

Mixed integer linear programming models for minimizing ergonomic risk dispersion in an assembly line at the Nissan Barcelona factory

Joaquín Bautista-Valhondo¹ , Rocío Alfaro-Pozo² 

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Abstract

We present a variant of the approach to the assembly line balancing problems, with the aim of reducing the ergonomic risk for operators of mixed-model assembly lines (MILP-3). Specifically, the MILP-3 model is focused on minimizing the average range between ergonomic risk values of workstations. Using a case study from Nissan's plant in Barcelona, not only are the differences between levels of ergonomic risk of stations reduced, but we attempt to reduce the average maximum ergonomic risk of the assembly line. The new model is compared with two others, MILP-1 and MILP-2, which minimize the average maximum ergonomic risk and the average absolute deviation of the risks, respectively.

Keywords

Assembly line balancing; Mixed-model assembly line; Ergonomic risk; Mixed integer linear programming.

1 Preliminaries

Currently, there are many manufacturing systems that operate mixed-model assembly lines. This type of production system facilitates flexible mass production, where different type of products, and with different features, levels of component consumption, and resource usage levels, must be assembled or disassembled without incurring excessive costs.

In the automotive industry, major auto-assemblers have begun to overhaul some of their previously specialized car-assembly plants into flexible factories in order to produce several vehicle models on the same production line (Eynan and Dong 2012, Moreno and Terwiesch 2015). Competition and customer demands, clearly evident in this industry, drive the proliferation of product varieties (AlGeddawy and El-Maraghy 2010).

However, such flexibility supposes two main problems with respect to establishing the configuration of the line and product sequence. Indeed, these issues have been discussed at length in literature under the names assembly line balancing problems or ALBPs (Salveson 1955; Baybars 1986; Scholl and Becker 2006; Boysen et al. 2007, 2008; Battaïa and Dolgui 2013) and mixed-model sequencing problems or MMSP (Miltenburg 1989; Yano and Rachamadugu 1991; Bautista et al. 1996; Boysen et al. 2009; Bautista and Cano

2011; Dörmer et al. 2015; Bautista-Valhondo 2016; Bautista and Alfaro-Pozo 2018; Bautista-Valhondo and Alfaro-Pozo 2018a).

The first problems are focused on assigning the set of tasks or operations needed to manufacture the products to the set of workstations that make up the line, in accordance with an optimization criterion. The second ones consist of determining the manufacturing order of product types that make up the production plan, in order to maximize line productivity.

With reference to ALB problems, one realistic variant is the time and space assembly line balancing problem (TSAL-BP) (Bautista and Pereira 2007; Chica et al. 2010). It considers the availability of space in the stations on the line in order to make operations more productive. Further, it makes use of a multi-objective problem definition (Greco 2005) to search for a set of optimal solutions to three optimization criteria: (i) number of stations m , (ii) cycle time c , and (iii) linear area of the workstations A .

However, the latest research does not only include the productive and physical aspects of the assembly line, but also aspects related to:

- Uncertainty in the input attributes of the tasks, such as operation time, caused by defining interval values or by setting different plausible scenarios with a set of possible values for the input attributes depending on historical data (Simaria et al. 2009; Xu and Xiao 2011; Dolgui and Kovalev 2012; Gurevsky et al. 2012, 2013)



¹ Joaquín Bautista-Valhondo
joaquin.bautista@upc.edu

² Rocío Alfaro-Pozo
ralfaro@eae.es

¹ IOC-ETSEIB, Universitat Politècnica de Catalunya, 08028
Barcelona, Spain.

² EAE Business School, 08015 Barcelona, Spain

- The robustness of the assembly line configuration to mitigate the uncertainty defined by a set of possible demand scenarios or different demand plans (Chica et al. 2013, 2016; Li and Gao 2014; Papakostas et al. 2014; Chica et al. 2018)
- Human resources, such as the ergonomic risks or the comfort of the production line (Otto and Scholl 2011; Bautista et al. 2013, Bautista, Batalla-García and Alfaro-Pozo 2016, Bautista, Alfaro-Pozo and Batalla-García 2016; Bortolini 2017; Otto and Battařa 2017; Bautista-Valhondo et al. 2018; Bautista-Valhondo and Alfaro-Pozo 2018b)

In our framework, an ergonomically comfortable assembly line involves setting the maximum risk to a minimum level for any operator from the assembly line, as well as achieving a balanced sharing of ergonomic risks between the set of workstations.

Somatic comfort refers to the set of physical demands to which workers are exposed during the workday. They can potentially cause muscle contractions that then induce chronic pain. There are several methods that analyze different risk factors to evaluate ergonomic risks that include postural loads, repetitive movements, and manual handling.

In response to postural loads, workers may adopt inappropriate, asymmetrical, or uncomfortable postures during the workday. These postures can cause stress to the worker's anatomy. The frequently used methods to analyze these types of ergonomic risk factors include the rapid upper limb assessment or RULA (Manghisi et al. 2017) and the Ovako working posture analysis system or OWAS (Brandl et al. 2017).

Additionally, workers can perform activities that involve effort and rapid or repetitive movements of a muscle group. Repeated movements of the upper limbs can cause long-term musculoskeletal injuries. To assess the ergonomic risk involved in this type of movement, the occupational repetitive action or OCRA checklist (Rosecrance et al. 2017) is frequently used.

In manual handling, some tasks performed by workers involve lifting, moving, pushing, holding, and transporting objects that can cause physical damage. The Revised NIOSH Lifting Equation (Arjmand et al. 2015), from the National Institute for Occupational Safety and Health, is a frequently used method to analyze this risk factor.

When assessing the ergonomic risk in a workstation of an assembly line, one of the main drawbacks is the lack of unification of the disparate methods mentioned above. The specialization of each method to a single muscular disorder complicates the evaluation and designation of an ergonomic level of risk given to a task or set of tasks assigned to an as-

sembly line workstation. For this reason, similar to the work of Bautista, Alfaro-Pozo and Batalla-García (2016), we propose a unified classification of risk levels in four categories:

- Category 1: Acceptable level of risk. No action is required because there is no risk to the worker.
- Category 2: Low/moderate level of risk. An analysis of the workstation is necessary. Corrective actions are recommended for its improvement in the immediate future.
- Category 3: High level of risk. An analysis and improvement of the tasks assigned to the workstation are required immediately, as is medical supervision. Regular medical checks on workers are also recommended.
- Category 4: Unacceptable level of risk. This requires an immediate modification of the workstation, its tasks, and the methods used. The continuity of workers in a job with this category of risk level can lead to serious bodily harm.

Obviously, the evaluation and subsequent assignment of the level of risk (according to these categories) of a specific task with respect to a workstation must be established by an expert with knowledge in ergonomics, as well as the methods and processing times appropriate to the assembly line.

With these considerations in mind, the remainder of this paper is structured as follows: In section 2, we briefly formalize the assembly line balancing problems with temporal, spatial, and ergonomic risk attributes. In section 3, we propose using mixed integer linear programming to model the problems under examination in this study. In section 4, we perform a computational experiment to analyze the behavior of the generated models with the help of a case study on the Nissan plant's engine. Finally, section 5 outlines the conclusions, and proposals for future research.

2 Problems TSALB-erg: TSALB with ergonomic risks

Formalization:

TSALB-erg is a family of ALB problems that establishes a surjective application between the elements of a set J of indivisible tasks (n elements) and the elements of a set K of workstations (m elements, with $\leq n$).

The tasks in group J are classified into exclusive classes called workstations S_k ($S_k \subseteq J$), which satisfy $J = \bigcup_{k \in K} S_k$ and $S_k \cap S_{k'} = \emptyset, \forall \{k, k'\} \in K$. Each task $j \in J$ is assigned to a single workstation $k \in K$, and has a set P_j of direct preceding tasks that must be completed before the task j is started.

Each task $j \in J$ requires a processing time for its execution $t_j > 0$ that is determined as a function of the manufacturing technologies and employed resources. Each station $k \in K$ has a workload time $t(S_k)$ that is equal to the sum of the processing times of its assigned tasks, and cannot exceed the cycle time of the assembly line c .

Each task $j \in J$ requires a linear area calculation that must be performed, that is, $a_j \geq 0$, which is determined as a function of the spatial needs of the workers, robots, and the parts of the product. Each station $k \in K$ has a workload linear area $a(S_k)$ that is equal to the sum of the linear areas of its assigned tasks, and cannot exceed the available space or linear area assigned to each workstation A .

In addition, each task $j \in J$ has an associated ergonomic risk $R_{\phi,j} \geq 0$ that depends on the risk factor $\phi \in \Phi$ and the processing time t_j . Each station $k \in K$ has a workload ergonomic risk $R_\phi(S_k)$ for the factor $\phi \in \Phi$ that is equal to the sum of the ergonomic risks of its assigned tasks, and cannot exceed the maximum ergonomic risk for the risk factor $\phi \in \Phi$, R_ϕ^{\max} .

The purpose of the problems in the TSALB-erg family is to address assigning all tasks to workstations in order to achieve maximum efficiency regarding some of the considered attributes, while all constraints imposed are fulfilled. In this work, we will focus on minimizing the ergonomic risk of the line and its dispersion between workstations. To formalize this purpose, three mathematical models adapted to mixed integer linear programming (MILP) are presented here.

3 MILP models for minimizing the ergonomic risk and its dispersion in lines with fixed number of workstations

There are different ways to address the balancing problem in order to obtain comfortable line configurations in terms of ergonomics.

- Simultaneously minimizing the maximum ergonomic risk and the risk differences between workstations using a multi-objective model
- Prioritizing one objective over the other one
- Solving the problem mono-objectively, and assessing the other objective afterwards

Accordingly, this work addresses three mono-objective mathematical models that aim at minimizing: (i) the average maximum ergonomic risk, (ii) The average absolute deviation of the ergonomic risk, and (iii) the average range of the ergonomic risks of workstations. Thus, the size of the smallest interval that contains all the ergonomic risks of the workstations is measured.

BASIC NOMENCLATURE

Parameters:

J	Set of elemental tasks ($j = 1, \dots, J $); $n = J $
K	Set of workstations ($k = 1, \dots, K $)
Φ	Set of ergonomic risk factors ($\phi = 1, \dots, \Phi $)
t_j	Processing time of the elemental task $j \in J$ at normal activity levels
a_j	Linear area required by the elemental task $j \in J$
$\chi_{\phi,j}$	Category of task $j \in J$ associated with the risk factor $\phi \in \Phi$
$R_{\phi,j}$	Ergonomic risk of task $j \in J$ associated with the risk factor $\phi \in \Phi$, $R_{\phi,j} = t_j \cdot \chi_{\phi,j}$
P_j	Set of direct precedent tasks of task $j \in J$
c	Cycle time: standard time assigned to each station to process its workload (S_k)
m	Number of workstations $m = K $, which is known and fixed
A	Available space or linear area assigned to each workstation
R_ϕ^{med}	Average ergonomic risk for the risk factor $\phi \in \Phi$, $R_\phi^{\text{med}} \equiv 1/m \cdot \sum_{j=1}^{ J } R_{\phi,j}$
R_{med}	Average ergonomic risk of the line or ideal ergonomic risk of each workstation $R_{\text{med}} \equiv 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } R_\phi^{\text{med}}$

Variables:

$x_{j,k}$	Binary variable equal to 1 if the elemental task $j \in J$ is assigned to the workstation $k \in K$, and to 0 otherwise	$\delta_{\phi,k}^+$ Ergonomic risk defect associated with the risk factor $\phi \in \Phi$ at workstation $k \in K$ with respect to the average (ideal) value R_{ϕ}^{med} , $\delta_{\phi,k}^+ = \max\{0, R_{\phi}^{med} - R_{\phi}(S_k)\}$
S_k	Workload of station $k \in K$: set of tasks assigned to $k \in K$: $S_k = \{j \in J : x_{j,k} = 1\}$	
$R_{\phi}(S_k)$	Ergonomic risk for the factor $\phi \in \Phi$ associated with the workload S_k ($k \in K$), $R_{\phi}(S_k) = \sum_{j \in S_k} R_{\phi,j}$	MILP-1 • min R_{max} $\min Z = R_{max} \equiv \frac{1}{ \Phi } \cdot \sum_{\phi=1}^{ \Phi } R_{\phi}^{max}$ (1)
$R(S_k)$	Average ergonomic risk associated with the workload S_k ($k \in K$) with respect to the full set of ergonomic risk factors Φ , $R(S_k) \equiv 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } R_{\phi}(S_k)$	Subject to: $\sum_{k=1}^m x_{j,k} = 1 \quad \forall j = 1, \dots, J $ (2) $\sum_{j=1}^{ J } t_j x_{j,k} \leq c \quad \forall k = 1, \dots, m$ (3) $\sum_{j=1}^{ J } a_j x_{j,k} \leq A \quad \forall k = 1, \dots, m$ (4) $\sum_{k=1}^m k(x_{i,k} - x_{j,k}) \leq 0 \quad \forall \{i, j\} \subseteq J: i \in P_j$ (5) $\sum_{j=1}^{ J } x_{j,k} \geq 1 \quad \forall k = 1, \dots, m$ (6) $R_{\phi}^{max} - \sum_{j=1}^{ J } R_{\phi,j} \cdot x_{j,k} \geq 0 \quad \forall k = 1, \dots, m \quad \forall \phi = 1, \dots, \Phi $ (7) $x_{j,k} \in \{0, 1\} \quad \forall j = 1, \dots, J \quad \forall k = 1, \dots, m$ (8) $R_{\phi}^{max} \geq 0 \quad \forall \phi = 1, \dots, \Phi $ (9)
R_{max}	Average maximum ergonomic risk with respect to the full set of ergonomic risk factors Φ , $R_{max} \equiv 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } R_{\phi}^{max} = 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } \max_{k \in K} R_{\phi}(S_k)$	
R_{ϕ}^{min}	Minimum ergonomic risk for the risk factor $\phi \in \Phi$, $R_{\phi}^{min} = \min_{k \in K} R_{\phi}(S_k)$	
R_{min}	Average minimum ergonomic risk with respect to all sets of ergonomic risk factors Φ , $R_{min} \equiv 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } R_{\phi}^{min} = 1/ \Phi \cdot \sum_{\phi=1}^{ \Phi } \min_{k \in K} R_{\phi}(S_k)$	
$\delta_{\phi,k}^+$	Ergonomic risk excess associated with the risk factor $\phi \in \Phi$ at workstation $k \in K$ with respect to the average (ideal) value R_{ϕ}^{med} , $\delta_{\phi,k}^+ = \max\{0, R_{\phi}(S_k) - R_{\phi}^{med}\}$.	The objective function (1) expresses the minimization of the average maximum ergonomic risk. Constraint (2) forces the assignment of all tasks. Constraints (3) and (4) impose the maximum limitation of the workload time and the maximum linear area allowed by each station. Constraint (5) corresponds to the precedence task bindings, while constraint (6) ensures that there are no empty workstations. Constraint (7) determines the maximum ergonomic risk associated with the workload at each workstation and with each ergonomic factor analyzed. Finally, constraints (8) and (9) necessitate that the assigned variables be binary and the maximum ergonomic risk variables for the risk factors be non-negative.

3.2 Model for minimizing the average absolute deviation of ergonomic risk

MILP-2 • min $AAD(R)$:

$$\min Z = \frac{1}{m|\Phi|} \sum_{\phi=1}^{|\Phi|} \sum_{k=1}^m (\delta_{\phi,k}^+ + \delta_{\phi,k}^-) \quad (10)$$

Subject to:

$$\sum_{k=1}^m x_{j,k} = 1 \quad \forall j = 1,..,|J| \quad (11)$$

$$\sum_{j=1}^{|J|} t_j x_{j,k} \leq c \quad \forall k = 1,..,m \quad (12)$$

$$\sum_{j=1}^{|J|} a_j x_{j,k} \leq A \quad \forall k = 1,..,m \quad (13)$$

$$\sum_{k=1}^m k(x_{i,k} - x_{j,k}) \leq 0 \quad \forall \{i,j\} \subseteq J: i \in P_j \quad (14)$$

$$\sum_{j=1}^{|J|} x_{j,k} \geq 1 \quad \forall k = 1,..,m \quad (15)$$

$$\sum_{j=1}^{|J|} R_{\phi,j} \cdot x_{j,k} = R_{\phi}^{med} + \delta_{\phi,k}^+ - \delta_{\phi,k}^- \quad \forall k = 1,..,m \quad \forall \phi = 1,..,|\Phi| \quad (16)$$

$$x_{j,k} \in \{0,1\} \quad \forall j = 1,..,|J| \quad \forall k = 1,..,m \quad (17)$$

$$\delta_{\phi,k}^+, \delta_{\phi,k}^- \geq 0 \quad \forall k = 1,..,m \quad \forall \phi = 1,..,|\Phi| \quad (18)$$

In the MILP-2 (min $AAD(R)$) model, it is obvious that the constraint blocks (11)–(15) and (17) consecutively match formulas (2)–(6) and (8) of the MILP-1 (min R_{max}) model. The changes that are added by considering the absolute deviations are:

- The objective function (10) expresses the minimization of the average absolute deviation of the ergonomic risk with respect to the average ergonomic risk of the line
- Restriction (16) determines the ergonomic risk excess and defect associated with the risk factor $\phi \in \Phi$ at workstation $k \in K$ with respect to the ideal value R_{ϕ}^{med}
- Condition (18) forces the deviation variables $(\delta_{\phi,k}^+, \delta_{\phi,k}^-)$ to be non-negative

3.3 Model for minimizing the average range of the ergonomic risk

MILP-3 • min $AR(R)$:

$$\min Z = \frac{1}{|\Phi|} \cdot \sum_{\phi=1}^{|\Phi|} (R_{\phi}^{max} - R_{\phi}^{min}) \quad (19)$$

Subject to:

$$\sum_{k=1}^m x_{j,k} = 1 \quad \forall j = 1,..,|J| \quad (20)$$

$$\sum_{j=1}^{|J|} t_j x_{j,k} \leq c \quad \forall k = 1,..,m \quad (21)$$

$$\sum_{j=1}^{|J|} a_j x_{j,k} \leq A \quad \forall k = 1,..,m \quad (22)$$

$$\sum_{k=1}^m k(x_{i,k} - x_{j,k}) \leq 0 \quad \forall \{i,j\} \subseteq J: i \in P_j \quad (23)$$

$$\sum_{j=1}^{|J|} x_{j,k} \geq 1 \quad \forall k = 1,..,m \quad (24)$$

$$R_{\phi}^{max} - \sum_{j=1}^{|J|} R_{\phi,j} \cdot x_{j,k} \geq 0 \quad \forall k = 1,..,m \quad \forall \phi = 1,..,|\Phi| \quad (25)$$

$$R_{\phi}^{min} - \sum_{j=1}^{|J|} R_{\phi,j} \cdot x_{j,k} \leq 0 \quad \forall k = 1,..,m \quad \forall \phi = 1,..,|\Phi| \quad (26)$$

$$x_{j,k} \in \{0,1\} \quad \forall j = 1,..,|J| \quad \forall k = 1,..,m \quad (27)$$

$$R_{\phi}^{max}, R_{\phi}^{min} \geq 0 \quad \forall \phi = 1,..,|\Phi| \quad (28)$$

In the MILP-3 (min $AR(R)$) model, the constraint blocks (20)–(25) and (27) consecutively match formulas (2)–(8) of the MILP-1 (min R_{max}) model. The changes that are added by considering the range of the ergonomic risks are:

- The objective function (19) expresses the minimization of the average range of the ergonomic risks of workstations, that is, $R_{max} - R_{min}$
- Restriction (26) determines the minimum ergonomic risk associated with the workload at each workstation and with each ergonomic factor analyzed
- Condition (28) forces the maximum and minimum ergonomic risk variables for the risk factors to be non-negative

4 Computational experiment

4.1 Data

The computational experience is focused on analyzing the performance of the mathematical model proposed in this work, MILP-3, against the mathematical models MILP-1 and MILP-2 proposed in Bautista et al. (2016b).

Like Bautista et al. (2016a, b), the analysis depends on a case study from Nissan's plant in Barcelona, which has an assembly line wherein nine types of engines—grouped into three families (SUVs - sport utility vehicles, vans, and trucks)—are assembled with a cycle time of 180 seconds. Figure 1 shows an M1 type engine that belongs to the SUVs - sport utility vehicles family.

The assembly line features are as follows:

- Number of workstations: $|K| \equiv m$; $m = \{19,20,21,22,23,24,25\}$.

- Number of elemental tasks (see Appendix A): $|J| = 140$ ($j = 1, \dots, 140$).
- Cycle time: $c = 180$ s.
- Available linear area by workstation: $A = \{4,5,10\}$ meters.
- Number of risk factors: $|\Phi|=1$ ($\phi = 1$).
- Number of demand plans $|E|=1$. Demand plan $\varepsilon = 1$ (Bautista, Batalla-García and Alfaro-Pozo 2016). Table 4 shows the elemental tasks and subsets of immediate precedent tasks. Table 5 shows the processing time of tasks, the linear area required by the tasks, and the category of tasks associated with the risk factors.

Daily demand: $T \equiv D_\varepsilon = 270$ engines ($\varepsilon = 1$).

Figure 1 Nissan Pathfinder Engine.

Characteristics: (i) 747 parts and 330 references (ii) 378 elemental assembly tasks grouped into 140 production line tasks.



4.2 Procedures

The compiled codes for the procedures involved were executed on a DELL Inspiron-13 (Intel(R) Core(TM) i7-7500U @ 2.70 GHz CPU 2.90 GHz, 16 GB of RAM, x64 Windows 10 Pro) using IBM ILOG CPLEX solver (Optimization Studio v.12.2, win-x86-64). The characteristics of the three procedures are:

- MILP-1 (min R_{max}) model: (i) Objective function that minimizes the average maximum ergonomic risk of workstations of the assembly line in accordance with the risk factors and without considering the risk dispersion between stations
- MILP-2 (min $AAD(R)$): (i) Objective function addressed to equally allocate the risk between all workstations by minimizing the average absolute deviations from risks of workstations and without considering the maximum risk minimization
- MILP-3 (min $AR(R)$): (i) Objective function addressed to the minimization of the average range of the

ergonomic risks of workstations and without considering the maximum risk minimization

The common characteristics of the three procedures are: (i) maximum CPU time available to run each demand plan equal to 1,000 seconds; and (ii) 21 executions: seven possible values for m (19...,25), and three for A (4, 5, 10).

4.3 Results

Table 1 shows the best results with respect to the average maximum ergonomic risk R_{max} from MILP-1, MILP-2, and MILP-3, for the 21 data sets of the problem $\theta \in Z$; the winning algorithm for each data set is highlighted; and the unity gains of MILP-3 against MILP-1 ($\Delta M3vM1$), MILP-3 against MILP-2 ($\Delta M3vM2$), and MILP-1 against MILP-2 ($\Delta M1vM2$), which are determined as follows (29).

$$\Delta P_v P'(\theta) = \frac{R_{\max} P'(\theta) - R_{\max} P(\theta)}{\min(R_{\max} P'(\theta), R_{\max} P(\theta))} \quad (29)$$

$\forall \theta \in Z, \forall P \in \{\text{MILP-3, MILP-1}\}, \forall P' \in \{\text{MILP-1, MILP-2}\}$

Table 1 R_{max} value for each data set $\theta \in Z$ in accordance with the different procedures (MILP-1, 2, and 3). Unity gain between pairs of procedures ($\Delta M3vM1, \Delta M3vM2, \Delta M1vM2$), best solution BS, and winner procedure.

$\theta \in Z$	R_{max} : Average maximum ergonomic risk				$\Delta P_v P'(\theta)$: Gain P versus P'				Winner
	m/A	MILP-1	MILP-2	MILP-3	M3vM1	M3vM2	M1vM2	BS	
19/4	-	-	-	-	-	-	-	Infeasible	-
19/5	375	390	375	0.00	0.04	0.04	375	M1-M3	
19/10	355	375	350	0.01	0.07	0.06	350	M3	
20/4	-	-	-	-	-	-	-	Infeasible	-
20/5	340	420	340	0.00	0.24	0.24	340	M1-M3	
20/10	325	335	315	0.03	0.06	0.03	315	M3	
21/4	-	450	405	-	0.11	-	405	M3	
21/5	310	320	310	0.00	0.03	0.03	310	M1-M3	
21/10	315	300	305	0.03	-0.02	-0.05	300	M2	
22/4	-	420	345	-	0.22	-	345	M3	
22/5	300	315	300	0.00	0.05	0.05	300	M1-M3	
22/10	285	285	290	-0.02	-0.02	0.00	285	M1-M2	

23/4	-	435	325	-	0.34	-	325	M3
23/5	280	280	275	0.02	0.02	0.00	275	M3
23/10	278	280	275	0.01	0.02	0.01	275	M3
24/4	300	320	300	0.00	0.07	0.07	300	M1-M3
24/5	275	281	270	0.02	0.04	0.02	270	M3
24/10	265	260	265	0.00	-0.02	-0.02	260	M2
25/4	280	-	-	-	-	-	280	M1
25/5	285	255	255	0.12	0.00	-0.12	255	M2-M3
25/10	255	255	270	-0.06	-0.06	0.00	255	M1-M2
Average				0.011	0.066	0.024		

From Table 1 we can conclude the following points about the average from the maximum ergonomic risk of the assembly line:

- No procedure guarantees optimal solutions within a time limit of 1,000 seconds.
- No procedure gives a solution for assembly lines with 19 and 20 workstations and an available area of 4 meters. IBM ILOG CPLEX solver proves that instances 19/4 and 20/4 are infeasible within a time limit of 1,000 seconds.
- MILP-1 also does not give solution when the assembly line has 21, 22 and 23 workstations and 4 meters within a time limit of 1,000 seconds. MILP-2 and MILP-3 do not give solution when the assembly line has 25 workstations and 4 meters within a time limit of 1,000 seconds.
- MILP-3 is the winner with respect to the number of best solutions, with 14 successes out of 21 instances; MILP-1 is in the second position with 8 best solutions, and lastly, MILP-2 with five successes.
- MILP-3 is also the winning procedure with respect to the unity gain. The overall average unity gain of MILP-3 against MILP-1 and MILP-2 is 1.12% and approximately 6.62%, respectively. Under this criterion, MILP-2 is the procedure with the worst results. Indeed, MILP-1 overtakes MILP-2 with an overall average unity gain of 2.36%.

- Comparing MILP-3 with MILP-1, the former wins in seven instances, loses in two, and ties in six, considering the 15 cases in which MILP-1 or MILP-3 give a solution. However, the unity gains of one procedure against the other one are similar—3.49% when MILP-3 wins, and 3.82% when MILP-1 is the winner.
- MILP-3 wins against MILP-2 in 13 cases, loses in 4 instances, and ties in 1 instance, considering the 18 cases in which these give solutions. The average gain of MILP-3 against MILP-2 is 10.02%, and the average loss is 2.81%.
- MILP-1 wins in nine instances, loses in three, and ties in three cases in a comparison of its results with those given by MILP-2, considering the 15 cases in which MILP-1 or MILP-2 give a solution. Specifically, MILP-1 improves on solutions from MILP-2 by 6.0%, but when it loses, solutions become worse by 6.23%, in terms of average unity gain.

In order to measure the ergonomic risk dispersion between stations, we use the standard deviation from the set of values (S_k) ($\forall k \in K$), that is, $SD(R(S_k))$.

$$SD(R(S_k)) = \sqrt{\frac{1}{m} \cdot \sum_{k=1}^m (R(S_k) - R_{med})^2} \quad (30)$$

Additionally, the relative standard deviation (*RSD*) is also used to compare the quality of solutions given by a pair of procedures (*P* versus *P'*), that is, $RSD(PvP'(\theta))$.

$$RSD(PvP'(\theta)) \equiv \frac{SD(R(S_k))_{P'}(\theta) - SD(R(S_k))_P(\theta)}{R_{med}(\theta)} \quad (31)$$

$\forall \theta \in Z, \forall P \in \{\text{MILP-3, MILP-1}\}, \forall P' \in \{\text{MILP-1, MILP-2}\}$

Table 2 shows best results with respect to the standard deviation from the average ergonomic risk associated with the workstations.

In accordance with the *RSD* values (Table 2), we can state the following:

- IBM ILOG CPLEX solver proves that instances 19/4 and 20/4 are infeasible within a time limit of 1,000 seconds.
- MILP-2 is the winning procedure in terms of best *RSD* value. Indeed, considering all instances, MILP-2 achieves 14 best solutions, MILP-3 achieves another four and MILP-1 gets 1 better solution.

- MILP-2 also wins in terms of average *RSD* gain. The overall average gain of MILP-2 against MILP-3 and MILP-1 is 0.64% and 3.75%, respectively. MILP-1 is the loser, as MILP-3 improves on its results by 3.01%.
- MILP-2 improves results given by MILP-1 in 15 instances out of 15. The *RSD* average gain when MILP-2 wins against MILP-1 is 3.75%.
- MILP-3 obtains 12 best solutions and three worst solutions against MILP-1. MILP-3 improves on solutions given by MILP-1 an average gain of 3.94%, while MILP-1 improves results from MILP-3 by 0.71%, when it gives better solutions than MILP-3.

- Conversely, MILP-3 gets worse solutions than MILP-2 in 14 instances and wins in four cases. However, the differences between their respective *RSD* average gains are not so relevant—1.95% when MILP-3 wins against MILP-2, and 1.38% in the opposite case.

Table 2 $SD(R(S_k))$ values per procedure and instance $\theta \in Z$ (MILP-1, MILP-2, MILP-3)). RSD differences between pairs of procedures ($RSD(M3vM1, M3vM2, M1vM2)$), best solution BS, and winner procedure.

$\theta \in Z$	$SD(R(S_k))$				$RSD(PvP'(\theta))$: Gain <i>P</i> versus <i>P'</i>					
	<i>m/A</i>	MILP-1	MILP-2	MILP-3	R_{med}	M3vM1	M3vM2	M1vM2	BS	Winner
19/4	-	-	-	-	323.4	-	-	-	Infeasible	-
19/5	54.56	42.96	46.28	323.4	0.03	-0.01	-0.04	42.96	M2	
19/10	38.53	19.33	26.31	323.4	0.04	-0.02	-0.06	19.33	M2	
20/4	-	-	-	307.3	-	-	-	Infeasible	-	
20/5	43.57	37.32	30.09	307.3	0.04	0.02	-0.02	30.09	M3	
20/10	23.81	10.17	8.43	307.3	0.05	0.01	-0.04	8.43	M3	
21/4	-	71.70	84.07	292.6	-	-0.04	-	71.70	M2	
21/5	29.07	19.67	19.82	292.6	0.03	-0.00	-0.03	19.67	M2	
21/10	25.19	5.29	6.83	292.6	0.06	-0.01	-0.07	5.29	M2	
22/4	-	57.71	59.35	279.3	-	-0.01	-	57.71	M2	
22/5	16.79	12.83	18.07	279.3	-0.00	-0.02	-0.01	12.83	M2	
22/10	5.03	4.56	7.84	279.3	-0.01	-0.01	-0.00	4.56	M2	

23/4	-	59.27	47.35	267.2	-	0.04	-	47.35	M3
23/5	15.23	7.16	6.07	267.2	0.03	0.00	-0.03	6.07	M3
23/10	9.62	6.75	6.88	267.2	0.01	-0.00	-0.01	6.75	M2
24/4	47.07	38.40	43.12	256.0	0.02	-0.02	-0.03	38.40	M2
24/5	16.19	7.49	9.52	256.0	0.03	-0.01	-0.03	7.49	M2
24/10	10.51	3.13	6.41	256.0	0.02	-0.01	-0.03	3.13	M2
25/4	32.41	-	-	245.8	-	-	-	32.41	M1
25/5	35.46	5.20	6.19	245.8	0.12	-0.00	-0.12	5.20	M2
25/10	11.35	4.96	13.02	245.8	-0.01	-0.03	-0.03	4.96	M2
Average					0.030	-0.006	-0.038		

Finally, we used the average range of the ergonomic risks of workstations in order to measure the ergonomic risk dispersion between stations in a different way, that is, $AR(R)$.

$$AR(R) \equiv R_{\max} - R_{\min} = \frac{1}{|\Phi|} \cdot \sum_{\phi=1}^{|\Phi|} (R_{\phi}^{\max} - R_{\phi}^{\min}) \quad (32)$$

The unity gains to compare the quality of solutions given by a pair of procedures (P versus P') are determined as follows (33).

$$AR(PvP'(\theta)) = \frac{AR(P_{\theta}) - AR(P'_{\theta})}{\min(AR(P_{\theta}), AR(P'_{\theta}))} \quad (33)$$

$\forall \theta \in Z, \forall P \in \{MILP-3, MILP-1\}, \forall P' \in \{MILP-1, MILP-2\}$

Table 3 $AR(R)$ value for each data set $\theta \in Z$ in accordance with the different procedures (MILP-1, 2, and 3). Unity gain $AR(PvP'(\theta))$ between pairs of procedures (M3vM1, M3vM2, M1vM2), best solution BS, and winner procedure.

$\theta \in Z$	AR(R): Average Range				AR($PvP'(\theta)$): Gain P versus P'				
	m/A	MILP-1	MILP-2	MILP-3	M3vM1	M3vM2	M1vM2	BS	Winner
19/4	-	-	-	-	-	-	-	Infeasible	-
19/5	175	150	125	0.40	0.20	-0.17	125	M3	
19/10	135	90	70	0.93	0.29	-0.50	70	M3	
20/4	-	-	-	-	-	-	-	Infeasible	-
20/5	180	200	90	-	1.22	0.11	90	M3	
20/10	95	50	30	2.17	0.67	-0.90	30	M3	
21/4	-	290	245	-	0.18	-	245	M3	
21/5	135	84	60	1.25	0.40	-0.61	60	M3	
21/10	85	16	20	3.25	-0.25	-4.31	16	M2	

22/4	-	270	185	-	0.46	-	185	M3
22/5	60	75	50	0.20	0.50	0.25	50	M3
22/10	15	15	20	-0.33	-0.33	0.00	15	M1-M2
23/4	-	285	165	-	0.73	-	165	M3
23/5	60	32	25	1.40	0.28	-0.88	25	M3
23/10	43	25	20	1.15	0.25	-0.72	20	M3
24/4	170	220	140	0.21	0.57	0.29	140	M3
24/5	65	36	25	1.60	0.44	-0.81	25	M3
24/10	45	10	20	1.25	-1.00	-3.50	10	M2
25/4	150	-	-	-	-	-	150	M1
25/5	115	15	15	6.67	0.00	-6.67	15	M2-M3
25/10	40	19	40	0.00	-1.11	-1.11	19	M2
Average				1.409	0.194	-1.300		

Table 3 shows best results with respect to the average range of ergonomic risk $AR(R)$. From Table 3 we can conclude the following:

- IBM ILOG CPLEX solver proves that instances 19/4 and 20/4 are infeasible within a time limit of 1,000 seconds.
- MILP-3 is the winner with respect to the number of best solutions, with 14 successes; MILP-2 is in the second position with five best solutions, and is followed by MILP-1 with two successes.
- MILP-3 is also the outstanding winner with respect to the unity gain of average range of ergonomic risk. The overall average unity gain of MILP-3 is 140.95% over MILP-1, and 19.43% over MILP-2. Under this criterion, MILP-1 is the procedure with the worst results because MILP-2 wins against MILP-1 with an overall average unity gain of 130.02%.
- Comparing MILP-3 with MILP-1, the former wins in 13 instances, loses in 1 instance, and ties in one, considering the 15 cases in which MILP-1 or MILP-3 give a solution. MILP-3's unity gain over MILP-2 is 165.20% and MILP-2's unity gain over MILP-3 is 33.33%.
- MILP-3 wins against MILP-2 in 13 cases, loses in four, and ties in one instance, considering the 18 cases in which these give solutions. The average gain of MILP-

3 against MILP-2 is 47.59% and the average loss is 67.21%.

- MILP-2 wins in 11 instances, loses in three, and ties in one case in a comparison of its results with those given by MILP-1. Specifically, MILP-2 improves solutions from MILP-1 by 183.26%, but when it loses, solutions become worse by 21.84%, in terms of average unity gain.

5 Conclusions

In this work, we proposed a MILP solution to solve a mixed-model assembly line problem with the objective of balancing the ergonomic risk for the operators. The proposed model is focused on minimizing the average range of ergonomic risk of the assembly line.

The new model, MILP-3, was evaluated through a case study. This case study, based on an assembly line from Nissan's engine plant in Barcelona, was also used to assess the MILP-1 and MILP-2 models that are the frame of reference for this work.

Specifically, the computational experience was to obtain different line configurations in accordance with different values for the number of workstations and the maximum available area. The variety of attributes of the production line has allowed us to assess the quality of procedures with respect to three metrics: (i) the average maximum ergonomic risk of

workstations of the assembly line, (ii) the relative standard deviation from the different risk levels between stations, and (iii) the average range of ergonomic risks.

The assessment shows MILP-3 as the most promising procedure, obtaining, on average, a percentage gain from MILP-1 by 1.12%, 3.01%, and 140.95%, according to the three metrics. In addition, MILP-3 improves the results from MILP-2 by 6.62% in terms of average maximum ergonomic risk and 19.43% in terms of average range of ergonomic risk; MILP-3 almost equals the results from MILP-2 if we consider the criterion of relative standard deviation (-0.64%). Obviously, MILP-1, wherein the objective is to minimize the average maximum ergonomic risk, cannot compete against the other procedures with respect to the minimization of ergonomic dispersion.

In future works, we will attempt to formulate new models and procedures for maximizing the productivity of assembly lines with restrictions on both the maximum ergonomic risk and linear area.

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Appendix A

Table 4 Instance $\varepsilon = 1$ from the Nissan-9Eng's Set of Demand Plans: Set of elemental tasks ($j = 1, \dots, 140$), and subsets of immediate precedent tasks of task j : P_j ($j = 1, \dots, |J|$).

$j \in J$	Precedent tasks: P_j	$j \in J$	Precedent tasks: P_j	$j \in J$	Precedent tasks: P_j
1	-	48	46	95	94
2	3, 31	49	42, 43	96	93, 95, 99
3	1	50	47, 48, 49	97	93, 95, 99
4	3, 5	51	47, 48, 49	98	92
5	1	52	47, 48, 49	99	89, 90, 91
6	4, 5	53	47, 48, 49	100	98, 99
7	1	54	47, 48, 49	101	98, 99
8	1	55	47, 48, 49	102	100, 101
9	1	56	47, 48, 49	103	100, 101
10	1	57	50, 51, 52, 53, 54, 55, 56	104	102, 103
11	1	58	57, 59, 60	105	106
12	11	59	41	106	100, 101
13	1	60	42, 43	107	100, 101, 104
14	1, 13	61	57, 58	108	100, 101, 104
15	9, 10, 11, 13, 14	62	61	109	108
16	9, 10, 11, 13, 14	63	57	110	108
17	9, 10, 11, 13, 14	64	57	111	11, 109
18	9, 10, 11, 13, 14	65	61, 62, 63, 64	112	11, 109
19	9, 10, 11, 13, 14	66	61, 62, 63, 64	113	108
20	9, 10, 11, 13, 14	67	66	114	113
21	9, 10, 11, 13, 14	68	65, 67	115	113
22	26, 27	69	68	116	111, 112, 114, 115
23	26, 27	70	67	117	118
24	26, 27	71	68	118	116
25	26, 27	72	68	119	116

26	15, 16, 17, 18, 19, 20, 21	73	71, 72	120	119
27	15, 16, 17, 18, 19, 20, 21	74	68, 69, 70, 73	121	105, 107, 117, 120
28	22, 23, 24, 25	75	74	122	121
29	28	76	74	123	122
30	29	77	75	124	123
31	6, 7, 8, 30	78	79	125	124
32	31	79	74	126	125
33	32	80	76, 77, 78	127	126
34	32	81	76, 77, 78	128	12, 117
35	36	82	80, 81	129	126
36	32	83	82	130	127, 128, 129
37	32, 35	84	83	131	12, 117
38	33, 34, 36, 37	85	75, 84	132	131
39	33, 34, 36, 37	86	82	133	130
40	33, 34, 36, 37	87	82	134	132
41	38, 39, 40	88	84	135	134
42	38, 39, 40	89	88	136	135
43	38, 39, 40	90	88	137	136
44	41, 42, 43	91	85, 86, 87, 88	138	136
45	41, 42, 43	92	89, 90, 91	139	137, 138
46	44, 45	93	92	140	133, 139
47	46	94	89, 90, 91		

Table 5 Instance $\varepsilon = 1$ from the Nissan-9Eng's Set of Demand Plans: Elemental tasks ($j = 1, \dots, 140$), processing time of tasks (t_j), linear area required by the tasks (a_j), and category of tasks ($\chi_{\phi,j}$) associated with the risk factor ϕ .

$j \in J$	t_j	a_j	$\chi_{\phi,j}$	$j \in J$	t_j	a_j	$\chi_{\phi,j}$	$j \in J$	t_j	a_j	$\chi_{\phi,j}$
1	60.00	300	1	48	35.00	50	3	95	20.00	50	3
2	75.00	200	2	49	5.00	50	3	96	10.00	50	3
3	20.00	50	1	50	15.00	50	3	97	5.00	50	3
4	60.00	100	1	51	25.00	0	3	98	80.00	0	2
5	20.00	50	1	52	30.00	0	3	99	30.00	0	3
6	60.00	150	1	53	15.00	0	3	100	10.00	50	2
7	45.00	100	2	54	15.00	0	3	101	10.00	50	2
8	10.00	50	2	55	20.00	0	3	102	20.00	50	2
9	20.00	50	2	56	10.00	0	3	103	30.00	50	2
10	30.00	50	2	57	10.00	50	3	104	5.00	0	3
11	15.00	50	2	58	20.00	50	2	105	30.00	50	2
12	15.00	50	2	59	5.00	0	3	106	25.00	50	2
13	15.00	100	1	60	20.00	50	3	107	5.00	0	3
14	10.00	50	2	61	45.00	100	2	108	5.00	0	2
15	8.00	100	2	62	30.00	50	2	109	5.00	50	2
16	8.00	50	2	63	30.00	50	2	110	5.00	0	2
17	80.00	100	2	64	10.00	50	2	111	10.00	0	2
18	40.00	50	2	65	5.00	0	2	112	10.00	0	2
19	5.00	50	2	66	10.00	50	2	113	15.00	50	2
20	5.00	50	2	67	15.00	50	2	114	20.00	0	2
21	5.00	50	2	68	60.00	150	2	115	20.00	0	2
22	7.00	50	2	69	10.00	50	2	116	45.00	100	2
23	7.00	50	2	70	30.00	100	2	117	20.00	50	2
24	30.00	50	2	71	10.00	50	2	118	25.00	0	2
25	30.00	50	2	72	10.00	50	2	119	25.00	0	2
26	5.00	50	2	73	40.00	150	2	120	20.00	50	2

27	5.00	50	2	74	25.00	50	2	121	45.00	150	2
28	30.00	100	2	75	10.00	50	2	122	15.00	50	1
29	10.00	50	2	76	10.00	100	2	123	10.00	50	1
30	15.00	100	2	77	15.00	50	2	124	10.00	0	1
31	10.00	0	2	78	15.00	50	2	125	20.00	100	1
32	15.00	50	2	79	15.00	50	2	126	30.00	50	2
33	30.00	100	3	80	10.00	50	2	127	10.00	50	2
34	10.00	50	3	81	10.00	100	2	128	25.00	50	2
35	5.00	50	3	82	10.00	0	2	129	30.00	50	2
36	25.00	100	2	83	20.00	50	2	130	30.00	75	2
37	15.00	0	3	84	10.00	0	2	131	40.00	50	2
38	5.00	50	3	85	20.00	50	3	132	25.00	100	1
39	5.00	50	3	86	25.00	50	2	133	25.00	50	1
40	5.00	50	3	87	20.00	50	2	134	20.00	50	1
41	60.00	50	3	88	15.00	25	3	135	15.00	50	1
42	15.00	150	3	89	20.00	50	3	136	20.00	50	1
43	15.00	150	3	90	30.00	50	3	137	30.00	50	2
44	25.00	50	3	91	20.00	50	3	138	30.00	50	2
45	25.00	50	3	92	25.00	50	3	139	15.00	100	2
46	5.00	50	3	93	10.00	50	3	140	120.00	0	1
47	35.00	50	3	94	5.00	50	3				