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ASSEMBLY AND AUTOMATION

Sensitivity analysis and validation of a genetic approach to enhance ergonomics in assembly lines

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Abstract
Manual assembly processes are largely performed today in the industry to benefit from human features of dexterity and flexibility. For this reason, the human factor should be properly regarded when designing assembly processes and systems, where repetitive and physically demanding operations are frequent. This work aims to present and validate a software tool for solving a bi-objective version of the assembly line balancing problem, in which, besides the efficiency of the process, the optimization of ergonomics is pursued. The software, based on a genetic algorithm, aims to distribute assembly tasks on the line to smooth the energetic workload among the different workers assigned to manual workstations, considering their physical capabilities and limits. To validate the system and assess its robustness, tests for different case studies taken from the industrial reality are presented and discussed, together with a sensitivity analysis conducted on problem parameters. Experimental results show that the developed tool optimizes the two objectives in different scenarios, thus demonstrating its profitable use in the industrial reality for planning manual assembly processes that do not overload workers assigned to the line.

Keywords Assembly · Line balancing · Ergonomics · Sensitivity analysis · Validation · Genetic algorithm

1 Introduction

Assembly is one of the most important manufacturing processes in which dexterity and flexibility, proper of human operators, are required to accomplish many tasks [1]. For this reason, in industry assembly processes are still largely executed manually. However, assembly tasks frequently entail repetitive and monotonous movements, as well as physically demanding work, like load handling, thus making it essential to consider the human factor when planning the process [2]. Ergonomics, human-centered science that studies the interactions between people and surrounding elements [3], becomes a key point in the design of safe and secure workplaces [4], so as to avoid workers' health damages and related medical costs, but also a negative impact on productivity parameters [5]. As a matter of fact, numerous studies demonstrate that ergonomics greatly affects the efficiency of manual assembly processes [6].

Assembly lines are among the main system solutions to organize an efficient workflow, by means of a series of stations placed along the transportation system, to which assembly tasks are assigned according to the production cycle time [7]. The Assembly Line Balancing Problem (ALBP) is to determine the optimal assignment of tasks to the workstations of an assembly line and is an NP-hard optimization problem [8]. ALBP represents one of the main problems to be solved in the field of manufacturing systems, not only for the combinatorial complexity, but also for the great impact its resolution may have on productivity parameters.

2 State of the art

2.1 Literature review

In recent years, several approaches have been modeled in the scientific literature to optimize ergonomics while solving the ALBP [9]. Most of them are related to the reduction of

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ergonomic risk in terms of worker posture [10]. A research by Scholl [11] presents different models of ALBP, named ErgoSALBP, to incorporate ergonomic considerations, based on postural risk assessment techniques, into the assembly line balancing problem. Various studies have been then presented to minimize the ergonomic risk on the line using traditional indexes, such as OCRA (Occupational Repetitive Actions) that take into account posture and repetitiveness [12], RULA (Rapid Upper Limb Assessment) that assesses strain of upper limbs, neck, and torso [13], ARPs (Accumulated Risk of Postures) that evaluates the load on back, arms and legs [14].

Focusing on the assignment of the assembly operations to the workstations of the line, a different approach can be modeled to pursue ergonomics in ALBP. It conceives ergonomics on the basis of workers' energy expenditure while performing the assembly process and is based on the distribution of tasks to smooth workers' energy expenditures. The method was first introduced by Battini et al. [15] and then referred to in other works, such as [16]. The proposed objective is to distribute the physical load in terms of energy expenditure among the different stations of the assembly line in which workers are placed, considering a standard example of a worker. As humans are all different with physical capabilities and limits depending on individual features, such as gender and age [17], a more realistic approach should also take into account that energy expenditures and limits vary from person to person. Thus, ergonomic planning of manual processes should consider the personal characteristics of the workers in a company.

In this regard, the authors of the present paper have developed a method presented in [18] able to design assembly lines that comply with the capabilities of the available labor force.

2.2 Motivations of the work

The present work deals with the single-model version of the ALBP in which the number of workstations is minimized for a given cycle time, known as the Simple Assembly Line Balancing Problem of type 1 (SALBP-1) [8], whose main assumptions are:

- mass production of one homogeneous product;
- paced line with fixed cycle time;
- deterministic execution times;
- serial line layout, one-sided stations;
- constant repositioning time throughout the workstations.

In particular, the present paper aims at testing and validating a different version of the Genetic Algorithm (GA) approach presented in [18]. In this work, a bi-objective SALBP-1 with optimization of economic and ergonomic aspects is considered. The objectives concern the minimization of the workload variance and of the energy variance on the assembly line. The first objective is to balance the workload in terms of task execution times among stations, whose number is minimized, coherently with SALBP-1. The latter is to uniformly smooth the energy expenditures of workers. The new aspects that are introduced relate to the evaluation of energy expenditure, dependent not only to the workers' movements for performing tasks, but also to their personal characteristics and individual features, such as gender, age and weight, which differentiate their expendable energy and physical limits. In this way, the assignment of workers available in a company to the stations of the assembly line is effected in accordance to workers capabilities in terms of energy expenditure, in order not to exceed their physical limits and improve ergonomics.

The main scope of the present paper is to validate the proposed system by means of a sensitivity analysis. The motivations of the work are to assess the robustness of the developed tool, by analyzing the effects of changes in problem parameters on returned results. The sensitivity analysis is aimed at showing the effectiveness of the genetic approach to be used for designing efficient and ergonomic assembly lines depending on the specific context, by simulating different scenarios.

3 Developed approach

3.1 Problem modeling

This section presents the problem formulation for the proposed version of the SALBP-1.

The SALBP-1 assumes that the assembly process is executed in an assembly line with Ns stations, where Nt tasks are allocated so that each station does not exceed the cycle time CT [min]. Each task i is characterized by a duration t_i [min]. In the assembly line, Nw workers are assigned one per station, so that $Ns = Nw$. Each assembly sequence is represented by a vector $\mathrm{x} \in \{0,1\}^{Nt \times Nw \times Nt}$, where $i, k \in \{1,\dots,Nt\}$ and $j \in \{1,\dots,Ns\}$, whose elements x_{ijk} are explained as follows:

$$x_{ijk} = \begin{cases} 1 & \text{if task } i \text{ is the } k\text{th in the sequence and is assigned to station } j; \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Precedence constraints are contained in a square matrix $P = \left[p_{hi}\right]$ of dimensions $Nt \times Nt$, in which each element can be:

$$p_{hi} = \begin{cases} 1 & \text{if task } h \text{ precedes task } i; \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The optimization problem can be formulated with following objective function and constraints:

$$\min f(x) = \left(\overline{f_1}(x) \cdot \alpha + \overline{f_2}(x) \cdot (1-\alpha)\right)\beta \tag{3}$$

subject to

$$\sum_{i=1}^{Nt}\sum_{k=1}^{Nt} x_{ijk} t_i \le CT \quad \forall j = 1, \dots, Ns \tag{4}$$

$$x_{ijk} \le \sum_{u=1}^{j}\sum_{k=1}^{Nt} x_{huk} \quad \forall i = 1, \dots, Nt, \forall h : p_{hi} = 1 \tag{5}$$

$$\sum_{i=1}^{Nt}\sum_{j=1}^{Ns} x_{ijk} = 1 \quad \forall k = 1, \dots, Nt \tag{6}$$

$$E_{jw} \le OEL_{jw} \cdot CT \forall w = 1, \dots, Nw, \quad \forall j = 1, \dots, Ns \tag{7}$$

Equation (3) is the objective function, whose elements $\overline{f}_1$ and $\overline{f}_2$ are the normalized values of the workload variance f_1 and of the energy variance $f_{2,}$ respectively. α and *(1-α)* are the relative weights of objectives, while β is a penalty value, so that:

$$\beta = \begin{cases} 1 & \text{if all constraints are respected;} \\ 0.5 & \text{otherwise.} \end{cases} \tag{8}$$

The workload variance is modeled as follows:

$$f_1(x) = \sqrt{\frac{\sum_{j=1}^{Ns}\left(\frac{\sum_{j=1}^{Ns} IT_j}{Ns} - IT_j\right)^2}{Ns}} \tag{9}$$

where IT_j [min] is the idle time of station *j*:

$$IT_j = CT - \sum_{i=1}^{Nt}\sum_{k=1}^{Nt} t_i x_{ijk} \tag{10}$$

This objective function minimizes the number of workstations, coherently with SALBP-1.

The energy variance formulation is as follows:

$$f_2(x) = \sqrt{\frac{\sum_{j=1}^{Ns}\left(\frac{\sum_{j=1}^{Ns} \Delta E_{jw}}{Ns} - \Delta E_{jw}\right)^2}{Ns}} \tag{11}$$

where ΔE_{jw} is the energy gap at workstation *j* where worker *w* is placed:

$$\Delta E_{jw} = 1 - \frac{E_{jw}}{OEL_{jw} \cdot CT} \tag{12}$$

E_{jw} [kcal] is the total amount of energy expenditure of worker *w* assigned to workstation *j*, which can be calculated as the sum of the energy consumption of the different movements that worker *w* performs to execute tasks assigned to workstation *j*. The formulations used for energy calculations are based on the model proposed by Garg in [19], in which a list of possible movements to be carried out during assembly operations, such as walking or lifting an object, is defined. For each movement, formulations are given to calculate the energy expenditure based on parameters related to both the type of movement (e.g. the distance walked or the weight of the object lifted) and to the worker's personal characteristics (e.g. gender, weight, age). In Eq. (12), the total energy expenditure is compared to the energetic limit. In particular, OEL_{jw} [W] is the occupational energy limit of worker *w* assigned to workstation *j,* which represents the physical limit used for professional applications and again calculated according to workers' individual features. More details on these expressions are given in [18].

The constraints are as follows: Eq. (4) ensures the cycle time to be respected at each workstation; Eq. (5) ensures the respect of precedence constraints, preventing each task *i* from being assigned to station *j* if all the tasks that must be performed before *i* are not assigned to station *j* or to the previous ones; Eq. (6) ensures that each task is assigned to at most one workstation; Eq. (7) ensures not to exceed the energetic limit for each worker *w*.

3.2 Genetic algorithm

The proposed approach has been developed using a Genetic Algorithm (GA), an evolutionary technique based on mechanisms proper of biological survival and chosen for its proven efficiency in solving large-scale combinatorial problems with high complexity [20]. In a GA, solutions for the problem are encoded as chromosomes or individuals, containing numerical values as genes. The algorithm starts generating a population of individuals and for each of them, a fitness function evaluates the goodness in meeting the objectives of the problem. Individuals with better fitness values have a higher probability of being selected for reproduction by genetic operators. Crossover recombines genes of individuals in pairs, while mutation operates on a single chromosome. The offspring generated replace partly or completely the population. The steps of the algorithm are reiterated until a stopping criterion is reached.

The main distinguishing features of the GA proposed in this paper and developed in MatLab® are outlined below.

3.2.1 Chromosome structure

For the first generation of individuals of the algorithm, several chromosomes are randomly generated by a sequence planner so that precedence constraints are respected.

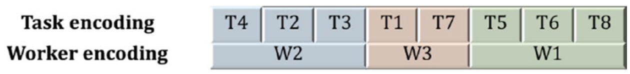

Fig. 1 Example of chromosome structure with assembly sequence in *task encoding* and workers in *worker encoding*

Each chromosome is structured in two parts: the first one uses the task-oriented representation for the assembly sequence; the other one uses a worker-oriented representation, related to workers. The worker-oriented part of the chromosome contains the sequence of workers, selected among the ones available in a company and assigned one per station to the assembly line.

An example of a chromosome is reported in Fig. 1, where line stations are differentiated by colors. The first string (*Task encoding*) is the task-oriented part with 8 genes encoding 8 assembly tasks (*T1,…,T8*), placed in the order of execution. The other is the worker-oriented chromosome (*Worker encoding*), which is composed of 3 genes representing 3 different workers (*W1,W2,W3*) of the company, assigned to the 3 stations of the line.

3.2.2 Fitness function

The objective function of the proposed problem involves the minimization of two objectives: the workload variance and the energy variance. The fitness function of the developed GA evaluates each chromosome based on these objectives (Eq. 3). As the problem deals with a minimization function, the lower the value of fitness is, the higher the probability is for the related chromosome to survive to the following generations of the algorithm.

3.2.3 Genetic operators

The chromosomes of the developed GA undergo genetic operations, starting from the roulette wheel selection through which individuals of the current population with better values of the fitness function are selected to generate offspring.

Following that, the order-based crossover is applied to task encoding to produce chromosomes with assembly sequences respecting the precedence constraints. In particular, the crossover operator selects two parents to be divided into an initial, an intermediate, and a final part; these parents produce two children, the first made by initial and final part of the first parent and by missing genes ordered as they are in the second parent; vice versa for the second child. This operator is illustrated in Fig. 2.

The swap mutation is then used to enable proper randomness on the algorithm and is applied to worker encoding, by reversing the position of two workers on the line, as represented in Fig. 3. Elitism is finally applied to only preserve

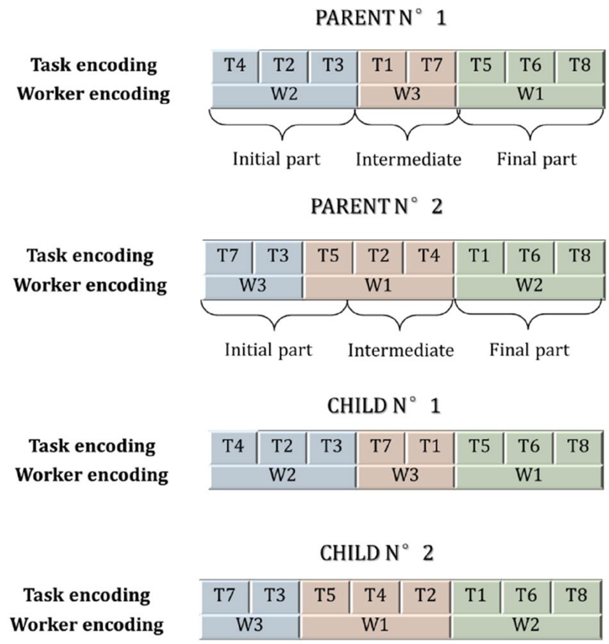

Fig. 2 Order-based crossover applied to the task encoding part of a pair of chromosomes

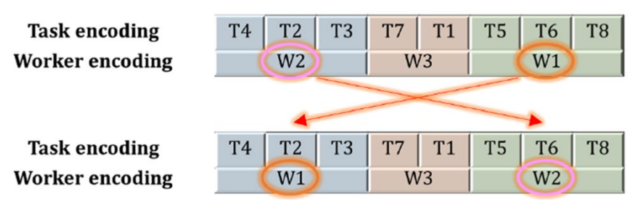

Fig. 3 Swap mutation applied to the worker encoding part of a chromosome

individuals with outperforming values of the fitness function, so as to enforce a steady improvement of solutions.

4 System validation

To analyze how the software performs under different conditions, various real case studies representing industrial assembly problems have been selected and tested, with a view of discussing the energy expenditure of workers in light to medium-weight components handling operations. Also, the selected examples of products are representative of industrial applications, as their mass production requires proper assembly line dimensioning and balancing.

The dataset for each assembly problem consists of case-specific data, reported in the following sections, and common parameters, related to the pool of available workers that have been simulated. In Table 1, individual characteristics

Table 1 Input data of workers for the basic configuration

Worker	Age [years]	Weight [kg]	Height [m]	Gender
W1	29	78	1.80	M
W2	45	85	1.71	M
W3	30	55	1.59	F
W4	49	69	1.65	F
W5	51	70	1.75	M
W6	56	83	1.54	F
W7	35	92	1.83	M
W8	26	63	1.62	M
W9	54	82	1.79	M
W10	52	69	1.75	F
W11	37	60	1.67	F
W12	22	51	1.50	F
W13	46	86	1.85	M
W14	31	82	1.76	M
W15	21	65	1.72	M

are shown for a basic configuration. Additionally, each case study has been analyzed using different variants, obtained by modifying workers' parameters, one at a time. Variants are presented in Table 2 and have been obtained as follows:

- Variant 1 (worker age decreased by 10%): using column 2 of Table 2 for workers' age;
- Variant 2 (worker age increased by 10%): using column 3 of Table 2 for workers' age;
- Variant 3 (worker age increased by 50%): using column 4 of Table 2 for workers' age;
- Variant 4 (worker weight decreased by 10%): using column 5 of Table 2 for workers' weight;
- Variant 5 (worker weight increased by 10%): using column 6 of Table 2 for workers' weight;
- Variant 6 (worker weight increased by 50%): using column 7 of Table 2 for workers' weight.

These variants have been chosen in order to analyze how the configuration of the assembly line changes in case of small and great modifications in the pool of available workers.

In addition, a reduction in the existing workforce has been considered as another aspect of the sensitivity analysis, thus involving further variants:

- Variant 7 (workforce reduction): using workers from W1 to W8 of Table 1.
- Variant 8 (workforce reduction with age increased by 50%): using workers from W1 to W8 of Table 1 with column 4 of Table 2 for workers' age;
- Variant 9 (workforce reduction with weight increased by 50%): using workers from W1 to W8 of Table 1 with column 7 of Table 2 for workers' weight.

Another analysis conducted to further investigate the robustness of the algorithm concerns input data related to GA parameters. These have been established through a first trial-and-error procedure, taking into account that the value of crossover probability is generally one or two orders of magnitude higher than mutation probability, to ensure a good compromise between exploration and exploitation [20]. The following values led to the best performance: 100–150–200 for population size; 0.90–0.95–0.98 for crossover probability; 0.04–0.05–0.06 for mutation probability. For each

Table 2 Modified data of workers for variants

Variant	1	2	3	4	5	6
Worker	Age [years]	Age [years]	Age [years]	Weight [kg]	Weight [kg]	Weight [kg]
W1	26	32	44	70	86	117
W2	41	50	68	77	94	128
W3	27	33	45	50	61	83
W4	44	54	74	62	76	104
W5	46	56	77	63	77	105
W6	50	62	84	75	91	125
W7	32	39	53	83	101	138
W8	23	29	39	57	69	95
W9	49	59	81	74	90	123
W10	47	57	78	62	76	104
W11	33	41	56	54	66	90
W12	20	24	33	46	56	77
W13	41	51	69	77	95	129
W14	28	34	47	74	90	123
W15	19	23	32	59	72	98

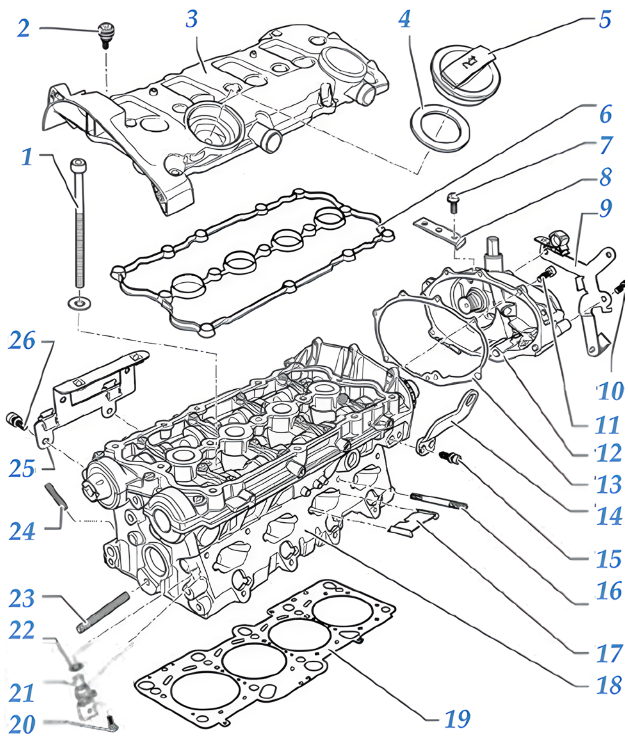

Fig. 4 Exploded view of assembly case n.1

Table 3 Dataset of assembly case n.1

Task	Precedence constraints	Execution time [min]	Energy expenditure for worker W1 [kcal]
T1	T18	0.33	0.68
T2	T3	0.05	0.13
T3	T6	0.33	0.68
T4	T3	0.08	0.19
T5	T4	0.03	0.10
T6	T18	0.15	0.35
T7	T8	0.24	0.36
T8	T12	0.25	0.52
T9	T12	0.33	0.68
T10	T9	0.21	0.36
T11	T12	0.17	0.36
T12	T13	0.42	0.85
T13	T18	0.25	0.52
T14	T18	0.25	0.52
T15	T14	0.17	0.36
T16	T18	0.25	0.52
T17	T18	0.17	0.36
T18	-	0.50	1.31
T19	T18	0.31	0.68
T20	T21	0.05	0.13
T21	T22	0.12	0.26
T22	T18	0.08	0.19
T23	T18	0.13	0.29
T24	T18	0.17	0.36
T25	T18	0.42	0.83
T26	T18	0.08	0.19

possible combination of these values, the average fitness has been calculated by running the algorithm 30 times and then choosing the combination producing the best value.

4.1 Assembly case n.1

The first case study concerns the assembly of a cylinder head of a combustion engine, chosen because characterized by a massive cast part and several other components mounted on it.

4.1.1 Dataset and parameters

The assembly sequence requires 26 operations to assemble the 26 parts depicted in Fig. 4 and is performed on an assembly line having a 1.40 min/product cycle time, i.e., the maximum time for the product to be spent at each workstation. The cycle time is determined on the basis of the production rate and the line efficiency. The production rate has been obtained by considering an industrial context where 80,000 cylinder heads are assembled in a line that works 50 weeks/year, with 5 shifts/week and 8 h/shift, giving a value of 40 products/h. The line efficiency indicates the time ratio during which the line operates to the total time that includes downtimes for set up, maintenance, and faults. This parameter is set to 93%.

The dataset of the problem is in Table 3, where, for each task *i*, the following parameters are reported: precedence constraints, i.e. the tasks that must be performed before task *i*; execution time, i.e. the time a worker takes to perform task *i*; energy expenditure for an example of worker (W1). This last value is calculated for the worker identified with W1 in Table 1, to exemplify the energy expenditure evaluation of elementary operations.

4.1.2 Results and discussion

The best solution of the first case study has been obtained by using 100 as population size, 0.98 as crossover probability and 0.05 as mutation probability, according to the criteria established in Sect. 4.

Results for the basic configuration are reported in Fig. 5, where the energy and workload histograms are illustrated as a function of the resulting workstations (on the axis of the abscissas). The energy histogram is reported in green bars showing, on the axis of the ordinates, the energy saturation that is the energy expenditure of workers assigned

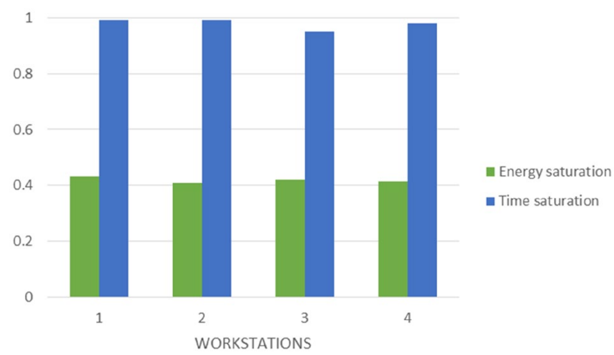

Fig. 5 Results for basic configuration of assembly case n.1 in terms of energy and workload histogram

to the different stations to their physical limits, i.e. ΔE_{jw} (Eq. 12). The workload histogram, in blue bars, highlights the time saturation that is the distribution of the assembly tasks to workstations according to execution times, i.e. $(\sum_{i=1}^{Nt}\sum_{k=1}^{Nt} t_i x_{ijk})/CT$ (Eq. 10). These parameters are reported in normalized values between 0 and 1 to be comparable to each other.

The details of the solutions in terms of tasks and workers assigned to the different stations are reported in Table 4 (*basic configuration*), together with results obtained for variants 1, 2, 4, 5, 8 and 9, for the sake of brevity. As an example, for the basic configuration, four workstations are needed; in the first, tasks 18, 1, 6, 22, 24, and 23, reported in Table 4, are executed by worker W7 presented in Table 1; the ratio of the total duration of tasks to the cycle time for the first station is 99%, while the energy used by worker W7 to accomplish the tasks is 43% of his expendable energy. Figure 6 reports the same information of Fig. 5 for variants 1, 2, 4, 5, 8 and 9 presented in Table 4.

As viewable from Fig. 5, the workload appears well-smoothed both from an energy and a time perspective. Workers are not overloaded, as for each of them the allocated assembly operations do not even reach half of the limit in expendable energy (mean energy saturation is 41.75%). Furthermore, the assembly process is assigned to the minimum number of workstations, and the time at disposal is well used, as for every station the cycle time is nearly reached. As far as tested variants are concerned, from Fig. 6 and Table 4 it can be noticed that limits in time and energy expenditure are always respected. Additionally, time and energy are well balanced in every case, meaning that the developed GA can achieve the set objectives for all configurations of input data. Compared to the solution obtained for the basic configuration, results for variants are coherent with changes in the dataset. As an example, the energy saturation of different workers in variant 1 (0.36; 0.38; 0.40; 0.34) is lower than the energy saturation of the basic configuration (0.43; 0.41; 0.42; 0.41). This is due to the lower age of workers used in the dataset for variant 1, which causes higher expendable energy for them. Similarly, the energy saturation of variant 5 is higher (0.45; 0.45; 0.44; 0.44) because of the higher weight considered for workers, which leads to less expendable energy. It is interesting to note that for variant 8 the algorithm selects workers that, despite the higher age, are the younger in the pool at disposal, reduced to the first 8 workers of Table 1. Also in variant 9, workers with a lower weight compared to others are assigned to the four stations, confirming that the system in every situations aims at optimizing the energy expenditure.

To analyze more in detail how workers' parameters affect the assembly line configuration, results are also reported in Fig. 7, where mean energy saturation and mean time saturation, again reported in normalized values between, are shown as a function of the mean worker age (Fig. 7a) and of the mean worker weight (Fig. 7b). Mean values on the axis of the ordinates are obtained as average arithmetical of energy and time saturation values among workstations. Mean values on the axis of the abscissas are the average arithmetical of age and weight for the pool of workers simulated for variants.

As expected, the variation of workers' age and weight does not affect the time saturation (blue lines), which depends on duration parameters, thus remaining constant in both Fig. 7a and b. As regards energy saturation (green lines), it can be noticed that if age parameter is varied (Fig. 7a), an almost linear growth is obtained. This result is even more remarkable in Fig. 7b. In this case, if weight is changed by a large amount, the system demonstrates its sensitivity by proposing assembly line configurations with clearly increased energy expenditures, meaning that workers have a low expendable energy.

4.2 Assembly case n.2

Experimental case n.2 deals with the study of the assembly process of a fuel filter, composed of 21 parts reported in Fig. 8.

4.2.1 Dataset and parameters

The assembly sequence needs 24 operations to be completed in a line with 1.10 min/product cycle time. This value has been established by assuming an annual collection of 100,000 products that are assembled in a line characterized by a 92% efficiency and other parameters set at the same values as those of assembly case n.1. The other input data for the problem are in Table 5.

Table 4 Results of assembly case n.1

BASIC CONFIGURATION				
Tasks	T18,T1,T6,T22,T24,T23	T14,T19,T17,T3,T2,T16	T21,T13,T26,T15,T20,T12,T8	T11,T4,T5,T25,T7,9,T10
Workstation	1	2	3	4
Worker	W7	W9	W5	W2
Time saturation	0.99	0.99	0.95	0.98
Energy saturation	0.43	0.41	0.42	0.41
VARIANT 1				
Tasks	T18,T19,T13,T16	T12,T26,T25,T23,T22,T8	T14,T11,T21,T17,T6,T24,T1	T9,T10,T20,T3,T2,T15,T4,T7,T5
Workstation	1	2	3	4
Worker	W13	W2	W3	W5
Time saturation	0.95	0.99	0.99	0.98
Energy saturation	0.36	0.38	0.40	0.34
VARIANT 2				
Tasks	T18,T1,T19,T24	T16,T17,T26,T13,T25,T22,T23	T12,T21,T6,T8,T14, T15	T20,T3,T4,T2,T5,T11,T9,T7,T10
Workstation	1	2	3	4
Worker	W5	W12	W13	W2
Time saturation	0.95	0.98	0.99	0.99
Energy saturation	0.45	0.43	0.44	0.47
VARIANT 4				
Tasks	T18,T14,T6,T16,T17	T23,T19,T1,T24,T25	T13,T3,T22,T2,T26,T15,T12	T8,T21,11,T4,T9,T20,T10,T5,T7
Workstation	1	2	3	4
Worker	W2	W13	W5	W9
Time saturation	0.95	0.99	0.99	0.98
Energy saturation	0.40	0.41	0.40	0.40
VARIANT 5				
Tasks	T18,T25,T26,T1	T14,T22,T24,T15,T17,T16,T6,T21	T20,T13,T3,T4,T12, T8	T2,T7,T9,T23,T19,T1,T11,T5
Workstation	1	2	3	4
Worker	W7	W9	W13	W2
Time saturation	0.95	0.99	0.98	0.99
Energy saturation	0.45	0.45	0.44	0.44
VARIANT 8				
Tasks	T18,T14,T13,T6,T17	T24,T16,T23,T12,T19,T26	T3,T2,T25,T4,T15, T1	T22,T5,T21,T11,T20,T9,T8,T7,T10
Workstation	1	2	3	4
Worker	W3	W7	W1	W8
Time saturation	0.99	0.99	0.95	0.98
Energy saturation	0.55	0.53	0.57	0.54
VARIANT 9				
Tasks	T18,T26,T1,T1,T23,T19	T14,T15,T22,T13,T25,T17	T6,T24,T21,T16,T12, T8	T11,T9,T7,T10,T3,T2,T4,T20,T5
Workstation	1	2	3	4
Worker	W3	W4	W8	W5
Time saturation	0.95	0.99	0.98	0.99
Energy saturation	0.66	0.65	0.64	0.64

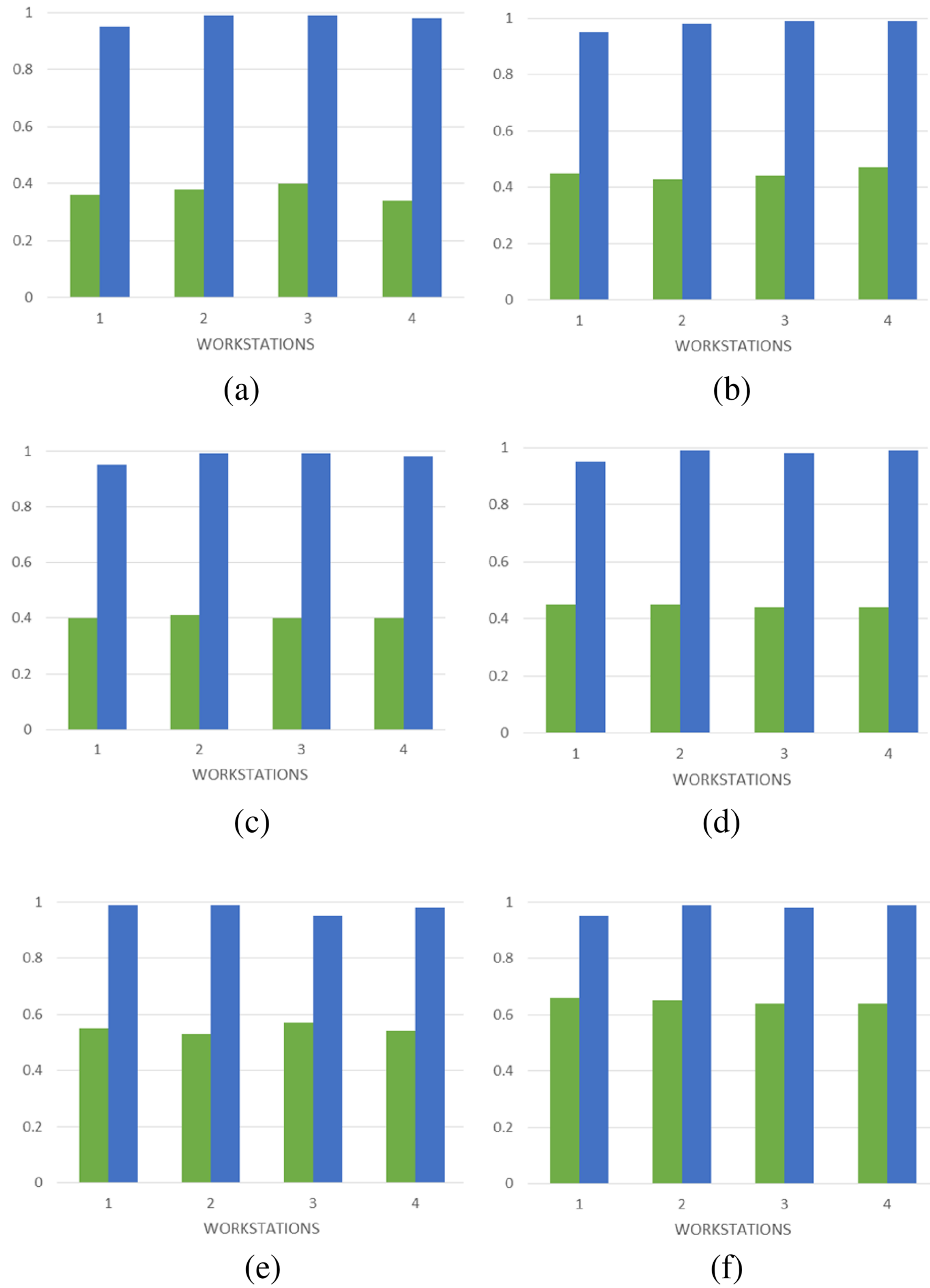

Fig. 6 Results of assembly case n.1 in terms of energy and workload histogram for: **a** variant 1; **b** variant 2; **c** variant 4; **d** variant 5; **e** variant 8; **f** variant 9

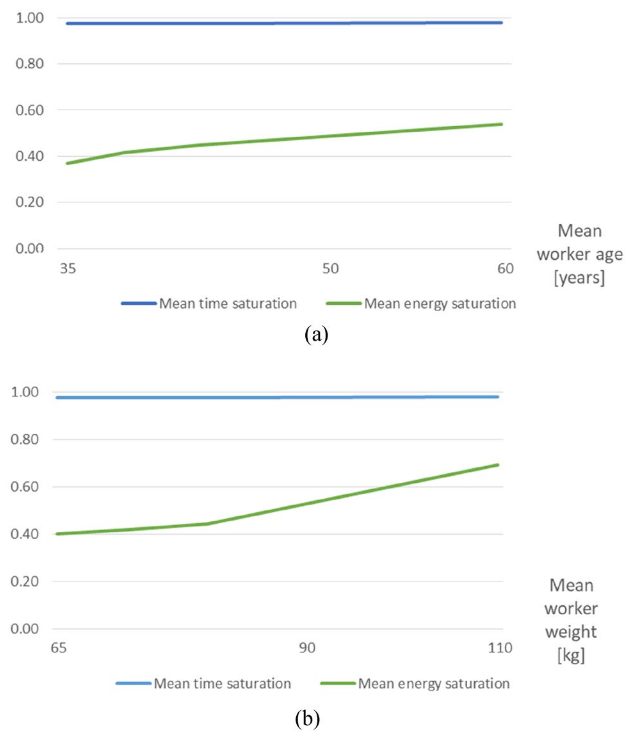

Fig. 7 Results for varying worker age (**a**) and worker weight (**b**) in assembly case n.1 in terms of mean time saturation and mean energy saturation

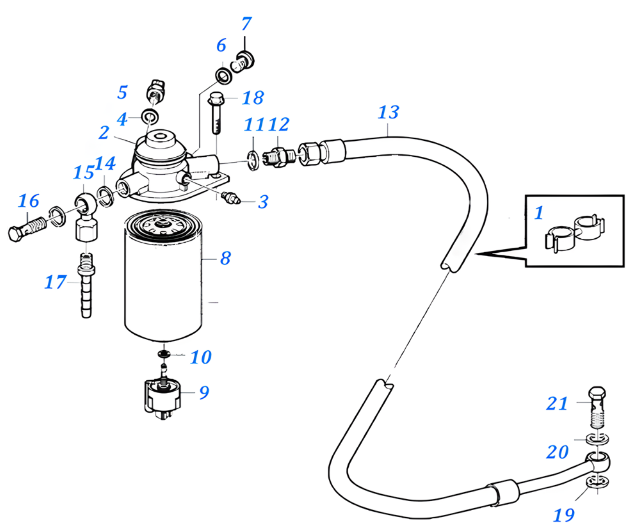

Fig. 8 Exploded view of assembly case n.2

Table 5 Dataset of assembly case n.2

Task	Precedence constraints	Execution time [min]	Energy expenditure for worker W1 [kcal]
T1	T15	0.17	0.35
T2	–	0.17	0.35
T3	T2	0.08	0.19
T4	T2	0.17	0.35
T5	T4	0.08	0.19
T6	T2	0.17	0.36
T7	T6	0.25	0.52
T8	T2	0.17	0.36
T9	T12	0.08	0.20
T10	T8	0.25	0.52
T11	T12	0.08	0.20
T12	T10	0.08	0.20
T13	T2	0.25	0.52
T14	T13	0.17	0.36
T15	T14, T20	0.08	0.20
T16	T2	0.08	0.20
T17	T16	0.33	0.68
T18	T24	0.33	0.67
T19	T17	0.08	0.19
T20	-	0.33	0.67
T21	T1	0.08	0.19
T22	T15	0.33	0.67
T23	T2	0.08	0.19
T24	T17	0.08	0.19

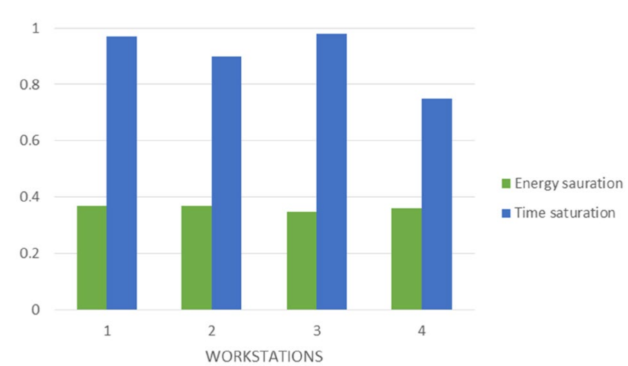

Fig. 9 Results for basic configuration of assembly case n.2 in terms of energy and workload histogram

4.2.2 Results and discussion

Results for the second assembly case have been obtained with 200 as population size, 0.95 as crossover probability and 0.05 as mutation probability.

The best solution for the basic configuration is illustrated in Fig. 9 in terms of the energy and workload histograms. As for the previous assembly case, the same solution is also shown in Table 6, where results obtained for variants 1, 2, 4, 5, 8 and 9 are reported. Figure 10 reports the energy and workload histograms for the same variants.

From presented results, it can be noted that similar considerations apply to this assembly example, as to the

Table 6 Results of assembly case n.2

BASIC CONFIGURATION				
Tasks	T2,T6,T13,T3,T20,T1,T23,T16,T17	T4,T19,T24,T8,T14	T5,T18,T15,T22	T25,T21,T11,T9
Workstation	1	2	3	4
Worker	W5	W14	W7	W13
Time saturation	0.97	0.90	0.98	0.75
Energy saturation	0.37	0.37	0.35	0.36
VARIANT 1				
Tasks	T20,T1,T2,T4,T23,T13,T6,T5	T7,T14,T15,T22,T25,T8	T21,T10,T12,T9,T3,T16,T17	T11,T24,T18,T19
Workstation	1	2	3	4
Worker	W13	W3	W9	W2
Time saturation	0.90	0.91	0.89	0.90
Energy saturation	0.33	0.34	0.31	0.33
VARIANT 2				
Tasks	T1,T2,T8,T10,T6,T7,T23	T20,T13,T14,T16,T12,T11,T15,T25	T22,T9,T21,T17,T4,T19	T24,T18,T3,T5
Workstation	1	2	3	4
Worker	W5	W9	W12	W11
Time saturation	0.98	0.97	0.97	0.68
Energy saturation	0.43	0.43	0.44	0.44
VARIANT 4				
Tasks	T20,T1,T2,T23,T6,T8,T13	T3,T10,T16,T7,T12,T14,T15,T17	T22,T4,T9,T11,T5,T19	T25,T24,T18,T21
Workstation	1	2	3	4
Worker	W5	W2	W9	W11
Time saturation	0.90	0.98	0.98	0.74
Energy saturation	0.40	0.37	0.38	0.39
VARIANT 5				
Tasks	T1,T20,T2,T3,T8,T23,T13	T16,T6,T17,T10,T12,T9,T19,T7	T14,T15,T11,T4,T25, T5	T21,T22,T24,T18
Workstation	1	2	3	4
Worker	W13	W3	W2	W11
Time saturation	0.98	0.96	0.91	0.75
Energy saturation	0.45	0.47	0.45	0.45
VARIANT 8				
Tasks	T2,T3,T16,T17,T20,T23,T1,T13,T24	T19,T8,T14,T15	T18,T10,T12,T11,T22,T6,T25	T21,T7,T4,T9,T5
Workstation	1	2	3	4
Worker	W7	W3	W8	W1
Time saturation	0.98	0.90	0.97	0.75
Energy saturation	0.59	0.59	0.56	0.55
VARIANT 9				
Tasks	T20,T1,T2,T13,T16,T4,T5,T3,T17,T24	T19,T8,T14	T18,T23,T10,T12,T11	T6,T15,T25,T21,T7,T9,T22
Workstation	1	2	3	4
Worker	W4	W3	W5	W8
Time saturation	0.91	0.90	0.90	0.91
Energy saturation	0.66	0.62	0.63	0.66

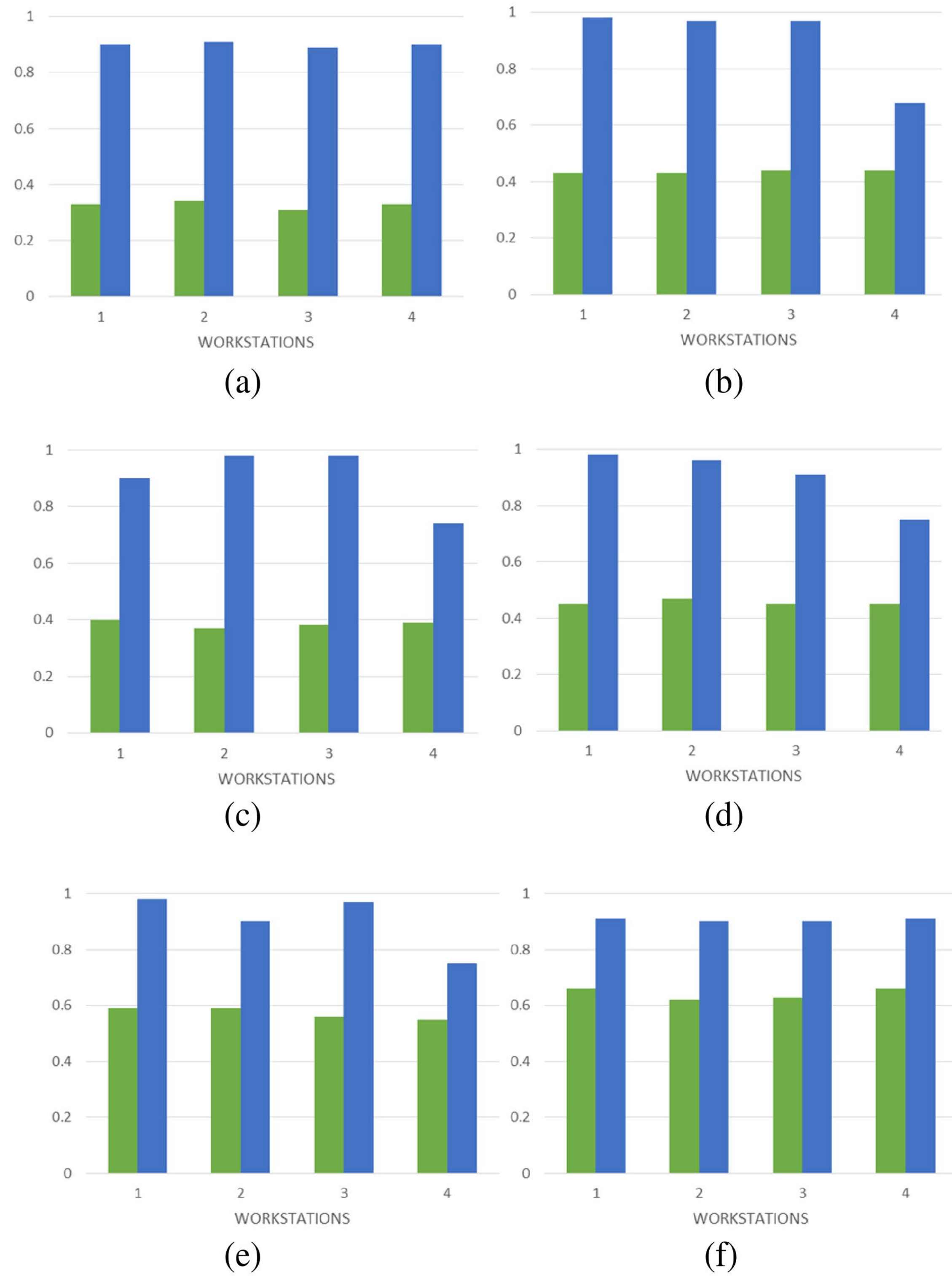

Fig. 10 Results of assembly case n.2 in terms of energy and workload histogram for: **a** variant 1; **b** variant 2; **c** variant 4; **d** variant 5; **e** variant 8; **f** variant 9

previous one. Also in this case, the energy of workers appears well smoothed and greatly under the limits; time saturation is sufficiently smoothed, even though constraints for this assembly case, such as precedence relationships, restrict the possibility of further improving time balancing. Solutions obtained for variants 2 and 5, involving the first a higher age and the second a higher weight of workers, present a higher energy expenditure if compared with the solution returned by the algorithm for the basic configuration. Also in the case of a reduction in the workforce, the tool minimizes and balances the energy expenditure, as shown for variants 8 and 9. This is coherent with the variation of input values in the different scenarios.

Similar considerations apply to Fig. 11, where it can be noted that time saturation appears to be independent from workers' parameters. Conversely, energy saturation increases as age (Fig. 11a) or weight (Fig. 11b) of workers increases, more notably in the second situation.

4.3 Assembly case n.3

Case study n.3 represents the assembly of an ignition distributor involving 25 parts, with exploded view in Fig. 12.

4.3.1 Dataset and parameters

The dataset for the problem concerning assembly tasks is shown in Table 7, again with examples of calculation on energy expenditure for worker W1 of Table 1. The entire process requires 32 tasks to be accomplished on an assembly line with a fixed cycle time set to 1.40 min/product.

4.3.2 Results and discussion

The energy and workload histograms for the best solution of assembly case n.3 are in Figs. 13 and 14, while in Table 8 results are reported for all the tested configurations, including the basic one and variants 1, 2, 4, 5, 8 and 9. Solutions presented refer to GA parameters set as follows: 100 as population size; 0.95 as crossover probability; 0.05 as mutation probability.

Also in this case, results show a good leveling of times and energy among workstations and workers. For variant 1 and variant 4, entailing a lower age and a lower weight of workers, the energy expenditures are lower if compared to other configurations, as expected, because of the lower age and the lower weight of workers in the two situations, respectively.

Figure 15 shows again the independence of time saturation from workers age and weight, while strengthening the consideration related to the energy saturation. This output, in facts, denotes that as a worker age or weight grows, the expendable energy decreases, thus causing an increased energy saturation.

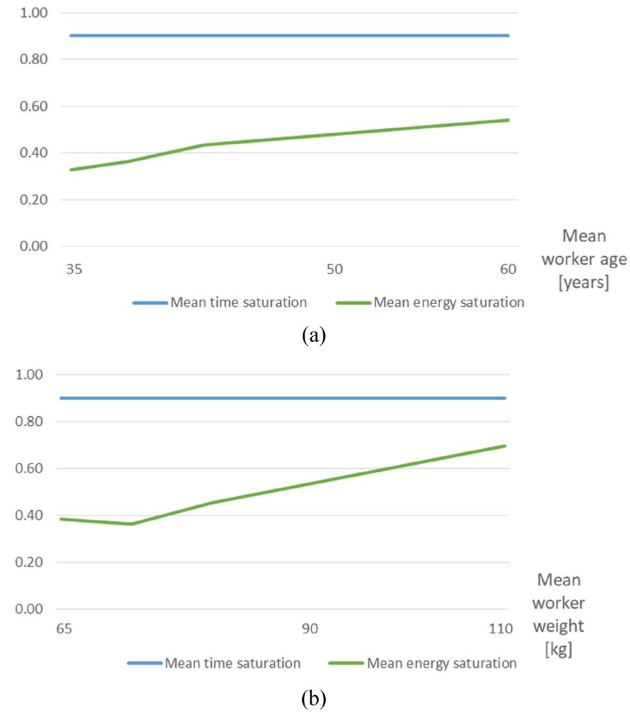

Fig. 11 Results for varying worker age (**a**) and worker weight (**b**) in assembly case n.2 in terms of mean time saturation and mean energy saturation

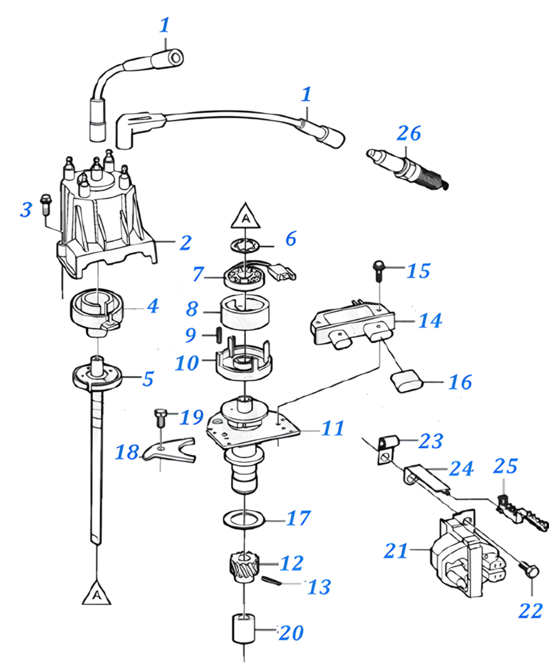

Fig. 12 Exploded view of assembly case n.3

The results obtained through the proposed changes in analyzed variables denote the robustness of the software tool.

Table 7 Dataset of assembly case n.3

Task	Precedence constraints	Execution time [min]	Energy expenditure for worker W1 [kcal]
T1	T2	0.08	0.20
T2	–	0.17	0.36
T3	T2	0.17	0.35
T4	T2	0.25	0.51
T5	T4	0.25	0.52
T6	T5	0.08	0.19
T7	T6	0.17	0.35
T8	T7	0.17	0.36
T9	T8	0.08	0.20
T10	T9	0.33	0.68
T11	T10, T15, T16	0.42	0.84
T12	T17	0.33	0.68
T13	T12	0.08	0.20
T14	T2	0.33	0.68
T15	T14	0.17	0.36
T16	T14	0.08	0.20
T17	T11	0.17	0.36
T18	T11	0.17	0.36
T19	T18	0.25	0.52
T20	T13	0.17	0.36
T21	T24	0.25	0.53
T22	T21	0.16	0.35
T23	T11	0.08	0.19
T24	T23	0.08	0.19
T25	T24	0.25	0.51
T26	T27	0.08	0.20
T27	T2	0.08	0.20
T28	T31	0.08	0.20
T29	T32	0.08	0.20
T30	T1	0.08	0.20
T31	T2	0.08	0.20
T32	T2	0.08	0.20

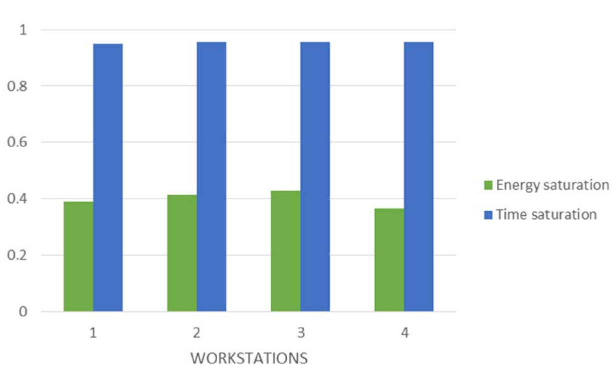

Fig. 13 Results for basic configuration of assembly case n.3 in terms of energy and workload histogram

5 Conclusions

This paper has presented a software tool based on a genetic approach to solving a bi-objective version of the SALBP-1, which aims at designing efficient and ergonomic assembly lines. The efficiency stems from minimizing the number of workstations, while balancing the idle times. Ergonomics is optimized by reducing and smoothing the energy expenditures of workers assigned to the assembly line.

The system validation demonstrates that the developed genetic approach achieves the proposed objectives in all investigated assembly cases, also when varying input parameters. Obtained solutions, in fact, minimize the workload variance, as the time saturation is almost 100%, on average, in every tested variant of each assembly case. This means that the available time is well used and the assembly sequence is perfectly distributed among workstations. As a result, cost-efficient configurations of the line using the minimum number of workstations are generated in every case, with a positive economic impact on the company. As regards ergonomics, results demonstrate that a smoothed distribution of energy expenditure among workers, calculated according to their personal characteristics, can be achieved. This means that the total energetic workload necessary to accomplish an assembly process can be almost equally allocated among workers. In addition, in all tested variants of the different assembly cases, the tool is capable of assigning operations not exceeding the physical capabilities of workers, while respecting at the same time the other constraints of the combinatorial optimization problem. Workers are thus never overloaded from an energetic point of view. The context-based efficacy of the developed tool in providing the optimal solution is shown and its validation carried out through the proposed sensitivity analysis is supported by the demonstrated robustness.

In particular, the sensitivity analysis, conducted by applying the system to different scenarios, shows how responsive the system is to changes in specific values. As expected, the system is insensitive to workers' age and weight variations as regards time saturation, but sensitive as regards energy saturation. This is because, in the present work, execution times are considered as deterministic values, independent from workers' parameters, while energy expenditure is calculated as a function of individual characteristics. This demonstrates that the tool can be successfully used in the industrial context improving decision making, through an assessment of the robustness of the decision made. The planning of manual assembly processes in line can be supported, taking into account the human factor. Ergonomics is still little treated in the scientific literature from a line-balancing perspective and,

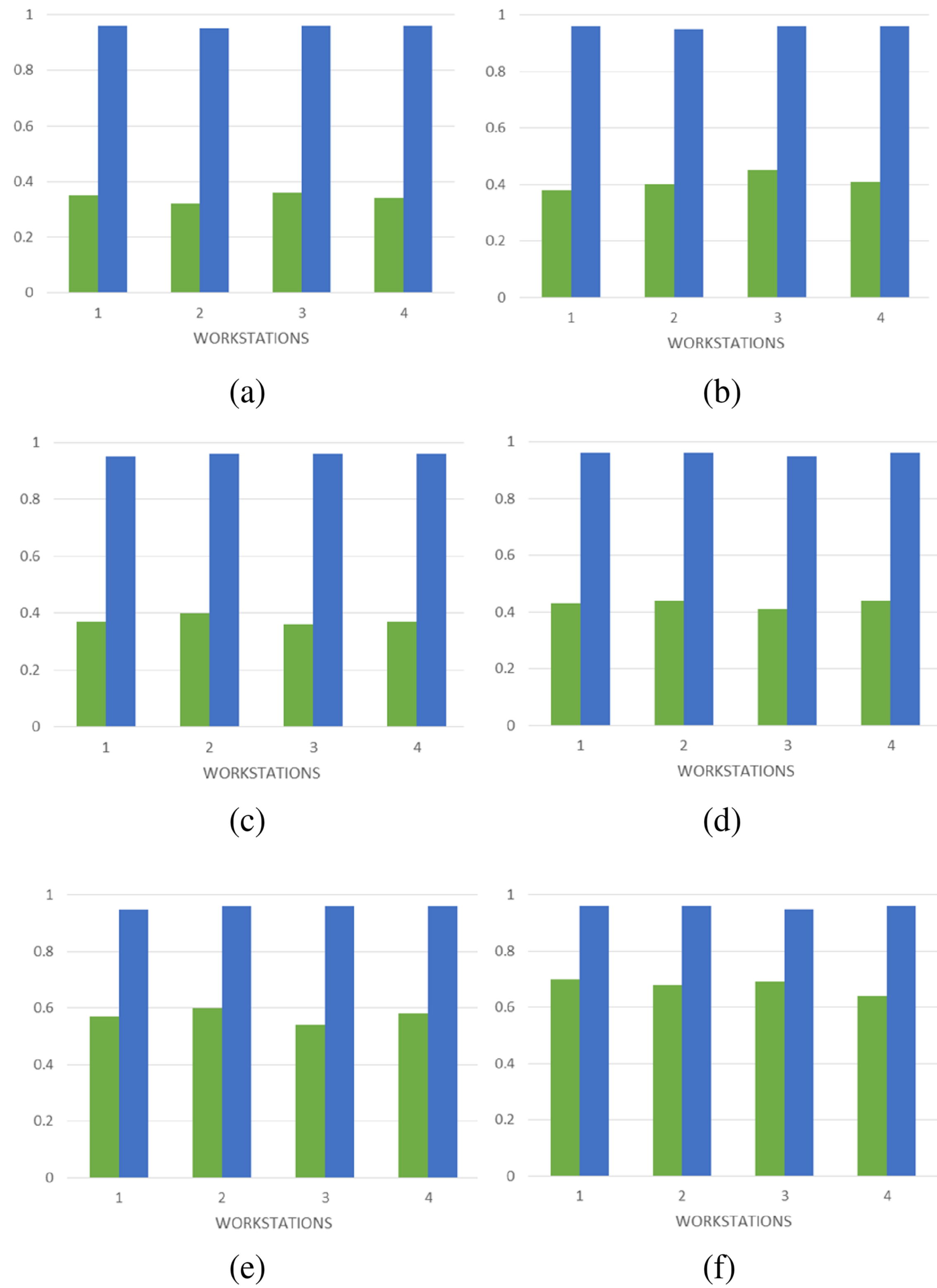

Fig. 14 Results of assembly case n.3 in terms of energy and workload histogram for: **a** variant 1; **b** variant 2; **c** variant 4; **d** variant 5; **e** variant 8; **f** variant 9

Table 8 Results of assembly case n.3

BASIC CONFIGURATION				
Tasks	T1,T2,T32,T31,T28,T27,T26,T14,T4,T3	T5,T6,T16,T15,T7,T8,T9,T10	T33,T29,T11,T18,T17,T12,T23	T30,T24,T21,T19,T25,T13,T20,T22
Workstation	1	2	3	4
Worker	W5	W12	W9	W13
Time saturation	0.95	0.96	0.96	0.96
Energy saturation	0.39	0.41	0.43	0.37
VARIANT 1				
Tasks	T2,T3,T1,T33,T27,T26,T4,T32,T14,T31	T5,T28,T29,T6,T7,T30,T8,T9,T10	T15,T16,T11,T23,T24,T25,T21	T22,T17,T12,T18,T13,T19,T20
Workstation	1	2	3	4
Worker	W5	W3	W2	W13
Time saturation	0.96	0.95	0.96	0.96
Energy saturation	0.35	0.32	0.36	0.34
VARIANT 2				
Tasks	T1,T2,T4,T5,T6,T14,T33,T15	T3,T16,T32,T29,T30,T7,T31,T8,T9,T10	T27,T26,T28,T11,T17,T12,T23,T24	T25,T21,T13,T18,T22,T19,T20
Workstation	1	2	3	4
Worker	W13	W5	W2	W9
Time saturation	0.96	0.95	0.96	0.96
Energy saturation	0.38	0.40	0.45	0.41
VARIANT 4				
Tasks	T1,T2,T4,T32,T29,T31,T33,T3,T30,T5,T6	T7,T27,T28,T8,T9,T14,T10,T26	T16,T15,T11,T23,T24,T17,T12	T21,T22,T25,T18,T19,T13,T20
Workstation	1	2	3	4
Worker	W5	W9	W13	W2
Time saturation	0.95	0.96	0.96	0.96
Energy saturation	0.37	0.40	0.36	0.37
VARIANT 5				
Tasks	T1,T2,T33,T4,T32,T5,T31,T6,T3,T30,T27	T14,T7,T16,T8,T9,T15,T10	T29,T28,T11,T17,T18,T12,T23	T13,T26,T20,T19,T24,T25,T21,T22
Workstation	1	2	3	4
Worker	W13	W9	W3	W2
Time saturation	0.96	0.96	0.95	0.96
Energy saturation	0.43	0.44	0.41	0.44
VARIANT 8				
Tasks	T2,T4, T1,T14,T3,T33,T5,T27	T6,T26,T7,T31,T8,T9,T30,T32,T28,T29,T10,T16	T15,T11,T17,T12,T18,T13	T20,T19,T23,T24,T25,T21,T22
Workstation	1	2	3	4
Worker	W1	W7	W3	W8
Time saturation	0.95	0.96	0.96	0.96
Energy saturation	0.57	0.60	0.54	0.58
VARIANT 9				
Tasks	T2,T4,T5,T3,T1,T27,T33,T14	T26,T32,T6,T31,T30,T7,T29,T28,T8,T9,T10	T16,T15,T8,T17,T12,T13,T23	T18,T24, T25,T21,T20,T22,T19
Workstation	1	2	3	4
Worker	W8	W4	W3	W5
Time saturation	0.96	0.96	0.95	0.96
Energy saturation	0.70	0.68	0.69	0.64

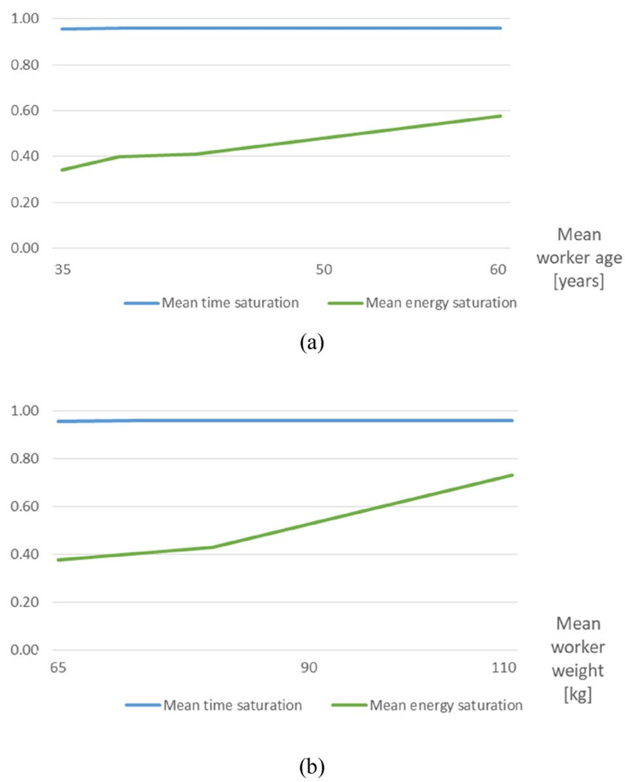

Fig. 15 Results for varying worker age (**a**) and worker weight (**b**) in assembly case n.3 in terms of mean time saturation and mean energy saturation

with this software tool, distinguishing features of workers are considered to determine their physical capabilities. Conversely, balancing tools only optimizing profit-related objectives, but not human issues, could return solutions for which workers are unable or overloaded in performing the assigned tasks.

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Availability of data and material Not applicable.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The research activity envisaged in this work has been conducted applying fundamental ethical principles. We confirm that all the authors involved in the writing of this article are aware of this work and approve all its contents. In addition, the paper has not been published or submitted to any other journal.

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