure 12). The configuration undergoes two reconfiguration actions, the first one during the third time period to cope the request for product C, and the second one for addressing the processing of product D and E, i.e., during the fourth time period. With the first reconfiguration action, a tool module is added to the *FAG* module devoted to the spot welding obtaining the configuration in Figure 11a, with a cost of $21,000$ € for the equipment acquisition. With the second reconfiguration, a new *FAG* module is installed together with two tool modules dedicated to the roll hemming and the associated fixtures (Figure 11b), with an investment cost of $138,000$ €. The associated *CVaR* cost is $592,611$ €. On the other hand, the solution identified in the previous section has a new *CVaR* cost of $595,269$ €, smaller than the old one ($611,595$ €) due to the null impact of the single reconfiguration considered. This one is still a good solution with a cost slightly bigger than the optimal one.

On the contrary, considering a higher reconfiguration cost, i.e., $100,000$ €, the impact of the reconfiguration on the total cost becomes higher and, thus, the optimal solution will change less often. The new optimal solution considers to install the entire set of equipment needed for the production of all the five products in the first config-

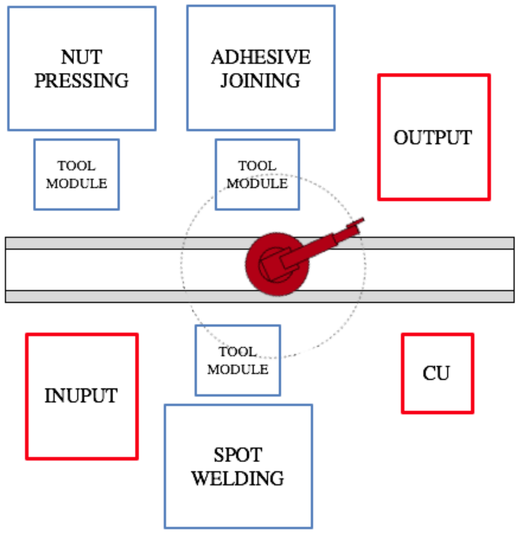


Figure 12.: configuration used in the first time period considering a reconfiguration cost equal to 0 €.

uration (Figure 11b). In this way, the *Robust approach* works in an overcautious way by including a set of equipment that could be not needed in the whole time horizon. The associated $CVaR$ cost of this solution is $620,620$ €. The new cost of the solution identified in the previous section is equal to $676,899$ €.

The operational cost depends on the time spent for processing parts, the *changeovers* and the *set-ups* with a linear impact on the total cost. With an increase or decrease of the unitary operational cost, the impact of the total operational cost on the $CVaR$ cost can change. As a consequence, the impact of different *execution modes* could increase or decrease accordingly.

Assume different levels of the operational cost considering which the new optimal $CVaR$ cost is reported in Table 7. Considering a null unitary operational cost $C^{hour} = 0$, the impact of the operational cost on the total $CVaR$ cost will be null as well. Thus, the choice about the *execution mode* to be used for each FAG will be always the number 3, that entails a smaller investment cost and worse performance than *execution mode* number 1. In this case, the new optimal solution considers the same configuration evolution as the old one, but using *execution mode* number 3 for both adhesive joining and nut pressing.

On the other side, with a very high unitary operational cost, the impact of the operational cost on the total $CVaR$ cost will be higher. Consider the optimal solution identified in the previous section using a unitary operational cost $C^{hour} = 50$ €/h. The associate $CVaR$ cost is $611,595$ € with $26,580$ € of operational cost over the whole time horizon, equal to the 4.35%.

Instead, considering a higher operational cost, e.g., $C^{hour} = 100$ €/h or $C^{hour} = 200$ €/h, the percentage of operational cost on the total increases (Table 7). The solution changes only with a very high unitary cost, for which the impact of the operational cost becomes significant on the total one. With a unitary cost $C^{hour} = 400$ €/h, the new optimal solution considers the same configuration evolution described in the previous section, but implementing both adhesive joining and nut pressing with *execution mode* 1. The associated $CVaR$ cost is $797,411$ €, for which the 24.63% is represented by operational cost.

It is possible to see how, when the impact of operational cost increases, the optimal choices is the one that prefers lower operational cost, thus, pieces of equipment with better performance.

5.4. *Solution time*

The proposed approach has been implemented in *MATLAB* version $R2015a$ and executed on a laptop with an Intel Core i5 processor at $2.4GHz$ and $8GB$ RAM. The computational times (in seconds) for the industrial case are reported in Table 8, with the details of the time spent for the generation of the set of *configurations* Z, the approximate and detailed performance evaluation, the cost evaluation and the *robust* optimization.

Table 8.: Time consumption for addressing the use-case, in seconds.

Phase	**Time spent**
Generation of *configurations*	62.12
Approximate evaluation	18,855.10
Detailed evaluation	106,005.00
Cost evaluation	10.64
Robust optimization	2.42
Total	**124,935.28**

Due to the high number of time periods, *scenario nodes* and *scenarios*, the total computational time is rather high, i.e., 124,935.28 seconds, equal to 34.70 hours. This high value is motivated by the need to evaluate the performance of every *tool set-up* included in Z using the *PR* approach with 1,000 replicates. More than the 99% of the candidate layouts have been deleted by the first approximate performance evaluation, without this reduction the solution time could have been much higher, thus the adoption of a solution approach with two performance evaluation methods is successful since many alternative solutions can be discarded. Despite this, 34.70 hours can be considered in line with the aim of designing an assembly cell to be used though 6 time periods (18 months).

Taking a look at each element in the list, it is possible to see how the two performance evaluation steps heavily affect the total time effort, representing about 99% of the total completion time.

6. Conclusions

In this paper, the problem of the design and configuration of a reconfigurable assembly cell has been carried out with the aim at providing a robust solution able to cope with an uncertain context. A solution approach has been designed, developed and applied to an industrial case in the automotive industry.

The configuration problem under study focuses on a new modular and reconfigurable assembly cell architecture to enable a fast reconfiguration and changeover through three different decision levels, namely the configuration, the *equipment selection and allocation* and the *tool set-up*. To support these decision levels with the proper level of details, a two-level performance evaluation method has been also developed.

Finally, a *Robust optimization* approach has been used to select a suitable configuration strategy for the assembly cell in relation to a set of *scenarios* to minimize the *Conditional Value at Risk* of the cost function. It has been demonstrated how the adopted strategy over-performs alternative configuration strategies that limit the investigation area to a particular *scenario* (e.g., the *single scenario optimum approach* and the *most probable scenario approach*) or a single *scenario node* (e.g., the *initial node optimum approach*).

Future improvements of the proposed approach will be focused on i) addressing the possibility to cope a set of assembly cells instead of a single one, also entailing the processing of a product in more than one cell and ii) improving the computation performances, e.g., with parallel calculus or an improved robust optimization approach.

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Appendix

Table 9.: Volume and batch size for each product in each scenario node of the use-case.

Scenario node	Parameter	Prod. A	Prod. B	Prod. C	Prod. D	Prod. E
ω_1	volume	200	250	0	0	0
	batch size	30	35	0	0	0
ω_2	volume	190	200	0	0	0
	batch size	30	35	0	0	0
ω_3	volume	200	210	0	0	0
	batch size	30	35	0	0	0
ω_4	volume	150	150	170	0	0
	batch size	30	30	35	0	0
ω_5	volume	150	130	150	0	0
	batch size	30	30	35	0	0
ω_6	volume	150	150	150	0	0
	batch size	30	30	35	0	0
ω_7	volume	100	150	150	0	0
	batch size	30	30	35	0	0
ω_8	volume	130	100	130	0	0
	batch size	30	30	35	0	0
ω_9	volume	100	130	130	150	0
	batch size	30	30	35	30	0
ω_{10}	volume	100	100	100	80	90
	batch size	30	30	35	30	25
ω_{11}	volume	90	150	130	0	0
	batch size	30	30	35	0	0
ω_{12}	volume	100	100	100	150	0
	batch size	30	30	35	30	0
ω_{13}	volume	100	100	130	150	0
	batch size	30	30	35	30	0
ω_{14}	volume	100	100	90	130	0
	batch size	30	30	35	35	0
ω_{15}	volume	100	100	90	100	0
	batch size	30	30	35	35	0
ω_{16}	volume	100	80	90	80	80
	batch size	30	30	35	35	25
ω_{17}	volume	80	100	150	0	0
	batch size	30	30	35	0	0
ω_{18}	volume	90	80	100	130	0
	batch size	30	30	35	35	0
ω_{19}	volume	100	150	150	100	0
	batch size	30	30	35	30	0
ω_{20}	volume	90	90	50	100	0
	batch size	30	30	35	35	0
ω_{21}	volume	90	90	50	100	100
	batch size	30	30	35	35	25
ω_{22}	volume	90	80	50	50	80
	batch size	30	30	35	35	35

Table 10.: Assembly processes' description in terms of tool needed and execution time, in seconds.

Op#	FAG	Product A		Product B		Product C		Product D		Product E	
		ex-mode 1	*ex-mode* 3	*ex-mode* 1	*ex-mode* 3	*ex-mode* 1	*ex-mode* 3	*ex-mode* 1	*ex-mode* 3	*ex-mode* 1	*ex-mode* 3
Op1	Nut pressing	-	-	T1, 35	T1, 40	T2, 20	T2, 30	T2, 30	T2, 40	T3, 42	T3, 55
Op2	Adhesive joining	T2, 41	T2, 51	T1, 44	T1, 54	T1, 50	T1, 60	T2, 20	T2, 30	T2, 50	T2, 65
Op3	Spot welding	T1, 102s	-	T1, 50	-	T1, 180 T3, 78	-	T1, 160 T4, 90	-	T2, 150 T5, 70 T2, 45	-
Op4	Roll hemming	-	-	-	-	-	-	T1, 40	-	T3, 52	-

Table 11.: Investment cost for different pieces of equipment and *FAG*'s tools, in €.

Equipment type	***ex mode* 1**	***ex mode* 3**
7-axis robot	75,000	100,000
Control unit	130,000	
Adhesive joining	55,000	45,000
Spot welding	50,000	
Nut pressing	30,000	20,000
Roll hemming	75,000	
Tool module	9,000	
Input station	48,000	
Output station	14,000	

Tool type	***ex mode* 1**	***ex mode* 3**
Adhesive joining	10,000	5,000
Spot welding	12,000	-
Nut pressing	15,000	7,000
Roll hemming	15,000	-

Table 12.: Miscellaneous costs and parameters.

Cost type	**Value**
Operational cost	50 €/h
Reconfiguration cost	20,000 €
Tool storage cost	6,000 €/time period
Equipment storage cost	6,000 €/time period
Robot's track cost	2000 €/m

Parameter	**Value**
Reconfiguration time	80 h
Changeover time	0.5 h
Set-up time	0.5 h