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Mixed-Model Assembly Line Design with New Product Variants in Production Generations ⋆

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Abstract: Among all the challenges which highlight the need of reconfigurability in manufacturing systems, taking into account the introduction of a new product has been rarely considered by the researchers. Indeed, taking into account the new product variants in the future production generation of the line at the initial design stage smooths the reconfiguration process of the line. This paper studies a mixed-model assembly line reconfiguration planning problem where the line consists of several resources (workers and robots). This study aims to design a line which produces a given product family with a set of product variants, and a new product variant will be added after a certain period of time, named production generation. At each generation, the production family can change with the addition/removal of a product variant. Therefore, the line needs to be reconfigured at each generation. We propose a new Mixed-Integer Linear Programming (MILP) which aims to minimize the total reconfiguration effort, the total cost of designing and reconfiguring the line taking into account the buying, selling, re-assigning the equipment and resources in the worst scenario of possible product families which are produced in several production generation. The MILP is validated through solving a simple example, and the results are given.

Keywords: Mixed-model assembly line, reconfigurability, new product variants, production generation, integer linear programming, robust optimization.

1. INTRODUCTION

The global competition, market changes and customers preferences changes lead to short product life cycles in the market. This situation leads to quick changes in product design and to the frequent introduction of new product variants. Introduction of new product variants and market demand changes are the main reasons to implement a reconfigurable manufacturing system (RMS). The concept of RMS has been introduced by Koren et al. (1999), and it is based on the physical reconfiguration of the system. An RMS is composed of the components such as workforce, machines, tools and material handling devices that can be easily added, removed or replaced.

There is a growing interest from the academic community in the study of the design of manufacturing systems that account for the evolution of product families. For instance, some researchers have developed methods to plan manufacturing system design changes over several generations of production (AlGeddawy and ElMaraghy, 2012; Bryan et al., 2013; Abbas and ElMaraghy, 2018). Studying the reconfiguration planning is an interesting research topic for an assembly line (Boysen et al., 2009), which aims to design a line able to cope with several generations of the product families, to account for the market demand changes of the product variants and the new product variant added to the production at each generation.

This study deals with the reconfiguration planning of a mixed-model assembly line containing several sequential stations. We study a line with human workers and robots at stations. The line must be designed to produce a given product family, and we account for future changes in the product family. More precisely, we consider several production generations on the line, where at each generation, the market demand of current product variants in the family may change, and a new product variant will be added to the production family. The new product variant remains in the same product family. Therefore, such a variant must be similar to the current variants of the product family which are produced in the line with slight differences in the set of required tasks, the precedence relationships, and processing times. Note that, in this study, the new product variants are assumed to be known in advance.

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Switching to a new generation requires a reconfiguration of the line which refers to the task re-assignment to stations and to change (removing/adding) of the equipment pieces at stations. Consecutively, the workers and robots may need to move between the stations. The goal is to study a robust optimization problem which selects the line reconfiguration plans that minimize the reconfiguration effort for the worst scenario of the line. The reconfiguration effort refers to the total cost of buying and (un)installation (re-assigning) the resources and equipment, the cost of hiring workers, the benefits of selling the resources and equipment. The line must produce only a set of product variants as a product family at each production generation.

The paper is organized as follows: Section 2 reviews the literature of the topic at hand. Section 3 defines the problem. Section 4 represents the Mixed-Integer Linear Programming (MILP). Section 5 validates the proposed MILP solving a small example. Finally, the paper ends with the conclusion and future research directions in Section 6.

2. LITERATURE REVIEW

In this section, we review the closest literature related to the key topics of our study, namely, mixed-model assembly line design and balancing, reconfiguration planning, product customization, production generations. Finally, this section summarizes the main contributions of the current paper compared to the reviewed literature.

In terms of product model variety, single, mixed and multi-model assembly lines are distinguished in the literature (Boysen et al., 2008). A single-model line produces a single type of product, whereas mixed/multi-model lines produce multiple types of products. In a multi-model line products enter in batches and the line has to be set up between the batches. In a mixed-model line, products enter in an arbitrary order, which increases the required level of flexibility compared to multi-model lines. Because of the variability in the market demand, manufacturing companies tend to shift from single-model to mixed-model lines (Manzini et al., 2018). The reconfiguration planning of a MMAL can be enhanced by taking into account the future customization of products and variable demands for different product models (Bryan et al., 2013).

There are many challenges in the industry to handle the future reconfiguration effort relying on the first configuration of the line (Maganha et al., 2018). For example, discussion with an automotive industry showed that reconfiguration of the line occur approximately every 6 months. These reconfigurations are costly since they require to stop the line. As a consequence, manufacturers aim to have short reconfigurations that can take place during the weekend (or vacations). Therefore, reconfiguration planning is one of the crucial problem which needs to be taken into account at the design stage of the line (the first configuration) (Bryan et al., 2013). The main criteria to minimize is the total reconfiguration effort such as reconfiguration time and/or cost. In fact, if we decrease the total design and reconfiguration cost, the reconfiguration effort decreases.

To the best of our knowledge this paper is an initial and interesting attempt to study the mixed-model assembly reconfiguration planning problem ($MALRP$), and we consider the task, equipment and resource (workers and robots) assignment to stations in several generations of production families. In this study, we propose and validate a new $MILP$ that aims to minimize the total reconfiguration effort, as defined, in the worst scenario. Each scenario represents the addition of new product variants and changes in the market demand over the life cycle of the line. The problem is new and motivated by the situation encountered at an automotive manufacturer in France.

3. PROBLEM DESCRIPTION

The considered problem is related to the situation encountered by an automotive producer in France.

We study a mixed-model assembly line design problem. The line is able to produce a part family of products, and in context of a mixed-model assembly line, these products enter in any arbitrary orders with negligible set-up time compare to the cycle time. The line is paced. It contains some sequential stations, a set of resources including human workers and robots, as well as a set of manual and automated equipment pieces. Each product model requires a certain set of tasks which can be manually and/or automatically performed by either a human worker or a robot. Manual and automated equipment are used to perform tasks by the worker and the robot, respectively.

The main assumptions of this study are listed. Stations can be filled by either a worker or a robot. The configuration of the line including the tasks, equipment, workers and robots assigned to stations are fixed during a production generation.

Each task requires a compatible resource and equipment for processing. The sets of resources and equipment are denoted $\mathcal{R}$ and $\mathcal{E}$, respectively. Note that the set of resources contains both workers and robots. Tasks can be either manually or automatically performed by a worker or a robot, respectively. In addition, the workers or robots require the specific equipment to perform the tasks. Therefore, the compatibilities are represented by two sets. CE_o consists of the equipment types which are capable to perform task o, and CR_e contains the resources certified to utilize equipment e. Note that only one resource (a worker or a robot) but several equipment pieces can be installed at each station.

The goal is to design a reconfigurable line able to evolve at different production generation. Companies change the product generation for various reasons. For instance, a manufacturer may introduce a new model variant with additional functionality, they may adjust their product based on customer feed-backs, or they may slightly change some parts due to change of supplier. A new generation means that a new product model from the same family is added to the current product family, or a model is discontinued. In addition, the demand for each product model changes in a new generation to adjust to the latest observation of the market. The reconfiguration of the line requires to stop the line which represent a huge cost for the company. Therefore, minimizing the reconfiguration time is critical for the economical performance of the company. Depending on the reconfiguration time, it may happen during a weekend or vacations. However, minimizing the reconfiguration time (or the number of reconfiguration) is important, since the technicians must be paid. Note that the reconfigurations occur approximately once (or more) per year.

At each production generation, a new part is added to the production family, and the current parts may be removed or kept. In addition, the demand for each part may change depending on the market situation. The reconfiguration of the line for each production generation refers to the new task assignment to stations, and subsequently, the corresponding equipment and resource re-assignment to stations depending on the type of tasks (manual or automated) and the considered constraints.

We study a paced line which consists of a set $\mathcal{S} = \{1 \dots S\}$ of sequential stations. We design a line which should be able to assemble a set $\mathcal{I} = \{1 \dots I\}$ of product models. We assume a set $\mathcal{G} = \{0 \dots G\}$ of production generations, in which the line may assemble a set $\mathcal{PS}_g = \{1 \dots PS_g\}$ of product families. Note that $g = 0$ refers to the current set of certain product models which are given and will be assembled in the line ($PS_0 = 1$). Each product family p at generation g contains the set $\mathcal{I}_{pg} = \{1 \dots I_{pg}\}$ of product models. The products units move from one station to the next one at a regular time interval C, called takt time. At each takt, there is only a single product unit at each station. Each product model $i \in \mathcal{I}$ requires a set of $\mathcal{O}_i$ tasks. Each task o of product model i has the process time pt_{oei} if it is performed by equipment e. We define a set A_i of precedence relationships (o, o') for each product model i, where task o must be performed before task o' for this product model. Moreover, each common task o may require different processing times for different product models.

We consider the product family representation used by Bryan et al. (2013) to build the product family precedence graph and the corresponding process time of tasks. The product family precedence graph A'_{pg}, is the integrated graph from all product models in the family p at generation g, and it is created with the approach introduced by Thomopoulos (1967). The set of all tasks needed for all product models in a product family is denoted as O'_p, where $O'_p = \cup_{i \in p} O_i$. The weighted average task times have been used to calculate the corresponding process time of tasks (Bryan et al., 2013). The advantage of this approach is that the researchers can adapt the traditional simple assembly line balancing techniques (Becker and Scholl, 2006). To this end, a joint precedence graph of all parts in the product family is created as the precedence graph of the product family in each generation. We denote by pt^g_{oep}, the average task time of each task o in the product family p at generation g, if o is performed with the equipment type e. We define the market demand ratio m^g_{ip} of product model i in product family p at generation g. pt^g_{oep} is computed based on the market demand ratio of the product models as follows (see Figure 2):

$$pt^g_{oep} = \sum_{i \in \mathcal{I}_{pg}} m^g_{ip}\ pt_{oei}$$
$$\text{g} \in \mathcal{G},\ p \in PS_g,\ o \in \mathcal{O'}_p,\ e \in \mathcal{E}$$

Figure 1 shows an illustrative example of two future production generations in a mixed-model line designed for two parts A and B from the same family. The marketing and product design departments decided to launch the additional product variant C in generation 1, and the variant D in generation 2. Note that, at each generation, the company may decide to keep production of the previous products or they may terminate the producing of one or more variants of current product models. In addition, the change of demand for each variant is unknown when the line is designed. Therefore, in each generation, marketing department provides several set of product variants along with the demand for each variant. Some restrictions are taken into account while moving from one product family p to another one p' in the next generation. More precisely, if the company stops producing a product model in a generation, this model cannot be part of the next generation. In the example of Figure 1, product A is discontinued in family $p = 2$ of generation $g = 1$, and the company will produce a part family of products where there is no product model A in the next generation ($g = 2$), such as product family $p = 2$, $p = 5$ or $p = 7$.

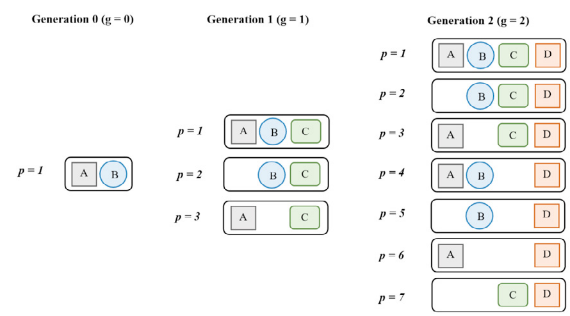

Fig. 1. The possible product sets in two production generations.

Figure 2 shows the construction of the precedence graph for a product family with two product models $\{A, B\}$. Precisely, Figure 2 shows the precedence graph of model A and B as well as the joint precedence graph, where the number above each task represents the processing time of the task.

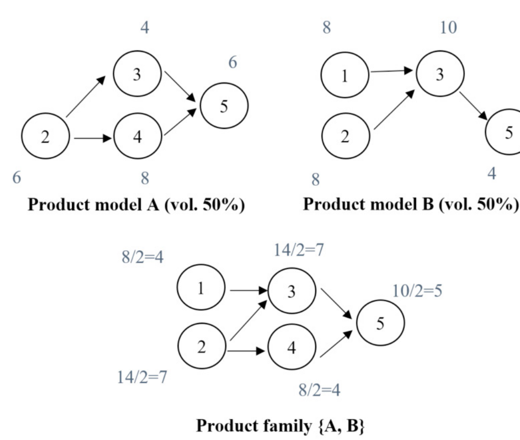

Fig. 2. The integrated precedence graph for a product family including two product models $\{A, B\}$.

The goal is to minimize the reconfiguration efforts for the worst scenario of product families in all possible generations. The part family of products is given in the current line. In the next generations, we consider different scenarios for all possible set of product models in the product family. The worst case refers to the combination of worst scenarios happening over all considered generations. We introduce the set $SC = \{1 \dots SC\}$ of scenarios where each scenario $n \in SC$ consists of possible pairs (p, p') of product families that production can move from family $p \in PS_{g-1}$ to family $p' \in PS_g$ for switching from two consecutive generations. A possible scenario of the example given in Figure 1 is producing parts A and B in the current line, parts A, B, and new part C in the first generation, and parts A, C, and the new part D in the second generation.

4. MIXED-INTEGER LINEAR PROGRAMMING (MILP)

This section provides a new MILP for the problem in hand. The model aims to minimize the total reconfiguration effort over upcoming production configuration for the worst scenario/case. The reconfiguration effort includes the equipment, the resources, and the task reassignment. The scenario relies on the set of products which are going to be produced at each production generation, as well as the required reconfiguration. The model makes decision on task, resource (worker and robots), and equipment assignment at each generation. To this end, the decision variables are as follows:

- w^g_{srp} is equal to 1 if resource r is assigned to station s for producing product family p in generation g, and 0 otherwise.
- x^g_{sop} is equal to 1 if task o performed on product family p is performed at station s in during production generation g, and 0 otherwise.
- b^g_{sep} is equal to 1 if equipment e is installed at station s for producing product family p in generation g, and 0 otherwise.
- b^g_{soep} is equal to 1 if equipment e is installed at station s to perform task o on product family p in generation g, and 0 otherwise.

We define the continuous variable Y which provides the worst (maximum) value of the total design and possible reconfiguration cost. The total cost includes the cost of buying equipment, robots and hiring the workers, the cost of installing and uninstalling the robots and equipment as well as the benefit from selling robots and equipment. Therefore, the objective function (1) aims to minimize the total design and reconfiguration in the worst scenario among all scenarios.

$$\min Y \tag{1}$$

The decision variable Y is computed using the Constraints (2). The continuous decision variable Q_n is the sum of purchasing cost and selling price of the equipment, Q'_n is the sum of purchasing cost and selling price of the robots as well as the hiring cost of workers, Z_n is the sum of (un)instalation cost of the equipment, Z'_n is the sum of (un)instalation cost of the robots computed for each scenario n by Equations (3), (4), (5), and (6), respectively.

$$Y \geq Q_n + Q'_n + Z'_n + Z'_n \quad n \in SC \tag{2}$$

$$\begin{aligned} Q_n = \sum_{g\in\mathcal{G}-0} \sum_{(p,p')\in SC_n} \Bigg[\sum_{e\in\mathcal{E}} \Bigg[\alpha_{e0} \Big[\sum_{s\in\mathcal{S}} b^0_{se0} \Big] + \\ \alpha_{eg} \Big[\sum_{s\in\mathcal{S}} b^g_{sep} - \sum_{s\in\mathcal{S}} b^{g-1}_{sep'} \Big]^+ + \\ \beta_{eg} \Big[\sum_{s\in\mathcal{S}} b^g_{sep} - \sum_{s\in\mathcal{S}} b^{g-1}_{sep'} \Big]^- \Bigg] \Bigg] \quad n \in SC \end{aligned} \tag{3}$$

$$\begin{aligned} Q'_n = \sum_{g\in\mathcal{G}-0} \sum_{(p,p')\in SC_n} \Bigg[\sum_{r\in\mathcal{R}} \Bigg[\alpha'_{r0} \Big[\sum_{s\in\mathcal{S}} w^0_{sr0} \Big] + \\ \alpha'_{rg} \Big[\sum_{s\in\mathcal{S}} w^g_{srp} - \sum_{s\in\mathcal{S}} w^{g-1}_{srp'} \Big]^+ + \\ \beta'_{rg} \Big[\sum_{s\in\mathcal{S}} w^g_{srp} - \sum_{s\in\mathcal{S}} w^{g-1}_{srp'} \Big]^- \Bigg] \Bigg] \quad n \in SC \end{aligned} \tag{4}$$

$$\begin{aligned} Z_n = \sum_{g\in\mathcal{G}-0} \sum_{(p,p')\in SC_n} \sum_{s\in\mathcal{S}} \Bigg[\sum_{e\in\mathcal{E}} \Bigg[\lambda_{eg} \Big[b^g_{sep} - \\ b^{g-1}_{sep'} \Big]^+ - \gamma_{eg} \Big[b^g_{sep} - b^{g-1}_{sep'} \Big]^- \Bigg] \Bigg] \quad n \in SC \end{aligned} \tag{5}$$

$$\begin{aligned} Z'_n = \sum_{g\in\mathcal{G}-0} \sum_{(p,p')\in SC_n} \sum_{s\in\mathcal{S}} \Bigg[\sum_{r\in\mathcal{R}} \Bigg[\lambda'_{rg} \Big[w^g_{srp} - \\ w^{g-1}_{srp'} \Big]^+ - \gamma'_{rg} \Big[w^g_{srp} - w^{g-1}_{srp'} \Big]^- \Bigg] \Bigg] \quad n \in SC \end{aligned} \tag{6}$$

Herein, α_{eg} and α'_{rg} are the purchasing cost of equipment e and robot r (or hiring cost of worker r) in production generation g, respectively. β_{eg} and β'_{rg} are the selling price of equipment e and robot r in production generation g, respectively. λ_{eg} and λ'_{rg} are the installation cost of equipment e and robot r in production generation g, respectively. γ_{eg} and γ'_{rg} are the uninstallation cost of equipment e and robot r in production generation g, respectively. Note that, we assume that firing of workers has no benefit for the company, as well as re-assigning the workers provide no cost for the company. Moreover, all these cost/benefit values depend on the generation since they can change during the period of production generation (e.g. because of inflation or amortization).

Constraints (3) - (6) are non-linear, and must be linearized.We define four binary decision variables for equipment reconfiguration: $b^+_{epp'} := \big[\sum_{s\in\mathcal{S}} b^g_{sep} - \sum_{s\in\mathcal{S}} b^{g-1}_{sep'}\big]^+$, $b^-_{epp'} := -\big[\sum_{s\in\mathcal{S}} b^g_{sep} - \sum_{s\in\mathcal{S}} b^{g-1}_{sep'}\big]^-$, $b'^+_{sepp'} := \big[b^g_{sep} - b^{g-1}_{sep'}\big]^+$, $b'^-_{sepp'} := -\big[b^g_{sep} - b^{g-1}_{sep'}\big]^-$, and four binary decision variables for resource reconfiguration: $w^+_{rpp'} :=$

$\left[\sum_{s\in\mathcal{S}} w^{g}_{srp} - \sum_{s\in\mathcal{S}} w^{g-1}_{srp'}\right]^{+}$, $w^{-}_{rpp'} := -\left[\sum_{s\in\mathcal{S}} w^{g}_{srp} - \sum_{s\in\mathcal{S}} w^{g-1}_{srp'}\right]^{-}$, $w'^{+}_{srpp'} := \left[w^{g}_{srp} - w^{g-1}_{srp'}\right]^{+}$, $w'^{-}_{srpp'} := -\left[w^{g}_{srp} - w^{g-1}_{srp'}\right]^{-}$. To linearize the model, these eight variables replace their corresponding expression in Constraints (3) - (6), and Constraints (7) - (14) and (24) - (27) are added.

$$\sum_{s\in\mathcal{S}} b^{g}_{sep} - \sum_{s\in\mathcal{S}} b^{g-1}_{sep'} \le b^{+}_{epp'} \quad n \in SC,\ (p,p') \in SC_n,\ e \in \mathcal{E} \tag{7}$$

$$\sum_{s\in\mathcal{S}} b^{g-1}_{sep'} - \sum_{s\in\mathcal{S}} b^{g}_{sep} \le b^{-}_{epp'} \quad n \in SC,\ (p,p') \in SC_n,\ e \in \mathcal{E} \tag{8}$$

$$b^{g}_{sep} - b^{g-1}_{sep'} \le b'^{+}_{sepp'} \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ e \in \mathcal{E} \tag{9}$$

$$b^{g-1}_{sep'} - b^{g}_{sep} \le b'^{-}_{sepp'} \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ e \in \mathcal{E} \tag{10}$$

$$\sum_{s\in\mathcal{S}} w^{g}_{srp} - \sum_{s\in\mathcal{S}} w^{g-1}_{srp'} \le w^{+}_{rpp'} \quad n \in SC,\ (p,p') \in SC_n,\ r \in \mathcal{R} \tag{11}$$

$$\sum_{s\in\mathcal{S}} w^{g-1}_{srp'} - \sum_{s\in\mathcal{S}} w^{g}_{srp} \le w^{-}_{rpp'} \quad n \in SC,\ (p,p') \in SC_n,\ r \in \mathcal{R} \tag{12}$$

$$w^{g}_{srp} - w^{g-1}_{srp'} \le w'^{+}_{srpp'} \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ r \in \mathcal{R} \tag{13}$$

$$w^{g-1}_{srp'} - w^{g}_{srp} \le w'^{-}_{srpp'} \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ r \in \mathcal{R} \tag{14}$$

The rest of constraints are given as follows:

$$\sum_{s\in\mathcal{S}} x^{g}_{sop} = 1 \quad g \in \mathcal{G},\ p \in PS_g,\ o \in \mathcal{O}'_p \tag{15}$$

$$\sum_{s\in\mathcal{S}} b^{g}_{sep} \le 1 \quad g \in \mathcal{G},\ p \in PS_g,\ e \in \mathcal{E} \tag{16}$$

$$\sum_{s\in\mathcal{S}} w^{g}_{srp} \le 1 \quad g \in \mathcal{G},\ p \in PS_g,\ r \in \mathcal{R} \tag{17}$$

$$\sum_{r\in\mathcal{R}} w^{g}_{srp} \le 1 \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S} \tag{18}$$

$$x^{g}_{sop} \le \sum_{e\in CE_o} b^{g}_{soep} \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ o \in \mathcal{O}'_p \tag{19}$$

$$b^{g}_{soep} \le \sum_{r\in CR_e} w^{g}_{srp} \quad g \in \mathcal{G},\ p \in PS_g,\ o \in \mathcal{O}'_p,\ e \in CE_o \tag{20}$$

$$b^{g}_{soep} \le b^{g}_{sep} \quad g \in \mathcal{G},\ p \in PS_g,\ o \in \mathcal{O}'_p,\ e \in CE_o \tag{21}$$

$$\sum_{o\in\mathcal{O}'_p} \sum_{e\in CE_o} pt^{g}_{oep} b^{g}_{soep} \le C \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ r \in \mathcal{R} \tag{22}$$

$$\sum_{s\in\mathcal{S}} s\ x^{g}_{sop} \le \sum_{s'\in\mathcal{S}} s'\ x^{g}_{s'o'p} \quad g \in \mathcal{G},\ p \in PS_g,\ (o,o') \in \mathcal{A}'_{pg} \tag{23}$$

Constraints (15) ensure that each task is assigned to only one station for each production family of a production generation. Constraints (16) and (17) state that if an equipment piece and a resource are needed, they are assigned to only one station for each production family of a production generation, respectively. Constraints (18) assign a single resource at each station. Constraints (19) force to install the capable equipment at the station when a task is performed there. Constraints (20) locate a compatible (manual or automated) resource at a station when a task is performed using the required equipment there. Equations (21) set the value of b^{g}_{sep} depending on the value of b^{g}_{seop}. Constraints (22) and (23) are the classical takt time and precedence relationship constraints, respectively. Note that, due to the companies requirement, the model let the possible free stations in the line to improve the flexibility of the line as needed.

Finally, Constraints (24) - (33) give the bounds on the decision variables.

$$b^{+}_{epp'}, b^{-}_{epp'} \in [0,1] \quad n \in SC,\ (p,p') \in SC_n,\ e \in \mathcal{E} \tag{24}$$

$$b'^{+}_{sepp'}, b'^{-}_{sepp'} \in [0,1] \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ e \in \mathcal{E} \tag{25}$$

$$w^{+}_{rpp'}, w^{-}_{rpp'} \in [0,1] \quad n \in SC,\ (p,p') \in SC_n,\ r \in \mathcal{R} \tag{26}$$

$$w'^{+}_{srpp'}, w'^{-}_{srpp'} \in [0,1] \quad n \in SC,\ (p,p') \in SC_n,\ s \in \mathcal{S},\ r \in \mathcal{R} \tag{27}$$

$$x^{g}_{sop} \in \{0,1\} \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ o \in \mathcal{O}'_p \tag{28}$$

$$b^{g}_{sep} \in \{0,1\} \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ e \in \mathcal{E} \tag{29}$$

$$w^{g}_{srp} \in \{0,1\} \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ r \in \mathcal{R} \tag{30}$$

$$b^{g}_{soep} \in \{0,1\} \quad g \in \mathcal{G},\ p \in PS_g,\ s \in \mathcal{S},\ o \in \mathcal{O}'_p,\ e \in \mathcal{E} \tag{31}$$

$$Q_n, Q'_n, Z_n, Z'_n \ge 0 \quad n \in SC \tag{32}$$

$$Y \ge 0 \tag{33}$$

5. COMPUTATIONAL TEST

This section provides experimental results for a simple example with the product generations proposed in Figure 1. The goal is to validate the proposed MILP. The line is currently producing two product models $\{A, B\}$ through a line with 3 stations. These product models require 5 tasks with different precedence relationships and process times. We take into account two next production generations of the line, where a new variant of product is added to the production line at each generation, product model C requiring 8 tasks in the first generation and product model D requiring 10 tasks in the second one. We assume that the demand ratio of all product models in all product families at all generations are equal (e.g. 50% product model A and 50% product model B must be produce in the current production line/generation). We extend the data generator, proposed by Otto et al. (2013) to the specificity of the problem in hand. The processing times and precedence graphs are taken from the instances of

Otto et al. (2013) as explained in Hashemi-Petroodi et al. (2020).

Alternatively, we consider 15 equipment pieces, 10 manual equipment and 5 automated ones, and as well as 3 resources, 2 workers and 1 robot, in the resource library of the company. The process time of a task performed using the robots and the automated equipment is significantly less than the process time of the task performing by a worker and the manual equipment. Moreover, the compatibility of tasks, equipment, and resources (sets CE_o and CR_e) are randomly generated with respect to their natures based on two manual and automated types. All the cost values are randomly generated for the equipment and resources. The costs of equipment relies on their ability to perform the tasks, as well as the costs of resources are significantly more than equipment ones with a huge share.

The instance is solved using IBM ILOG CPLEX Optimization Studio V12.10. The experiments were run on an Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz 2.11 GHz processor with 32 GB of RAM in MS Windows 10 Pro (64 bit) operational system.

Table 1 shows the results of the worst scenario of the proposed example, where the total cost of 1252 including 1065 the purchasing/selling cost of resources and equipment and 187 the (un)installation cost of resources and equipment. In this Table, $Q^*_n + Q'^*_n$ and $Z^*_n + Z'^*_n$ stand for the total purchasing/selling and (un)installation costs of resources and equipment in the worst scenario n, respectively.

Table 1. The solution of the illustrative example.

Y	Purchasing/selling cost ($Q^*_n + Q'^*_n$)	(Un)Installation cost ($Z^*_n + Z'^*_n$)
1252	1065	187

6. CONCLUSION

This work deals with a mixed-model assembly line design problem with reconfiguration planning encountered in an automotive industry in France. The line is able to meet new production generations taking into account the market changes and evolution of the part family of products by adding a new product model into the production at each generation. We study a robust optimization problem aiming to minimize the total cost of designing and reconfiguration of the line over some future production generations in the worst case. The worst case is created by taking into account different scenarios of possible product families at each generation depending on the market demand. We develop an Mixed-Integer Linear Programming (MILP) model. The initial computational test is performed on a simple example to validate the proposed MILP.

This study is an initial effort on the topic at hand. We aim to extend this work to take into account the case where product designers cannot provide precise data on the future variants in advance. Another interesting variant of the problem is to simultaneously design the line and the product family. In addition, we aim to design efficient solution approaches to solve large-scale instances of the considered problem. This study also deserves more computational experiments in the future works.

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