Minimizing the ergonomic risk and its dispersion in a mixed model assembly line using GRASP

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Abstract

This work addresses a balancing problem approach whose objective is to minimizing the ergonomic risk dispersion between the set of workstations of a mixed-model assembly line and the risk level of the workstation with the greatest hazard. A GRASP procedure is proposed to achieve these two challenges simultaneously. This new procedure is compared with two Mixed Integer Linear Programs, the MILP-1 that minimizes the maximum ergonomic risk of the assembly line, and the MILP-2 that minimizes the average deviation from ergonomic risks of the set of workstations of the line. The results from the case study linked with the automotive sector indicate that the proposed GRASP is a very competitive and promising tool for further researches.

Keywords: GRASP; Assembly line balancing; Ergonomic risk; Linear Area.

1 Introduction

Assembly Line Balancing Problems have been widely studied in scientific literature [1]. So much so that the problem has been categorized according to the restrictions imposed by line features [2]. This type of problems arises from dividing all tasks or operations that are necessary to assemble or disassemble among the set of workstations in series that make up the line. The assignment of tasks to workstations must satisfy line's constraints and optimize some performance measure. For example, the simplest category of problems, which is named Simple Assembly Line Balancing Problem (SALBP) only considers cumulative constraints that are associated with the available work time at workstations (i.e. cycle time) and precedence constraints that are established by the order in which tasks should be implemented. Accordingly, the problems type SALBP focuses on optimizing the number of workstations, the cycle time, or both, according to the problem type.

On the other hand, there are other families of problems that consider more attributes of the line when addressing the task assignment. One recent example is the family of problems known in the literature as the Time and Space Assembly Line Problems with Ergonomics (TSALBP_erg) [3].

The TSALBP_erg family focuses not only on balancing the line according with economic and managerial aspects such as the cycle time, the number of workstations and the spatial area required by workload of workstations, but also on the ergonomic aspect. This ergonomic balance of the line means assessing all elements that could give rise to an ergonomic risk for the operator; among them there are: the operator's dimensions, the physical and mental conditions of operator, the required movements, the necessary tools, the required force, the processing time of task, the vibrations, the temperature, etc. As a result, the TSALBP_erg can be defined by the following three elements and their characteristics or attributes:

1. The set of tasks needed to assembly or disassembly a product. The tasks, in turn, entails a set of attributes that must be also considered:
    a. The temporal attribute linked with the processing time of tasks or operations.
    b. The spatial attribute linked with the area that is necessary to carry out each task.
    c. The ergonomic attribute linked with the ergonomic risk level that each task involves.
2. The set of workstations of the line, which can be finite or infinite.
3. The set of sequencing constraints such as the precedence relationships between tasks, incom-

patibility between tasks, and restrictions that may affect the workstations in regard with their assignable time, their available area, and their admissible risk.

Like SALBP and TSALBP families [4], the TSALBP_erg family focuses on assigning all tasks to workstations in order to achieving the maximum efficiency regarding some of the considered attributes while all constraints imposed are fulfilled. Accordingly, this family of problems also comprises a set of problem types according to the optimization criteria.

One of the first approaches consisted of introducing the ergonomic concept through a new constraint for limiting maximum and minimum ergonomic risks while the number of workstations, the cycle time or the spatial area were optimized [5]. Secondly, the ergonomic risk was incorporated into the problem through the objective function. In this case the objective problem was minimizing the maximum ergonomic risk associated with the workload of workstations [6]. After, a new mathematical model was proposed in order to reduce differences between workstations. Specifically, the new model minimized the average absolute deviation from the ergonomic risks of the set of workstations [7].

In line with the previous researches [6],[7], this work presents a new non-exact procedure with the aim of ensuring that the assembly line involves the lowest possible level of risk for operators and the most balanced risk distribution among the set of workstations. Specifically, the proposed approach considers two hierarchized objectives: (1) the minimization of the maximum ergonomic risk of the assembly line; and (2) the minimization of the standard deviation from ergonomic risks of the line, which is contingent upon the first.

Besides, given the variety of resolution procedures for balancing problems, in this work we solve the problem with two different resolution approaches; the Mixed Integer Linear Programming (MILP), and a new Greedy Randomized Adaptive Search Procedure (GRASP). This type of algorithms [8] has been widely used in combinatorial optimization problems with diverse applications [9]. Indeed the proposed problem combines the necessary qualities for its use: first, because the line balancing involves a sequence of decisions on the assignment of a set of tasks; and secondly, because it is a procedure highly competitive in time against other metaheuristcs and other exact procedures, such as MILP.

The remainder of the work is organized as follows. In the next section we outline the mathematical model for the problem. The proposed GRASP is described in Section 3. Section 4 assesses the two resolution procedures though a case study and, finally, we conclude in Section 5.

2 Mathematical model: min *R_SD(R)*

An assembly line is ergonomically comfortable whether it presents the lowest possible ergonomic risk at any of its workstations and the lesser difference between the ergonomic risk levels of workstations. Therefore, it is possible to obtain ergonomically comfortable line configurations by solving the assembly line balancing problem in different ways.

- Minimizing both objectives simultaneously.
- Putting one objective second to the other.
- Solving the problem mono-objective and determining the other objective after.

Accordingly the second way, and taking as reference the previous work [10], a mathematical model to minimize firstly the maximum ergonomic risk of the line and secondly the ergonomic risk dispersion between workstations is presented. Specifically, the ergonomic risk dispersion is measured through the standard deviation, unlike [10] where the average absolute deviation was considered. The parameters, variables and the mathematical model formulation are the following:

Parameters	
J	Set of elemental tasks $(j = 1, \dots, \lvert J \rvert)$.
K	Set of workstations $(k = 1, \dots, \lvert K \rvert)$
Φ	Set of ergonomic risk factors $(\phi = 1, \dots, \lvert \Phi \rvert)$.
t_j	Processing time of elemental task $(j = 1, \dots, \lvert J \rvert)$ at normal activity.
a_j	Linear area required by the elemental task $(j = 1, \dots, \lvert J \rvert)$.
$\chi_{\phi,j}$	Category of task j $(j = 1, \dots, \lvert J \rvert)$ associated with the risk factor ϕ $(\phi = 1, \dots, \lvert \Phi \rvert)$.

$R_{\phi,j}$	Ergonomic risk of task j ($j = 1, \dots, \lvert J \rvert$) associated with the risk factor ϕ ($\phi = 1, \dots, \lvert \Phi \rvert$). Here: $R_{\phi,j} = t_j \cdot \chi_{\phi,j}$.
P_j	Set of direct precedent tasks of task j ($j = 1, \dots, \lvert J \rvert$).
c	Cycle time. Standard time assigned to each station to process its workload (S_k).
m	Number of workstations, $m = \lvert K \rvert$, that is known and fixed.
A	Available space or linear area assigned to each workstation.
R_ϕ^{med}	Average ergonomic risk present at each workstation regarding the risk factor $\phi \in \Phi$. That is: $R_\phi^{med} = \frac{1}{\lvert K \rvert} \sum_{j=1}^{\lvert J \rvert} R_{\phi,j}, \forall \phi \in \Phi$.

Variables	
$x_{j,k}$	Binary variable equal to 1 if the elemental task j ($j = 1, \dots, \lvert J \rvert$) is assigned to the workstation k ($k = 1, \dots, \lvert K \rvert$), and to 0 otherwise.
R_ϕ	Maximum ergonomic risk for the risk factor ϕ ($\phi = 1, \dots, \lvert \Phi \rvert$).
$\bar{R}(\phi)$	Average maximum ergonomic risk associated with the set of factors Φ.
S_k	Workload of station K. Set of tasks assigned to the station $k \in K: S_k = \{ j \in J : x_{j,k} = 1 \}$.
$R_\phi(S_k)$	Ergonomic risk for the factor $\phi \in \Phi$ associated with the workload: $S_k: R_\phi(S_k) = \sum_{j \in S_k} R_{\phi,j}$.

min *R_SD(R)* Model:

$$\min \mathcal{R}(\Phi, K) \equiv \bar{R}(\Phi) \prec SD\big(R(\Phi, K)\big) \tag{1}$$

Subject to:

$$\sum_{k=1}^{\lvert K \rvert} x_{j,k} = 1 \qquad (j = 1, \dots, \lvert J \rvert) \tag{2}$$

$$\sum_{j=1}^{\lvert J \rvert} t_j \cdot x_{j,k} \le c \qquad (k = 1, \dots, \lvert K \rvert) \tag{3}$$

$$\sum_{j=1}^{\lvert J \rvert} a_j \cdot x_{j,k} \le A \qquad (k = 1, \dots, \lvert K \rvert) \tag{4}$$

$$R_\phi(S_k) - \sum_{j=1}^{\lvert J \rvert} R_{\phi,j} \cdot x_{j,k} = 0 \qquad (k = 1, \dots, \lvert K \rvert) \wedge (\phi = 1, \dots., \lvert \Phi \rvert) \tag{5}$$

$$\sum_{k=1}^{\lvert K \rvert} k \big(x_{i,k} - x_{j,k} \big) \le 0 \qquad \forall \{i, j\} \subseteq J : i \in P_j \tag{6}$$

$$\sum_{k=1}^{\lvert K \rvert} k \cdot x_{j,k} \le m \qquad (j = 1, \dots, \lvert J \rvert) \tag{7}$$

$$\sum_{j=1}^{\lvert J \rvert} x_{j,k} \ge 1 \qquad (k = 1, \dots, \lvert K \rvert) \tag{8}$$

$$R_\phi(S_k) \ge 0 \qquad (k = 1, \dots, \lvert K \rvert) \wedge (\phi = 1, \dots., \lvert \Phi \rvert) \tag{9}$$

$$x_{j,k} \in \{0,1\} \qquad (j = 1, \dots, \lvert J \rvert) \wedge (k = 1, \dots, \lvert K \rvert) \tag{10}$$

Where:

$\bar{R}(\Phi)$ is the average from the maximum ergonomic risks associated with each one of ergonomic risk factors considered, Φ:

$$\bar{R}(\Phi) = \frac{1}{|\Phi|}\sum_{\phi=1}^{|\Phi|} R_\phi = \frac{1}{|\Phi|}\sum_{\phi=1}^{|\Phi|} \max_{k\in K} R_\phi(S_k) \tag{11}$$

$SD\big(R(\Phi,K)\big)$ is the standard deviation from the set of ergonomic risks of the line considering both the workstations (K) and the risk factors of tasks (Φ):

$$SD\big(R(\Phi,K)\big) = \sqrt{\frac{1}{m\cdot|\Phi|}\cdot\sum_{\phi=1}^{|\Phi|}\sum_{k=1}^{|K|}\left(R_\phi(S_k) - R_\phi^{med}\right)^2} \tag{12}$$

Objective function (1) expresses the minimization of $\mathcal{R}(\Phi,K)$ function that responds to two hierarchized criteria: the first, $\bar{R}(\Phi)$, that corresponds with the average from the maximum ergonomic risks by factors, and the second, $SD\big(R(\Phi,K)\big)$, that is linked with the risk dispersion of the line and measures the standard deviation from the risks of workstations in regard with the risk factors. Constraints (2) force the assignment of all tasks. Constraints (3) and (4) impose the maximum limitation for the cycle time and the maximum linear area allowed by station. Constraints (5) determine the real ergonomic risk associated with the workload at each workstation. Constraints (6) correspond to the precedence task bindings. Constraints (7) and (8) limit the number of workstations and force that there is no empty workstation, respectively. Finally, constraints (9) and (10) necessitate that variables be non-negative and the assigned variables be binary.

It should be noted that the formulated mathematical model couldn't be solved by MILP without modifying the objective function, because it is not linear. Therefore, to solve the problem by MILP we will consider the third way, that is we will solve the problem mono-objective and determining the other objective after.

3 GRASP for solving the min *R_SD(R)* problem

Next a GRASP procedure is proposed for solving the above mathematical problem with a hierarchized objective function.

GRASP is a multi-start metaheuristic algorithm ([8], [9]) with two phases: (1) the construction phase, where an initial solution is built through a non-deterministic Greedy procedure; and (2) the improvement phase in which a local optimum is sought in one or more neighborhoods of the solution obtained in the constructive phase. These two phases are consecutively applied until a stopping criterion is satisfied. Finally, GRASP gives as a final solution the best solution found between all iterations.

The first phase gives solutions that are acceptable regarding the objective function and representative of various regions from the exploration space.

To ensure solution diversity, given a sequence of decisions linked with a partial solution, the possible alternatives are randomly selected among the restricted candidate list (RCL). This list may contain all possible alternatives or a set of them. In the last case, the set of alternatives is selected on the basis of the best values for a function (bound, index, etc.) that is in line with the overall objective of the problem.

Specifically, the GRASP proposed in this paper is similar to [10]. However, here the main goal is to minimize the ergonomic risk of the critical workstation (station with greatest risk) and, subject to this first objective, the second goal is to minimize the standard deviation (SD) from the ergonomic risks of the assembly line.

Therefore, the construction phase consists of building progressively a sequence of tasks $\pi(N) = (\pi_1,..,\pi_N)$, according to a restricted candidate list, RCL, that is created from all possible task that can be incorporated into the sequence. Thus, at each stage associated with the position n ($n = 1,..,N$) of the sequence $\pi(N)$, the $RCL(n)$ list is made up for tasks that have not yet been incorporated into the $\pi(n-1) = (\pi_1,..,\pi_{n-1})$ sequence, but whose precedent tasks have already been assigned to $\pi(n-1)$. Once the $RCL(n)$ list is built, it is ordered according the following hierarchical priority indices:

– Pending linear area according to the assigned task, $j \in RCL(n)$, and its followings tasks F_j^* :

$$f_j^{(n)} = a_j + \sum_{h \in F_j^*} a_h \quad \forall j \in RCL(n) \tag{13}$$

- Pending ergonomic risk according to the assigned task, $j \in RCL(n)$, and its followings tasks F_j^* :

$$g_j^{(n)} = \sum_{\phi \in \Phi} R_{\phi,j} + \sum_{\phi \in \Phi} \sum_{h \in F_j^*} R_{\phi,h} \quad \forall j \in RCL(n) \tag{14}$$

After having calculated the indices ($f_j^{(n)}, g_j^{(n)}$), the $RCL(n)$ list is ordered according to a descending order of the $f_j^{(n)}$ values or in descending order of the $g_j^{(n)}$ values in case of a tie. Subsequently, the list is reduced by the admission factor, Λ. The Λ factor is defined as the percentage of tasks that are sorted among the best candidates; thus, the $\overline{RCL}(n, \Lambda)$ list is obtained for the selection process.

The constructive phase makes sure that the final task sequence $\pi(N)$ is consistent with precedent and succession constraints and it does not accumulate required linear area and the ergonomic risk at the end of the assembly line.

From the $\pi(N)$ sequence, the following stage consists of designing an assembly line configuration by imposing a fixed number of workstations, $m \geq 2$. Indeed, given a number of workstations (m), the $\pi(N)$ sequence is divided in m segments. These segments have the following properties: (i) they are compatible with the constraints (3) and (4), (ii) they are made up by adjacent tasks of the sequence, (iii) they are not empty, and (iv) they are disjoint between them and their union corresponds with the set of tasks, J.

Given a feasible solution obtained in the constructive phase, the improvement phase of the GRASP relies on sequentially applying four descent algorithms on four neighborhoods, repeatedly until solution does not improve at none stage. Between two solutions compatible with the cycle time and the maximum available area (constraints (3) and (4)), the solution with lower average from maximum ergonomic risk will be considered the best, and, in case of tie, the solution with lower standard deviation (SD) will be saved during iterations. In particular, the stages of the improvement phase of GRASP are the following:

- Insertion_1: Insertion of a task from the station with the greatest ergonomic risk (critical workstation) to any other station: the workstation with the greatest ergonomic risk inserts all its tasks, one by one, first into any previous station and second, into any next station. Obviously constraints (2)-(10) from the mathematical model must be satisfied and the average from maximum ergonomic risks must improve. In case of tie, the insertion will be consolidated if the standard deviation from the ergonomic risks is improved.
- Insertion_2: Insertion of a task from any station to the station with the lowest ergonomic risk: the workstation with lowest ergonomic risk increases its workload with the last task from any previous station and/or the first task from any next station. The constraints (2)-(10) from the model must be satisfied and the improvement conditions to consolidate the insertion are identical to those from previous stage.
- Exchange_1: Task exchange from the critical workstation to any other station: this stage consists of exchanging the tasks from the critical workstation, one by one, with the first task from the following workstations and, after, the last task from previous stations. The exchange will be consolidated when the conditions from the above stages are fulfilled.
- Exchange_2: Switch of tasks between workstations: the last step consists of exchanging tasks between two stations. Obviously, the exchanges will be consolidated in line with previous stages.

4 Case study: Nissan-9Eng

The computational experience is focused on analyzing the performance of the GRASP procedure proposed in this work, GRASP-3, against the linear programming. This comparison is based on the solution quality and the CPU times.

Because the mixed integer linear programming does not support hierarchical objective functions, the results given by the proposed GRASP will be compared with those obtained by two mono-objective mathematical models. Specifically, the exact procedures are the MILP-1 and the MILP-2 whose objectives are minimizing the maximum ergonomic risk of the assembly line and minimizing the risk dispersion between workstations, respectively (see [10]).

It should be noted that MILP-2 minimizes the absolute average deviation. Therefore, it will be necessary to calculate the standard deviation once the model has been run.

Like [3] and [10], the analysis lies with a case study from Nissan's Plant in Barcelona: an assembly line where 9 types of engines that are grouped into three families (SUVs - Sport Utility Vehicle, Vans and Trucks) are assembled with a cycle time of 180 s.

The assembly line features are the following:

- Number of workstations: $|K| \equiv m;\ m = \{19, 20, 21, 22, 23, 24, 25\}$.
- Number of elemental tasks: $|J| = 140\ (j = 1, .., 140)$.
- 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: $|\text{E}| = 1\ (\ \varepsilon = 1)$.
- Daily demand: $T \equiv D_\varepsilon = 270\ engines\ (\ \varepsilon = 1)$.

The computational features are the following:

- MILP-1: $\min - \max R$ model (see [7],[10]). (i) Objective function that minimizes the average from maximum ergonomic risks of workstations of the assembly line in accordance with the risk factors and without considering the risk dispersion between stations; (ii) mathematical model compiled and run on a Mac Pro (Intel Xeon, 3.0 GHz CPU and 2 GB RAM Windows- XP) using the CPLEX solver v11.0; (iii) maximum CPU time available to run each demand plan equal to 7200 *s*; (iv) 21 executions: 7 possible values for m (19,…,25) and 3 for A (4, 5, 10) ; (v) use of the previous solution for an available area A and for a number of workstations $m-1$ as initial solution given a spatial area, A, and a number of workstations, m.
- MILP-2: $\min AAD\_R$ model (see [7], [10]. (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; (ii) mathematical model compiled and run on a Mac Pro (Intel Xeon, 3.0 GHz CPU and 2 GB RAM Windows- XP) using the CPLEX solver v11.0; (iii) maximum CPU time available to run each demand plan equal to 7200 *s*; (iv) 21 executions: 7 possible values for m (19,…,25) and 3 for A (4, 5, 10) ; (v) use of the previous solution for an available area A and for a number of workstations $m-1$ as initial solution given an area, A, and m workstations.
- GRASP-3: GRASP procedure aimed at minimizing hierarchically the maximum ergonomic risk for the line and the risk dispersion between workstations, through the standard deviation; (i) procedure run on an iMac (Intel Core i7 2.93 GHz, 8 GB de RAM); (ii) 10000 iterations per execution as maximum (iii) three possible values for the admission factor $\Lambda = \{33\%, 66\%, 100\%\}$ (63 executions: 7 values for m, 3 values for A and 3 possible values for Λ); (iv) average CPU time per execution used by the two GRASP phases equal to 315.53 *s*.

Table 1 shows best results in regard with the average maximum ergonomic risk, $\bar{R}(\Phi)$ from MILP-1, MILP-2 and GRASP-3, for the 21 data sets of the problem, $\theta \in \text{Z}$; the winner algorithm for each data set is also highlighted; and the unity gains of GRASP-3 against MILP-1 ($\Delta G3vM1$), GRASP-3 against MILP-2 ($\Delta G3vM2$) and MILP-1 against MILP-2 ($\Delta M1vM2$), which are determined as follows (13):

$$\Delta\mathcal{P}v\mathcal{P}'(\theta) = \frac{\bar{R}(\Phi)_{\mathcal{P}'}(\theta) - \bar{R}(\Phi)_{\mathcal{P}}(\theta)}{min\left(\bar{R}(\Phi)_{\mathcal{P}'}(\theta), \bar{R}(\Phi)_{\mathcal{P}}(\theta)\right)} \qquad (13)$$

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

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

- No procedure guaranties optimal solutions.

- No procedure gives solution for assembly lines with 19 and 20 workstations and an available area of 4 meters.
- MILP-1 does not give solution when the assembly line has 19 and 20 workstations and 5 meters either.
- MILP-1 is the winner in regard with the number of best solutions, with 13 successes above all 21 instances. MILP-2 is in the second position with 10 victories and finally GRASP-3 with 7 successes.
- MILP-1 is also the winner procedure in regard with the unity gain, provided the instances without solutions (19/5 and 20/5) are not considered. The overall average unity gain of MILP-1 against GRASP-3 is by 2.1% and by 5%, approximately, against MILP-2. Under this criterion, MILP-2 is the procedure with the worst results. Indeed MILP-2 is overtaken by GRASP-3 with an overall average unity gain of 3.5%.
- MILP-1 wins in 7 data sets, loses in 3 and ties in 7 instances by comparing its results with those given by MILP-2. Specifically, MILP-1 improves solutions from MILP-2 by 14.2% but, when it loses, solutions become worse by 5.1%, respectively, in terms of average unity gain.
- GRASP-3 wins MILP-2 in 8 instances, loses 7 times and ties in 4 data sets, considering the 19 cases in which MILP-2 gives solution. The average gain of GRASP-3 against MILP-2 is 11% and the average loss is 3%.
- Comparing MILP-1 with GRASP-3, the first one wins in 10 data sets, loses in 3 and ties in 7 instances. However the unity gains of one procedure against the other one are balanced: 4.9% when MILP-1 wins and 4.4% when GRASP-3 is the winner.
- MILP-1 and MILP-2 use 7200 s per data set (CPU limit), while GRASP-3 needed 315.53 s on average to solve each instance.

$\theta \in \mathbb{Z}$	$\bar{R}(\Phi)$: Average from maximum risk			$\Delta\mathcal{P}v\mathcal{P}'(\theta)$: Gain $\mathcal{P}$ *versus* $\mathcal{P}'$				
m/A	MILP-1	MILP-2	GRASP-3	$\Delta G3vM1$	$\Delta G3vM2$	$\Delta M1vM2$	$\bar{R}(\Phi)^*$	$Winner$
19/4	-	-	-	-	-	-	-	-
19/5	-	440	405	-	0.09	-	405	G3
19/10	350	360	350	0.00	0.03	0.03	350	M1-G3
20/4	-	-	-	-	-	-	-	-
20/5	-	390	345	-	0.13	-	345	G3
20/10	315	315	330	-0.05	-0.05	0.00	315	M1-M2
21/4	375	450	435	-0.16	0.03	0.20	375	M1
21/5	310	320	320	-0.03	0.00	0.03	310	M1
21/10	300	300	310	-0.03	-0.03	0.00	300	M1-M2
22/4	330	420	345	-0.05	0.22	0.27	330	M1
22/5	300	300	300	0.00	0.00	0.00	300	All
22/10	285	285	295	-0.04	-0.04	0.00	285	M1-M2
23/4	310	375	320	-0.03	0.17	0.21	310	M1
23/5	280	275	285	-0.02	-0.04	-0.02	275	M2
23/10	275	275	280	-0.02	-0.02	0.00	275	M1-M2
24/4	280	345	300	-0.07	0.15	0.23	280	M1
24/5	280	265	270	0.04	-0.02	-0.06	265	M2
24/10	270	270	270	0.00	0.00	0.00	270	All
25/4	280	285	270	0.04	0.06	0.02	270	G3
25/5	275	255	260	0.06	-0.02	-0.08	255	M2
25/10	255	255	255	0.00	0.00	0.00	255	All
$Average$	-	-	-	-0.021	0.035	0.049	-	-

Table 1:, $\bar{R}(\Phi)$ value for each data set, $\theta \in \mathbb{Z}$, in accordance with the different procedures (MILP-1, MILP-2, GRASP-3)). Unity gain between pairs of procedures ($\Delta G3vM1, \Delta G3vM2, \Delta M1vM2$), best solution for $\bar{R}(\Phi)^*$, and winner algorithm.

On the other hand, in order to measure the dispersion between stations, the standard deviation from the ergonomic risk, $SD\big(R(\Phi, K)\big)$, is used. Besides, the relative standard deviation (RSD) is also used to compare the quality of solutions given by a pair of procedures; that is:

$$RSD(\mathcal{P}v\mathcal{P}'(\theta)) \equiv \frac{SD\big(R(\Phi,K)\big)_{\mathcal{P}'}(\theta)}{R_{\Phi}^{med}(\theta)} - \frac{SD\big(R(\Phi,K)\big)_{\mathcal{P}}(\theta)}{R_{\Phi}^{med}(\theta)} \tag{14}$$

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

In accordance with the risk dispersion values (Table 2), we can state the following:

- No procedure guaranties optimal solutions.
- No procedure gives solution for instances with 19 or 20 workstations and 4 meters.
- MILP-1 does not also give solution for data sets with less than 21 workstations and 5 meters as maximum linear area.
- MILP-2 is the winner procedure in terms of best RSD value. Indeed, considering all data set, MILP-2 achieves 16 best solutions, GRASP-3 achieves two ones (instances 22/4 and 25/4) and MILP-1 obtains only one best solution (instance 21/4).
- MILP-2 also wins in terms of average gain of RSD. The overall average gain of MILP-2 against GRASP-3 and MILP-1 is 2.6% and 4.8%, respectively. On the other hand, MILP-1 is the loser, since its results are improved by GRASP-3 by 2.0%.
- MILP-2 improves results given by MILP-1 in 16 instances. Indeed, RSD average gain when MILP-1 wins MILP-2 is only by 0.2%, however when MILP-2 wins MILP-1 the average gain is 5.1%.
- GRAP-3 obtains 11 best solutions and 6 worst solutions against MILP-1, considering only 17 data sets. GRASP-3 improves solutions given by MILP-1 by an average gain of 4.8%, while MILP-1 improves results from GRASP-3 by 2.9%, when it gives better solutions than GRASP-3.
- On the other hand, GRASP-3 gets worse solution than MILP-2 in 17 instances and wins in 2 cases. However, the RSD average gain are not so relevant: 2.9% when MILP-2 wins GRASP-3 and 0.2 in the opposite case.
- Again, it should be noted that MILP-1 and MILP-2 requires 7200 s per data set, while GRASP-3 only requires 315.53 s on average.

$\theta \in \mathrm{Z}$	$SD\big(R(\Phi,K)\big)$			$RSD(\mathcal{P}v\mathcal{P}'(\theta))$: Gain $\mathcal{P}$ $versus$ $\mathcal{P}'$					
m/A	MILP-1	MILP-2	GRASP-3	R_{Φ}^{med}	$G3vM1$	$G3vM2$	$M1vM2$	$SD(R)^{*}$	$Winner$
19/4	-	-	-	323.4	-	-	-	-	-
19/5	-	49.40	55.94	323.4	-	-0.02	-	49.40	M2
19/10	32.35	18.07	32.31	323.4	0.00	-0.04	-0.04	18.07	M2
20/4	-	-	-	307.3	-	-	-	-	-
20/5	-	34.25	38.52	307.3	-	-0.01	-	34.25	M2
20/10	10.06	8.28	25.31	307.3	-0.05	-0.06	-0.01	8.28	M2
21/4	73.47	73.97	82.98	292.6	-0.03	-0.03	0.00	73.47	M1
21/5	22.35	19.54	32.87	292.6	-0.04	-0.05	-0.01	19.54	M2
21/10	7.56	5.01	14.21	292.6	-0.02	-0.03	-0.01	5.01	M2
22/4	61.14	60.13	59.37	279.3	0.01	0.00	-0.00	59.37	G3
22/5	35.75	10.05	23.30	279.3	0.04	-0.05	-0.09	10.05	M2
22/10	6.65	4.03	15.35	279.3	-0.03	-0.04	-0.01	4.03	M2
23/4	47.08	43.36	47.68	267.2	-0.00	-0.02	-0.01	43.36	M2
23/5	18.73	4.88	16.44	267.2	0.01	-0.04	-0.05	4.88	M2
23/10	9.95	3.71	7.45	267.2	0.01	-0.01	-0.02	3.71	M2
24/4	41.46	33.93	34.70	256.0	0.03	-0.00	-0.03	33.93	M2
24/5	41.67	3.95	14.65	256.0	0.11	-0.04	-0.15	3.95	M2
24/10	23.65	3.95	5.27	256.0	0.07	-0.01	-0.08	3.95	M2
25/4	53.59	26.86	26.74	245.8	0.11	0.00	-0.11	26.74	G3
25/5	42.15	5.35	14.85	245.8	0.11	-0.04	-0.15	5.35	M2
25/10	13.46	4.56	6.20	245.8	0.03	-0.01	-0.04	4.56	M2
$Average$					0.02	-0.03	-0.05		-

Table 2: $SD\big(R(\Phi,K)\big)$ values per procedure and instance $\theta \in \mathrm{Z}$ (MILP-1, MILP-2, GRASP-3)). RSD differences between pairs of procedures ($RSD(G3vM1, G3vM2, M1vM2)$), best solution $SD(R)^{*}$ and winner algorithm.

5 Conclusions

We have proposed, in this work, a GRASP procedure for solving a mixed-model assembly line problem. The studied approach is focused on minimizing both the maximum ergonomic risk of the assembly line and the standard deviation from risk of workstations.

The procedure designed for the problem, GRASP-3, has been compared with two different problem approaches: MILP-1 and MILP-2, which were solved by mixed integer linear programming. Both reference models, MILP-1 and MILP-2, although having different mono-objective function have allowed us to assess the performance of the GRASP-3 against to an exact procedure, such as the linear programming.

Therefore, the three procedures have been compared through a case study linked with an assembly line from the Nissan's engine plant in Barcelona. Specifically, the computational experience has been to obtain different line configurations in accordance with different values for the number of workstations and the maximum available area. This variety in the line's attributes has allowed us to assess the procedures' quality in regard with two metrics: (1) the maximum ergonomic risk from each line configuration, and (2) the standard deviation from the different risk levels between stations.

Results show, as expected, that MILP-1 is the best procedure in regard with the maximum ergonomic risk of the line. GRASP-3 is in second position and finally MILP-2 is the procedure that gets a higher degree of risk in a greater number of line configurations.

On the other hand, MILP-2 wins other procedures regarding the standard deviation from ergonomic risk of workstations. GRASP-3 is again in the second position and MILP-1 is the procedure that offers worst results.

However, GRASP-3 is very competitive although not winning in maximum risk and standard deviation either, in average terms. Indeed, the results differ only by 2.1% on average from the best results for the maximum ergonomic risk (MILP-1) and, by 2.6% from the best results for the standard deviation (MILP-2). In addition, GRASP-3 is clearly the most competitive procedure regarding the CPU time, using 315.53 seconds against the 7200 seconds used by the linear programming.

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

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