17-20 sept 2013

MULTICONFERENCIA
CAEPIA'13

Madrid

- XV Conferencia de la Asociación Española para la Inteligencia Artificial (CAEPIA)
- IX Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB)
- IV Simposio sobre Lógica Fuzzy y Soft Computing (LFSC)
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Prefacio

Este volumen contiene los artículos que fueron seleccionados para su presentación en la XV Multiconferencia CAEPIA (Conferencia de la Asociación Española para la Inteligencia Artificial) 2013, celebrada en Madrid del 17 al 20 de Septiembre de 2013. Esta Multiconferencia se celebra dentro del Congreso Español de Informática (CEDI 2013), y en ella CAEPIA se ha coordinado con otros congresos con entidad propia, como son: IX Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB 2013), IV Simposio sobre Lógica Fuzzy y Soft Computing (LFSC), VI Simposio de Teoría y Aplicaciones de Minería de Datos (TAMIDA 2013), Fusión de la INfOrmación (FINO 2013) y Agentes y Sistemas Multiagente: De la Teoría a la Práctica (ASMas). Este volumen contiene los 15 artículos seleccionados por CAEPIA, los 78 seleccionados por MAEB, los 39 seleccionados por LFSC (incluyendo en estos dos últimos congresos los artículos de sesiones especiales), los 16 seleccionados por TAMIDA, los 3 de FINO y los 4 de ASMas. El objetivo de todas estas conferencias es proporcionar a los investigadores en Inteligencia Artificial un foro en el que intercambiar ideas y opiniones, y avanzar en la construcción de una comunidad de Inteligencia Artificial en España amplia, plural y abierta.

Con el fin de promover la participación de estudiantes de doctorado en la Multiconferencia, y su interacción con investigadores senior de los distintos campos involucrados, se realizó una sección de la Multiconferencia denominada Doctoral Consortium, transversal a todas las conferencias participantes. Esta actividad resultó particularmente exitosa, recibiendo un importante número de contribuciones (29). Los trabajos predoctorales presentados serán valorados por un Comité de 10 expertos, que junto con los dos Presidentes del Comité de Programa, aportarán sus opiniones, y concederán 6 becas de inscripción en la Multiconferencia CAEPIA 2013. Los tres proyectos de tesis mejor valorados recibirán además un certificado con dicho reconocimiento. El proyecto de tesis mejor valorado recibirá el premio GENIL del Campus de Excelencia BioTICs de la Universidad de Granada, el segundo proyecto mejor valorado recibirá un premio concedido por la Asociación Española para la Inteligencia Artificial (AEPIA), que asimismo otorga un diploma acreditativo al tercer proyecto de tesis mejor valorado.

También de forma transversal, la Multiconferencia incluye por primera vez una sesión de trabajos publicados recientemente en revistas y foros de reconocido prestigio, que se denomina Key Works, y consta de 14 trabajos recientes publicados durante el período 2011-2013. Estos trabajos, seleccionados por un Comité formado por 3 expertos, se presentarán en varias sesiones, organizadas en varias temáticas concordantes con las áreas específicas de trabajo de las conferencias integrantes de la Multiconferencia.

Los editores de este volumen desean manifestar su agradecimiento a todos aquellos que contribuyeron al éxito de la Multi-Conferencia CAEPIA 2013, en especial a los organizadores de todos los congresos que integran la Multiconfe-

rencia, así como los organizadores de las sesiones de Doctoral Consortium y Key Works por su colaboración y disponibilidad; a los miembros de los Comités Científicos y los revisores adicionales, los autores de los trabajos, y los conferenciantes invitados de todas las conferencias federadas.

Nada hubiera sido igual sin la ayuda de los comités Organizadores de las distintas conferencias, (incluido por supuesto el Comité Organizador del CEDI), de la Universidad Complutense de Madrid, Universidad Politécnica de Madrid , el Campus de Excelencia BioTICs de la Universidad de Granada y la Asociación Española de Inteligencia Artificial (AEPIA).

Por último una mención especial a Diego Fernández Francos, que compiló y ordenó todos los artículos de este volumen.

Amparo Alonso-Betanzos

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IX Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados [MAEB 2013]

Editores asociados:

José Manuel Colmenar
Abraham Duarte
Eduardo G. Pardo
José Ignacio Hidalgo
Juan Lanchares
Juan José Pantrigo
Antonio S. Montemayor

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Prefacio

Las Metaheurísticas, los Algoritmos Evolutivos y los Algoritmos Bioinspirados se encuentran entre los métodos más relevantes y exitosos para resolver un conjunto enorme de problemas complejos y computacionalmente muy costosos de interés teórico y práctico que aparecen en diversas áreas de la ciencia y la ingeniería. Estos métodos se pueden describir como entornos algorítmicos que requieren modificaciones relativamente pequeñas para ser adaptados a problemas concretos. Algunos ejemplos de este tipo de métodos son (manteniendo su nombre original en inglés): Simulated Annealing, Tabu Search, Multi-start Methods, Iterated Local Search, Variable Neighbourhood Search, GRASP, Memetic Algorithms, Scatter Search, Evolutionary Algorithms, o Ant Colony Optimization.

La investigación en Metaheurísticas, Algoritmos Evolutivos y Algoritmos Bioinspirados se ha convertido en un campo de investigación de marcado carácter interdisciplinar, en la que confluyen áreas de conocimiento como la Inteligencia Artificial, la Ciencia de los Computadores, o la Investigación Operativa, entre otras. Estas técnicas han recibido una enorme atención por parte de la comunidad científica, hecho que se aprecia si se considera la gran cantidad de trabajos publicados en revistas de alto impacto, como por ejemplo, IEEE Trans. on Evolutionary Computation, Evolutionary Computation o Journal of Heuristic; cientos de libros editados por las editoriales más prestigiosas (Springer, Kluwer o Taylor&Fracis) con una temática centrada en este tipo de técnicas; o las conferencias temáticas como MIC (Metaheuristic International Conference). IEEE CEC (IEEE Conference on Evolutionary Computation), GECCO (Genetic and Evolutionary Computation Conference) o Evostar.

El congreso MAEB se ha convertido, por derecho propio, en el foro de encuentro, discusión y transferencia de conocimiento entre investigadores de habla hispana del campo de las Metaheurísticas, los Algoritmos Evolutivos y Bioinspirados. Este volumen contiene los trabajos aceptados para su presentación oral en el IX Congreso Español sobre Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB 2013), celebrado en Madrid del 17 al 20 de Septiembre de 2013. No cabe duda de que MAEB es un congreso especial, que ha sabido crecer en estos años, a pesar de las diferentes vicisitudes en que se ha visto envuelto, como la variabilidad en la periodicidad de celebración, su inclusión o no en el CEDI, su celebración como congreso independiente o confederado con otras conferencias (como ocurre en esta edición con la Multiconferencia CAEPIA) o el hecho de no contar con el apoyo de ninguna asociación científica. El éxito de MAEB refleja la importancia de este campo de investigación en la comunidad científica española, pero también el hecho de que MAEB no es sólo una reunión de expertos, sino también una reunión de amigos, que se reúne cada 18 meses (aproximadamente) para intercambiar avances, experiencias, etc.

Este buen funcionamiento se ha puesto de nuevo de manifiesto si se observa el nivel de compromiso demostrado ante la llamada a la participación de MAEB 2013. Incluso en una situación tan difícil para la Ciencia en España (en particular) y en el mundo (en general) como la actual, hemos recibido la excelente cifra de 90 trabajos, de los cuales, 80 han sido seleccionados para ser presentados oralmente, tras un proceso de revisión anónimo. Además, en esta edición hemos contado como es habitual, con un excelente conferenciante invitado, al que queremos agradecer su predisposición a colaborar con MAEB 2013 desde el primer momento: Nenad Mladenovic. El resumen de su conferencia puede encontrarse en este volumen. Otra de las actividades destacadas de este MAEB 2013 es la exposición de pintura sobre Algoritmos Evolutivos Desconectados, presentada por la Universidad de Extremadura. Se trata de una exposición de 50 obras de pintura enmarcados dentro de un ambicioso proyecto de investigación dirigido por el Profesor Francisco Fernández de Vega, que ya ha recibido el reconocimiento internacional en conferencias como GECCO (best paper award) o CEC.

En esta edición se convocarán de nuevo tres premios a trabajos presentados en MAEB: premio al mejor artículo metodológico, premio para el mejor artículo aplicado (o de aplicación a problemas reales) y, por último, premio al mejor trabajo pre-doctoral. Los dos primeros premios están patrocinados por la Asociación Española para la Inteligencia Artificial (AEPIA), mientras que el último está patrocinado por Granada Excellence Network of Innovation Laboratories GENIL (genil.ugr.es). Como en la pasada edición, será la audiencia de MAEB la que elegirá los trabajos merecedores de este premio de entre un grupo de finalistas.

Nos gustaría expresar también nuestro agradecimiento al Comité Director de MAEB, por haber depositado su confianza en nosotros para la organización de esta edición y por su ayuda siempre que la hemos necesitado; a los miembros del Comité de Programa, por su diligencia a la hora de difundir la convocatoria y revisar los artículos asignados; y a los compañeros de nuestros respectivos grupos de investigación, sin cuyo esfuerzo como miembros del Comité Organizador de MAEB 2013, esta aventura no habría sido posible.

No podía faltar en estas actas un sentido y sincero homenaje al profesor Juan Manuel Sánchez Pérez, Catedrático de Universidad, que lo fue de la Universidad de Extremadura y uno de los promotores del primer MAEB que se celebró en Mérida en 2002. Animamos a todos los lectores a leer el obituario que incluimos en estas actas con todo nuestro aprecio y respeto.

Madrid, Septiembre 2013

Abraham Duarte
J. Ignacio Hidalgo

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A multiobjective genetic algorithm and robustness information function for time and space assembly line balancing

M. Chica[1], O. Cordón[1,2], S. Damas[1], and J. Bautista[3]

[1] European Centre for Soft Computing, Mieres (Asturias), Spain
{manuel.chica, oscar.cordon, sergio.damas}@softcomputing.es
[2] DECSAI and CITIC-UGR, University of Granada, 18071 Granada, Spain
[3] Universitat Politècnica de Catalunya, Barcelona, Spain
{joaquin.bautista}@upc.edu **

Abstract. The time and space assembly line balancing problem (TSALBP) is a realistic multiobjective version of assembly line balancing industrial problems involving the joint optimization of conflicting criteria such as the cycle time, the number of stations, and the area of these stations. However, the existing problem formulation does not consider the industrial scenario where the demand of a set of mixed products is variable and uncertain. In this contribution we introduce a novel robustness function to measure the robustness of the line configuration when the production plans demand changes. The function is used as additional *a posteriori* information for the non-dominated solutions found by an advanced multiobjective genetic algorithm. Because of their independence, these robustness functions can be used in conjunction with any other multiobjective metaheuristic. Results show how the use of the robustness function can help the decision maker to select robust non-dominated solutions when future demand conditions vary in the assembly line configurations.

1 Introduction

An assembly line is made up of a number of workstations, arranged either in series or in parallel. Since the manufacturing of a production item is divided into a set of tasks which require an operation time for their execution, a usual and difficult problem, called assembly line balancing (ALB), is to determine how these tasks can be assigned to the stations fulfilling certain restrictions such as precedence relations. The final aim of ALB is to get an optimal assignment of subsets of tasks to the stations of the plant (1, 2). An excellent review on ALB and the existing solving methods for the different problems is given in (3). Within ALB, a well-known family of problems is the simple assembly line balancing problem (SALBP) (4, 5, 6). The SALBP only considers the assignment of each task to a single station in such a way that all the precedence constraints are satisfied and no station workload time is greater than the line cycle time.

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As a result of the observation of the ALB operation in an automotive Nissan plant from Barcelona (Spain), (7) recently proposed a SALBP extension aiming to design a more realistic ALB model. They considered an additional space constraint to get a simplified but closer version to real-world situations, defining the time and space assembly line balancing problem (TSALBP). The TSALBP presents eight variants depending on three optimization criteria: m (the number of stations), c (the cycle time), and A (the area of the stations). In this paper we tackle the TSALBP-m/A variant[4] which tries to jointly minimize the number of stations and their area for a given product cycle time, a complex and realistic multicriteria problem in the automotive industry.

The multicriteria nature of the TSALBP-m/A favoured the application of multi-objective meta-heuristics (MOMHs) such as multiobjective ant colony optimization (MOACO) (8) or evolutionary multiobjective optimization (EMO) (9). Assembly lines are generally balanced for producing mixed products and their demand is not usually fixed and certain. When the assembly line is devoted to produce mixed products in a given sequence, the operation times of the required tasks are obtained from the average value of the different products and their demand. This is a problematic rough estimate of the actual operation times. If the demand changes, the operation times also change and a re-balancing could be necessary for the configuration.

Robustness can be applied to many components in an optimization process: noise in constraints, objective function, or uncertainties in data variables (10, 11). Real-world applications, as ALB, normally involve uncertainties because of operating conditions or manufacturing process (12). In our case, the interest lies on measuring the robustness of a specific operating condition, i.e. the operation times originated by the mixed products demand. In this work, a robustness function is defined based on the overloading production plans which occur when the demand changes and the line configuration is set. The latter robustness measure is used as additional *a posteriori* information associated to each non-dominated solution returned by the MOO method. The *advanced TSALBP-NSGA-II* is selected as the MOO method for the robustness experiments of this study because of the best performance of the metaheuristics with respect to others (9). However, the robustness functions can be applied to any other MOO method.

The rest of the paper is structured as follows. In Section 2, the TSALBP-m/A formulation and the uncertain demand scenario modelled by production plans are explained. Then, the metaheuristic applied for solving the TSALBP-m/A, the *advanced TSALBP-NSGA-II*, is described in Section 3. The numerical robustness function for assembly line balancing is given in Section 4. The experimentation results are discussed in Section 5. Finally, we present some concluding remarks in Section 6.

2 Demand variation in the TSALBP-m/A for mixed product products

We first introduce the TSALBP-m/A (Section 2.1) and then the real scenario of having a mixed products with changing demand (Section 2.2).

[4] Originally, this TSALBP variant is referred as TSALBP-1/3 (7). This new notation is introduced in this work for a better understanding.

2.1 Time and space assembly line balancing problem

The manufacturing of a production item is divided into a set J of n tasks. Each task j requires an operation time for its execution $t_j > 0$ that is determined as a function of the manufacturing technologies and the employed resources. Each station k ($k = 1, 2, ..., m$) is assigned to a subset of tasks S_k ($S_k \subseteq J$), called workload. Each task j can only be assigned to a single station k.

Each task j has a set of direct "preceding tasks" P_j which must be accomplished before starting it. These constraints are normally represented by means of an acyclic precedence graph, whose vertices stand for the tasks and where a directed arc (i, j) indicates that task i must be finished before starting task j on the production line. Thus, task j cannot be assigned to a station that is ordered before the one where task i was assigned. Each station k also presents a station workload time $t(S_k)$ that is equal to the sum of the tasks' processing time assigned to the station k. SALBP focuses on grouping tasks in workstations by an efficient and coherent way.

In this simplistic model there is a need of introducing space constraints in assembly lines' design based on two main reasons: (a) the length of the workstation is limited in the majority of the situations, and (b) the required tools and components to be assembled should be distributed along the sides of the line. Hence, an area constraint may be considered by associating a required area a_j to each task j and an available area A_k to each station k that, for the sake of simplicity, we shall assume it to be identical for every station and equal to $A = max_{k=1,2,...,m} A_k$. Thus, each station k requires a station area $a(S_k)$ that is equal to the sum of areas required by the tasks assigned to station k.

This leads us to a new family of problems called TSALBP (7). It may be stated as: given a set of n tasks with their temporal t_j and spatial a_j attributes ($1 \leq j \leq n$) and a precedence graph, each task must be assigned to a single station such that: (i) every precedence constraint is satisfied, (ii) no station workload time ($t(S_k)$) is greater than the cycle time (c), and (iii) no area required by any station ($a(S_k)$) is greater than the available area per station (A).

TSALBP presents eight variants depending on three optimization criteria: m (the number of stations), c (the cycle time) and A (the area of the stations). Within these variants there are four multiobjective problems and we will tackle one of them, the TSALBP-m/A. It consists of minimising the number of stations m and the station area A, given a fixed value of the cycle time c, mathematically formulated as follows:

$$f^0(x) = m = \sum_{k=1}^{UB_m} \max_{j=1,2,...,n} x_{jk}, \tag{1}$$

$$f^1(x) = A = \max_{k=1,2,...,UB_m} \sum_{j=1}^{n} a_j x_{jk}, \tag{2}$$

where UB_m is the upper bound for the number of stations m, a_j is the area information for task j, x_{jk} is a decision variable taking value 1 if task j is assigned to station k, and n is the number of tasks.

We chose this variant because it is realistic in the automotive industry since the annual production of an industrial plant (and therefore, the cycle time c) is usually set by some market objectives. For more information about the problem we refer the interested reader to (8; 13).

2.2 Production plans for modelling changing demand

The latter TSALBP-m/A formulation assumes both a constant demand and fixed operation times t_j. However, real assembly lines are normally employed to assemble more than one single product, and when the demand of each product changes, the operation times of the tasks change in consequence. The demand of a set of mixed products is defined by means of production plans. In this work, the engine assembly line of the Nissan Spanish Industrial Operations (NSIO) plant is the chosen uncertain environment to define the different production plans.

Nine different engines are assembled in the main line of the NSIO plant, $m_1, \ldots, m_9$, having different destinations and assembly characteristics. The first three engine products are built for 4×4 vehicles; products m_4 and m_5 are for VANs; and the remaining four products are used by medium tonnage trucks. When demand is balanced (identical for the nine products) and the cycle time is 3 minutes, the assembly line is divided into 21 workstations having an average length A_k of 4 meters each.

In (7), authors grouped the primary operations of this assembly line in the so called Nissan TSALBP instance having 140 tasks. For each type of engine, operation times change. In Table 1 the operation times of five tasks are listed for illustration. The average operation time when having a balanced demand for the nine products is also shown in the *t-average* column.

Table 1. Operation times and average time for five tasks belonging to the NSIO engine assembly line.

task	m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	t-average
1	64.8	61.2	60	54	58.8	55.2	63	66	57	60
3	18.4	18	20	19.6	19	21.6	21	20.4	22	20
5	19	19.6	18.4	20	21	20.4	18	21.6	22	20
8	9.8	9	10.5	10.8	9.5	11	9.2	10	10.2	10
9	20	19.6	19	18	20.4	18.4	21.6	21	22	20

Of course, it is difficult to always have the same uniform demand for all the engines within a global demand. Although the line is supposed to have a fixed daily production of, for instance, 270 products, the line should be capable of producing the required products for the specific product demand of a given production plan. In other words, the production plan of the 270 engines is not constant. Then, the goal is to have an assembly line configuration that is robust enough for different production plans.

There are currently 23 production plans for the nine engines and one working day at the NSIO. Each program corresponds to a set of operation times biased by the demand of each of the nine products. We have grouped them into seven categories according to the type of engine demand. The seven representative production plans, one per category, are shown in Table 2. Definitely, the demand variation of the production plan for mixed products conditions the average operation times of the 140 assembly line tasks. In that case, a re-balancing of the assembly line could be necessary. For example, task 1 has operation times of 64.8, 61.2, 60, 54, 58.8, 55.2, 63, 66, and 57 seconds for products m_1 to m_9, respectively. On the other hand, production plan #12 has a demand of 24, 23, 23, 45, 45, 28, 28, 27, and 27 products for each of the engine products. Consequently, the average time for task 1 in the latter plan is 59.44 seconds ($= (64.8 \times 24 + 61.2 \times 23 + \cdots + 66 \times 27 + 57 \times 27)/270$) in comparison with the 60 seconds needed by production plan #1.

Table 2. Production units of the engine models for each production plan.

		Production plans						
Family	Product	# 1	#2	# 3	# 6	# 9	# 12	# 18
4 x 4	m_1	30	30	10	50	70	24	60
	m_2	30	30	10	50	70	23	60
	m_3	30	30	10	50	70	23	60
VAN	m_4	30	45	60	30	15	45	30
	m_5	30	45	60	30	15	45	30
Trucks	m_6	30	23	30	15	8	28	8
	m_7	30	23	30	15	8	28	8
	m_8	30	22	30	15	7	27	7
	m_9	30	22	30	15	7	27	7

The selected representative production plans are used in this work to present additional information to the decision maker (DM) about how robust a new assembly line configuration is under demand changes, i.e. how good it is with respect to those changes.

3 Advanced NSGA-II-based approach for the TSALBP-m/A

This design is based on the original NSGA-II search scheme (14) with an appropriate representation and more effective operators are used to solve the TSALBP-m/A. The algorithm will be referred as *advanced TSALBP-NSGA-II* because of its problem-specific design and potential application to other TSALBP variants (9). The main features and operators of the *advanced TSALBP-NSGA-II* are described in the next subsections.

3.1 Representation scheme

The allocation of tasks among stations is made by employing separators. Separators are thus dummy genes which do not represent any specific task and they are inserted into the list of genes representing tasks. In this way, they define groups of tasks being assigned to a specific station. The maximum possible number of separators is $n-1$ (with n being the number of tasks), as it would correspond to an assembly line configuration with n stations, each one composed of a single task. Tasks are encoded using numbers in $\{1, \ldots, n\}$, as in the previous representation, while separators take values in $\{n + 1, \ldots, 2 \cdot n - 1\}$. Hence, the genotype is again an order-based representation.

The number of separators included in the genotype is variable and it depends on the number of existing stations in the current solution. Therefore, the algorithm works with

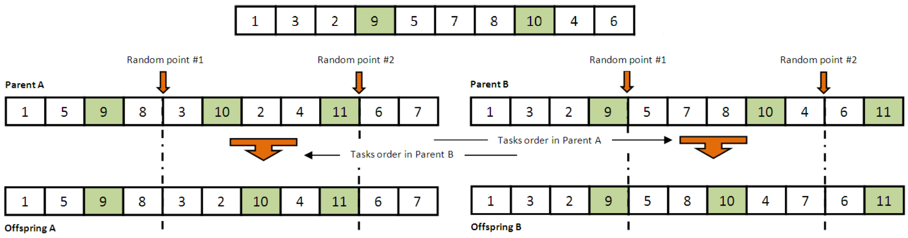

Fig. 1. Coding scheme and crossover example. Separators are those genes coloured.

a variable-length coding scheme, although its order-based representation nature avoids the need of any additional mechanism to deal with this issue. The maximum size of the chromosome is $2 \cdot n - 1$ to allow the presence of separators for the maximum number of possible stations. On the other hand, the representation scheme ensures the encoded solutions are feasible with respect to the precedence relations constraints. However, the cycle time limitation could be violated and it will be a task of the genetic operators to ensure feasibility with respect to that constraint. Figure 1 shows an example of the new coding scheme.

3.2 The crossover operator

As our representation is order-based, the crossover operator can be designed from a classical order-based one. Crossover operators of the latter kind which have been suggested in the literature include partially mapped crossover (PMX), order crossover, order crossover # 2, position based crossover, and cycle crossover, among others (15). We have selected one of the most extended ones, PMX, which has been already used in other genetic algorithm implementations for the SALBP (for example in (16)).

PMX generates two offspring from two parents by means of the following procedure: a) two random cut points are selected, b) for the first offspring, the genes outside the random points are copied directly from the first parent, and c) the genes inside the two cut points are copied but in the order they appear in the second parent. The same mechanism is followed up with the second offspring but with the opposite parents. Thanks to our advanced coding scheme and to the use of a permutation-based crossover, the feasibility of the offspring with respect to precedence relations is assured. See Figure 1 where an example of the operator is shown. In addition, a repair operator must be applied for each offspring after crossover.

3.3 Mutation operator

A mutation operator has been specifically designed and applied uniformly to the selected individuals of the population. It is based on reordering a part of the sequence of tasks and reassigning them to stations. It will be called scramble mutation operator.

The scramble mutation operator works as follows: after choosing two points randomly, the tasks between those points are scrambled forming a new sequence of tasks in such a way the mutated solution keeps on being feasible with respect to the precedence relations. The existing separators among the two mutation points are ignored and a new reallocation of those tasks is considered by randomly generating new separator locations within the task sequence.

4 Evaluating robust solutions for assembly line balancing when demand is uncertain

Solving the TSALBP when the mixed products demand is uncertain belongs to the robust optimization case where the operating conditions change after the optimal solution is found (17). In our case, the operating conditions are the operation times originated by the different mixed products demands represented by the production plans of Section 2.2. The overall goal is to find a set of non-dominated solutions for the TSALBP-m/A and calculate their robustness for all the possible production plans. In the next paragraphs we will present our proposal for evaluating this robustness.

Let E be the set of possible production plans based on the demand variation and ε^0 a reference production plan, our evaluation proposal is based on determining the workload of the set K of stations of an assembly line configuration in the plans of E.

First, being S_k^0 the tasks assignment to the station k in ε^0 (normally, the balanced plan), the workload of this station k is obtained for all the production plans $\varepsilon \in E$: $t(S_k^0, \varepsilon)$.

Then, the relative station overloads with respect to the available cycle time c are calculated for all the existing production plans ε by applying Equation 3.

$$\omega(S_k^0, \varepsilon) = \frac{\max\{0, t(S_k^0, \varepsilon) - c\}}{c} \qquad \forall k \in K, \forall \varepsilon \in E. \tag{3}$$

From these overload values, the average and maximum station overload values are also calculated through Equations 4 and 5:

$$\overline{\omega}(S_k^0) = \overline{\omega}_k = \frac{1}{|E|} \sum_{\varepsilon=1}^{|E|} \omega(S_k^0, \varepsilon) \qquad \forall k \in K, \tag{4}$$

$$\omega_{max}(S_k^0) = \max_{\varepsilon \in E} \{\omega(S_k^0, \varepsilon)\} \qquad \forall k \in K. \tag{5}$$

Analogously, the average and maximum overloading values for each production plan are obtained by applying Equations 6 and 7:

$$\overline{\omega}(\varepsilon) = \frac{1}{|K|} \sum_{k=1}^{|K|} \omega(S_k^0, \varepsilon) \qquad \forall \varepsilon \in E, \tag{6}$$

$$\omega_{max}(\varepsilon) = \max_{k \in K} \{\omega(S_k^0, \varepsilon)\} \qquad \forall \varepsilon \in E. \tag{7}$$

The latter values allow us to define and calculate our proposed robustness function. This is based on counting the number of overloaded stations and/or the number of overloading production plans. Given a station $k \in K$, a production plan $\varepsilon \in E$, a configuration line $(S_1^0, S_2^0, ..., S_m^0)$ for a reference production plan ε^0, and a cycle time c, we can state that there is an overload in $(k, S_k^0, \varepsilon, c)$ iff:

$$t(S_k^0, \varepsilon) > c \Leftrightarrow \omega(S_k^0, \varepsilon) > 0 \qquad \forall k \in K, \forall \varepsilon \in E. \tag{8}$$

Associated to the concept of overload, the set of total overloads can be defined as follows:

$$D = \{\forall \varepsilon \in E \wedge \forall k \in K \mid \omega(S_k^0, \varepsilon) > 0\}. \tag{9}$$

Finally and taking into account the set D, a robustness function R_3 can be defined in Equation 10. This will be the robustness function to be used in this study and represents the total number of overloads rate.

$$R_3 = \frac{|D|}{|E||K|} \in [0, 1] \tag{10}$$

5 Experiments

In this section we present the results of the experimentation and the analysis of them. The parameters of the *advanced TSALBP-NSGA-II* are presented in Table 3. The algorithm and the robustness function was applied to three TSALBP real-like instances (**P1, P2 and P4**) which have been created by the NTIGen software, publicly available at `http://www.prothius.com/TSALBP`.

Table 3. Used parameter values for the *advanced TSALBP-NSGA-II*.

Parameter	Value	Parameter	Value
Random seed	1212	Stopping criteria	300 s
Population size	100	Ishibuchi's similarity based mating γ, δ values	10
Crossover probability	0.8	Mutation probability	0.1
α values for scramble mutation	$\{0, 0.8\}$		

The obtained results of the robustness function for the non-dominated solutions are presented in Table 2. The first instance tackled by the algorithm is P1 (first table of Figure 2) where only two non-dominated solutions are found. However, even when having small non-dominated solution sets, the robustness information is important for the DM. Solution #2 reports robustness value of $R_3 = 0.12$. This value means that, when demand varies, the assembly line should support that a 12% of the stations are overloaded (R_3). Solution #2 is thus less robust than solution #1.

P2 is the original Nissan instance having 140 tasks. The number of non-dominated solutions obtained by the algorithm is five (see second table of Figure 2). The numerical value of R_3 allows us to conclude that solutions #1 and #2, those with objective values $(19, 5)$ and $(18, 6.09)$, respectively, are less robust than the remainder when demand changes. Then, if the number of stations (and then, workers) is not restricted, the best approach in terms of robustness is always choosing a solution with more than 19 stations.

There are seven non-dominated solutions for instance P4 (third table of Figure 2). Among them, there are two solutions which are less robust than the remainder. These are solutions #1 and #2 with 15 and 16 stations, respectively. In the latter pair of solutions, the 11% and 5.2% of the stations are overloaded by different production plans (R_3 function).

P1 Sols.	P1 R_3	P2 Sols.	P2 R_3	P4 Sols.	P4 R_3
S1	0.01	S1	0.139	S1	0.111
S2	0.12	S2	0.149	S2	0.052
		S3	0.092	S3	0.03
		S4	0.083	S4	0.046
		S5	0.029	S5	0.017
				S6	0.033
				S7	0.032

Fig. 2. Robustness values for the non-dominated solutions when solving the NTIGen instances of 100 tasks (P1), 140 tasks (P2), and 220 tasks (P4).

6 Concluding remarks

The existing TSALBP formulation and previous ALB works do not cover an important real scenario where the same assembly line is devoted to produce mixed products and their demand is not fixed. In this paper we have presented a new robustness function measure R_3. It is defined based on the number of overloaded stations. The proposed model was used to analyse the non-dominated solutions provided by the state-of-the-art MOO method for the TSALBP-m/A, the *advanced TSALBP-NSGA-II*, although the nature of the robustness model allows the use of any other MOO method instead. The results of the application of the robustness model are clear. There are some solutions which are less robust than others when demand changes and the DM can take advantage of this information before making her/his decision.

Some future works arise from this contribution: (i) propose and evaluate other robustness functions, (ii) include a graphical visualization model within the robustness representation of the non-dominated solutions, and (iii) integrate the robustness functions within the search of the MOO method (as a restriction or as another objective):

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