Human-oriented assembly line balancing and sequencing model in the Industry 4.0 era

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Abstract Ergonomics play a crucial role in the design process of manual assembly systems, since a poorly ergonomic workplace leads to injuries, accidents, and musculoskeletal disorders. Using Industry 4.0 solutions, smart technologies, and cloud platforms, the wellbeing of workers can be improved more easily than in the past. In this context, smartwatches can be used to monitor workers' health and to collect data about the physical efforts of each worker during the working day, in relation to energy expenditure or heart rate monitoring. Managers can use data collected via these smart solutions to improve sequencing and scheduling processes in terms of both ergonomics and time, achieving a trade-off between ergonomics and productivity. Using real-time monitoring, a dynamic scheduling and sequencing approach can be implemented to guarantee the right safety level for each worker. In this chapter, we give a general overview of smart tools for measuring and quantifying the ergonomics level. Based on the data from smartwatches, we propose a multi-objective assembly line balancing model and an ergo-sequencing model, and demonstrate the benefits of using smart solutions and Industry 4.0 tools. The limitations are discussed using a real case application. Our conclusions can guide managers and practitioners during the design phase.

1. Introduction

Two significant movements have engaged manufacturing systems over the past ten years. One is the Industry 4.0 revolution, entailing the digitalization of products and processes across manufacturing sectors and supply chains (i.e. Ivanov et al., 2016a Ivanov et al., 2016b, Panetto et al., 2019). The second development concerns social sustainability and in particular human-centered design (HCD), workplace safety and ergonomics (i.e. Battini et al., 2011).
The main objective of ergonomics is to achieve an optimal relationship between people and their work environment. However, to reach this optimal point, two main

conflicting factors must be addressed. On one hand, managers and companies require the maximum efficiency level and productivity, while on the other, workers need comfortable and safe workplaces to guarantee their health and physical well-being. For this reason, several studies have been carried out over recent decades to achieve the right trade-off between the needs of the workers and the companies, with the common goal of avoiding work-related musculoskeletal disorders (WMSDs), diseases and accidents. WMSDs represent a significant concern globally, not only from a workers' point of view but also due to their economic impact. According to some estimations for the manufacturing sector, 12.5% of the workforce missed days of work due to illness or injury in 2015. In the European Union, more than 40 million workers are affected by musculoskeletal disorders (MSDs) (about one in seven people), while in the US, MSDs represent about 30% of occupational injuries. In the US, the median number of days absent from work due to WMSDs was 10 in 2012, while in the European Union this figure was about 12 days.

Consequently, both companies and states must allocate extra financial resources to deal with this crucial problem, since these costs negatively impact both companies' earnings and the GDPs of countries. The decrease in the gross national product of the EU due to WMSDs was estimated at up to 2% in 2010, while in Canada (resp. US), the impact was estimated at up to 3.4% (resp. 2.5%) of the GDP.

However, according to several studies, MSDs can be avoided through ergonomic improvements to the workplace, and may have a pay-back period of less than one year. Starting from these assumptions, academics and experts have focused their attention on this problem in recent years, and research works have been published on strategies, approaches and methods for improving workers' wellbeing and safety, including the ergonomic features of manufacturing systems with an emphasis on manual assembly systems. Several studies have been performed to include classical ergonomic indexes such as OCRA, NIOSH, OWAS or RULA in assembly line balancing, scheduling or sequencing problems in the form of multi-objective functions or additional constraints.

More recently, other strategies for including ergonomic and human factors into the design of assembly systems have focused on general and local physical fatigue from performing single tasks or a set of activities. Moreover, new smart technologies and Industry 4.0 solutions can provide useful data concerning the workers' physical state, general health conditions or anthropological data. Wearables can also provide a wide range of sensors for measuring acceleration, motion and stress (e.g. number of steps, times of day when the operator is standing/sitting, and pace of work), which can be associated with the operators' physical workload.

Several benefits can be linked to the use of these new and innovative technologies. Firstly, the same device can be used to collect several types of data during the execution of tasks. These are also non-invasive solutions, since smart devices are light and easy to wear, and do not interfere with the working environment. All data collected with smart devices can be shared between managers or staff coordinators via cloud platforms. In this way, suggestions or warnings can be provided to workers within a few seconds, and dynamic scheduling or sequencing of the tasks to be performed can be done based on the workers' condition. In this way, the risk of injury among workers is reduced, and a correct balance can be found not only for working time but also ergonomic effort.

Moreover, using the cloud platform, all data can be used to implement new assembly workstations. The collected data can provide valuable measures of the ergonomics effort required to perform specific tasks or general activities, and thus can be used to correctly balance new workstations, not only from the point of view of time but also from an ergonomics perspective. In these circumstances, multi-objective approaches can be used to find a good trade-off between productivity and ergonomics.

In this chapter, we provide an overview of wearable 4.0 devices that can be used to evaluate ergonomics conditions. Energy expenditure will be used as an ergonomics constraint in a mixed-assembly line balancing and sequencing problem. In Section 2, general guidelines for direct ergonomics measurements and wearable tools are given, while in Section 3, general considerations about assembly systems are discussed. In Sections 4 and 5, the mixed-assembly line balancing problem and the sequencing problem will be detailed, while Section 6 presents a numerical case study. Finally, conclusions and general guidelines are provided in Section 7.

2. Methods and tools to measure fatigue

In this section, the main methods and tools used to quantify the physical effort required to execute a set of activities are described, and the pros and cons of each are listed.

When workers execute assembly tasks, they are subjected to a physical effort that may involve the whole body or only certain parts. When the whole body is used, general fatigue arises, while local muscle fatigue arises if only certain parts of the body are involved in a strenuous effort. In both cases, several methods and tools can be used to evaluate this fatigue. However, only some of the available tools can be considered wearable devices, and only a few can be connected to the cloud, allowing the possibility of evaluating workers' conditions in real time (Battini et al., 2018).

Firstly, these methods can be categorised into qualitative and quantitative approaches. From within the quantitative approaches, we identify direct measurement tools or observational methods, and these will be discussed below.

Qualitative methods consist of subjective evaluations, based on verbal estimations made by the operators during execution of the task. The advantages of using these techniques are related to their low cost in comparison to other methodologies, which require high levels of investment to buy the required equipment and significant amounts of time to understand how to use and test it in the specific industrial context. Moreover, subjective evaluations can give feedback not only on the stress on the muscles and joints during the activity but also on the central nervous system.

Despite these advantages, they are influenced by subjectivity, and this leads to difficulty in assessing the accuracy and variability of a given measure between different operators. Evaluations by operators for the same load may be different according to their physical capacity and general health. In addition, the precision of a measure may be different if the operator has previous exposure to the benchmark. For this reason, qualitative methods can be used as a practical tool to involve workers in some ergonomic decisions, giving them the opportunity to evaluate their working environment in a straightforward way.

The other approach involves quantitative methods, which are related to the real measurement of the load using existing devices. Observational methods fall into the category of quantitative approaches.

With regard to general muscular fatigue, the most widely used observation methods are those proposed by Garg in 1978 and the Predeterminate Motion Energy System (PMSE) proposed in 2016 by Battini et al. Both are based on a measure of energy expenditure. The positive aspect of both methods is that they can take into account the differences between one person and another in terms of age, body weight, and height. However, even if these approaches can provide accurate values, they cannot be put into practice quickly since they are based on an evaluation of every individual movement of the operator performing a task. Thus, these methods are very time-consuming approaches, and cannot be used to monitor workers' well-being in real-time. For this reason, wearable devices are preferable in order to collect data that can be compared and then used to make appropriate changes.

2.1. Wearable devices

From the point of view of muscular fatigue, two main types of tools can be used to obtain direct, quantitative values of the local effort expended by a worker executing a task.

An electromyography (EMG) sensor (Figure 1) is the first type of device that made it possible to evaluate muscular fatigue, and is used to detect electrical activity in the muscles. It involves the placement of electrodes on the skin surface above the muscle, and the contraction is monitored in order to evaluate the percentage maximum voluntary contraction (MVC) of the muscle during performance of the activity. The disadvantages of the EMG are the influence of other muscle movements, interference from the electrical supply, and mechanical problems with the recorded measurements of MVC.

Moreover, it is associated with certain problems related to the application, since different individuals may use different groups of muscles for the same task, and it is difficult to interpret the measure of MVC for multiple muscle groups.

This technology is complicated and costly for application in an industrial context. Moreover, the equipment used can affect the usual way of executing a task, since the electrodes are connected to the main hardware with wires.

Figure 1: EMG sensors (source: NexGen Ergonomics.com)

There are also dynamometers and grip force sensors (Figure 2), which are tools that are able to measure the peak and average force in kilograms during carrying, pushing and pulling activities. They are fixed to the object to be carried, pushed or pulled, and slipping must be prevented. Before they are used, it is essential to understand the direction of the forces representing the path of motion of the operator. These devices are easy to use, and the output data can reveal the kind of movement that a given operator performed in addition to the influence of the height and weight of the item. Based on the force level, it is then possible to estimate the local fatigue.

Figure 2: Hand dynamometer and hand-grip force sensors

General or global fatigue is measured using two main tools: oxygen consumption (VO2) monitoring systems or heart rate (HR) monitoring devices (available in the latest generation of smartwatches).

VO2 monitoring (Figure 3) is the most widely validated method in the literature, and its relationship with the activity performed has been demonstrated. However, it cannot be easily applied in an industrial context, since the investment required is considerable, and a certain level of preparation is needed for the use of the equipment. In addition, the most significant limitations are the size of the equipment and the inconvenience of using a mask for taking measurements, as it can influence the operator's performance due to stress and difficulties in breathing.

In recent years, the technology related to VO2 measurements has developed a great deal; wearable wireless equipment is now available, and data can now be processed in real time. However, a laboratory testing phase is needed in order to evaluate whether additional effort is linked to wearing this technology, and only if positive laboratory results are achieved can this technology be implemented in companies.

Figure 3: VO2 monitoring system

Another type of tool that can be used to evaluate general fatigue is the HR monitoring system. Nowadays, this tool is included in all smartwatches, and can provide and predict also some other important data such us the stress level of each workers, the number of steps perform during the day.

The traditional HR monitor (Figure 4) is based on a Bluetooth HR sensor connected to a watch, where the trend of the HR and the duration of the activity are visualized. It is commonly used to obtain feedback regarding training status and to improve the physical fitness of a person through accurate planning of the next training activities. It does not require specific knowledge, and does not interfere with the operator's activity. It allows real-time feedback to be given to the operator, who can be conscious of his or her physical condition, and if appropriate can speed up or slow down the rate of the activity. Moreover, it recognises the effect that personal characteristics such as age, weight, VO2, HR at rest, and training status can have on the accumulation of fatigue. The use of HR as a measure of energy expenditure has been analysed both in the past and in more recent literature, and several works have demonstrated its applicability in evaluating general fatigue in terms of energy expenditure.

Measurements taken with an HR monitor are easier than those with a VO2 mask. Everyone can use the HR monitor without difficulty, and the measurement of HR to monitor fatigue levels can be carried out for several activities without disturbing the operators. It can also be connected to a cloud platform, and real-time values can be used to evaluate the workers' physical state.

Due to these advantages, an HR device may be the best device to carry out a fatigue analysis and to evaluate the energy expenditure required to perform a task or a set of activities.

Figure 4: HR monitoring systems (source: polar.com)

Using these devices, sequencing solutions can be analysed and continuously changed with the aim of finding a solution that can assign more strenuous and heavier activities first and lighter ones afterwards. However, these solutions may change according to the type of worker and his/her features, and for this reason, HR devices play a crucial role during this phase. It used correctly, they can provide continuous information on the health status of workers.

3. Manual assembly systems: A general overview

Manual assembly systems, also known as manual assembly lines, are used in several industrial contexts since they allow workers to collect and fit together various parts or components to create a final product. They were initially introduced to increase efficiency in the mass production of standardised products, but more recently they have gained importance in the low-volume production of customised products.

Assembly systems or lines consist of several workstations at which a set of operations, generally called tasks, are performed by one or more workers.

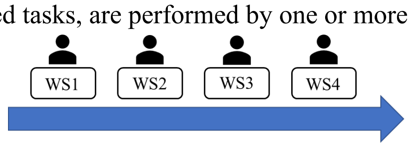

Figure 4: A simple assembly line

Due to technological and organisational restrictions, certain tasks can be performed only after the execution of others, and it is therefore necessary to define a so-called precedence graph (Figure 5).

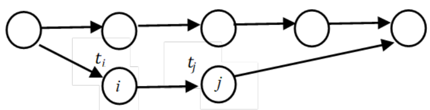

Figure 5: Precedence graph

Depending on the variety of products assembled on the same line, three types of assembly lines (Figure 6) may be used:

1. Single-model lines: The same product is manufactured in massive quantities in the same line. In this case, the tasks executed at each workstation are always the same, as is the workload.
2. Multi-model lines: Several similar products are constructed on one or more lines. In this case, there are significant differences in the manufacturing processes of different products, and setups are generally required.
3. Mixed-model lines: Several versions of the same family of an item are produced on the same line. In this case, models differ in terms of certain attributes or features. Some products may or may not require certain tasks, and a given task may require a variable process time depending on the variety of product. In this case, since products are very similar to each other, no or short setup times are required when the product changes.

The execution of the tasks required to obtain the final product is called manual assembly, and this represents one of the most critical phases of the production systems due to its high added value, its contribution to the final product quality, and its direct connection with the final market. For these reasons, practitioners and academics are continuously developing new approaches and improving the existing ones to increase efficiency and productivity, and to guarantee the required flexibility.

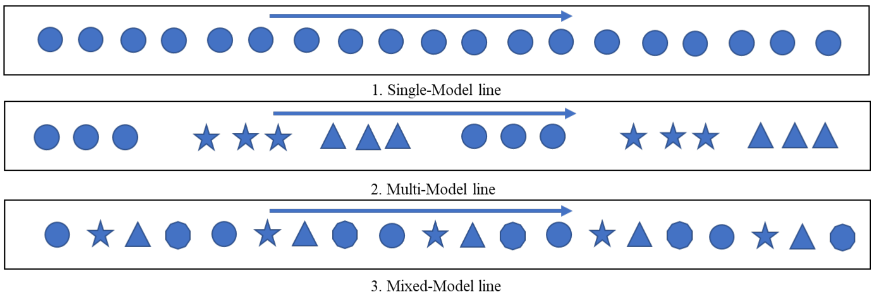

Figure 6: Examples of assembly lines

The problem of defining which tasks must be executed at each workstation is called the assembly line balancing problem (ALBP). The first attempt to create a balancing model was made by Salveson (1955), who suggested a linear program to describe all possible task assignments for an assembly line.

Three different methodologies to address the ALBP are described in the literature: the single-model assembly line balancing problem (SALBP), the mixed-model assembly line balancing problem (MALBP), and the batch-model (or multi-model) assembly line balancing problem (BMALBP).

In an ALBP, the objective or goal function may be the minimisation of the number of workstations (ALBP-1), minimisation of the cycle time (ALBP-2), or maximisation of efficiency (ALBP-E). In each case, the aim is to evaluate the quality of a feasible solution based on the final goal and the constraints.

There also the feasibility problem (ALBP-F), in which the number of stations and the cycle time are known, and the problem involves evaluating whether or not a line with these characteristics can be operated.

To solve ALBPs, it is necessary to take into account different kinds of constraints (such as assignment or cycle time constraints). The solution methods might be exact, simple heuristics or metaheuristics, and a compromise is required between two or more conflicting objectives. This is known as a multi-criteria approach, and includes lexicographic resolution, fuzzy goal programming, and Pareto-based ranking.

As discussed in Section 1, during recent decades, many studies have highlighted the relevance of integrating ergonomics aspects into the design of an assembly system, and for this reason, several studies have been carried out in the ALBP field.

Most of the proposed methods integrate ergonomics using multi-criteria approaches, and single-model assembly lines are generally analysed. Finco et al. (2018) proposed a heuristic approach to integrate human energy expenditure into SALBP-1. Moreover, to improve workers' well-being Finco et al. (2019) developed a mathematical model able to minimize smoothness index by integrating also workers' recovery time. However, the single-model assembly line represents a strong restriction for many companies, since the customisation level is very high nowadays, and thus mixed-model assembly lines are preferable over single-model alternatives.

3.1. Mixed-model assembly line

In this subsection, the characteristics of mixed-model assembly lines are described as part of our discussion of approaches that are able to integrate ergonomics into mixed-model assembly systems.

As stated above, in a mixed-model assembly line, different models of the same product family are processed with no or minor setups or rearrangements required between the different workpieces. In this case, the production process is similar fr each product, and the differences are mainly due to customised features.

For this type of assembly system, several decision problems may arise depending on the planning horizon. The first decision concerns the design of the assembly line in which the number of workstations, production rates, and workload must be defined. All of these decisions are linked to the MALBP. A practical example of Mixed model line balancing and sequencing is provided by Azzi et al., 2012a and 2012b. In addition to the SALBP, the MALBP-1, MALBP-2, MALBP-E, and MALBP-F consist of defining the number of workstations, cycle time, line efficiency, and the feasibility problem, respectively. However, in these cases, the problem is more complicated, since each workstation must be balanced in each model. Smart solutions and cloud platforms could help managers and practitioners in this regard, since historical data on energy expenditure or the physical effort by workers in similar tasks could be used and adapted to the context under analysis. In this context, multi-objective approaches are preferable over mono-objective ones, since ergo-time solutions can achieve higher efficiency levels and improvements in the health status of workers.

Results obtained over a long period represent a basis for the division of the labor force and the production rate in the short-term. The short-term decision problem is known as a mixed-sequencing problem, and consists of finding a sequence of model units for assembly, based on the short-term production program of maximising or minimising an objective function. Smart and Industry 4.0 solutions can also lead to improvements in the working environment. In this phase, real-time measures can be taken, and real-time sequencing adjustments can be made based on physical effort data that are continuously monitored through smartwatches.

The two problems described above are closely connected, since results obtained over the long term form the input data for a problem in the short-term. This means that the quality and efficiency of sequencing decisions and planning are strongly correlated with workload balancing. On the other hand, the quality of balancing solutions depends on the model mix and the possible sequences. However, these data are generally not available before line balancing, since demand cannot be forecast exactly, and inefficiency can therefore occur.

Moreover, the planning horizons are different, and problems must be solved separately. For this reason, a hierarchical planning system is generally used.

Based on these assumptions, a MALPB and a sequencing model will be developed in the following sections. In both cases, ergonomics will be integrated according to the energy expenditure required to execute each task. A hierarchical approach is followed.

4. Ergo-mixed-model assembly line balancing problem

In this section, an ergo-mixed-model assembly line balancing problem is discussed. The ergonomic level of each assembly task is defined using the energy expenditure rate, which can be measured with an HR monitoring device.

A multi-objective MALB model that evaluates both the energy and time required for each task is developed to evaluate the effects of moving from a time-optimal solution to an energy-time optimal one.

First, the MALBP is converted into an SALBP using the joint precedence graph. Then, the virtual average model (VAM) is considered, since this can simulate a set of various products, and the SALBP model is then solved. It is not easy to evaluate the behavior and efficiency of a mixed-model assembly line, and the use of a VAM can help make the balancing problem easier; however, for a multi-objective model that optimises time and energy, this approach can lead to optimal solutions in terms of time and energy that are different from those found by considering the entire mix instead of the VAM.

In the following, the steps required to solve the MALBP will be described.

4.1. Virtual average model with time and ergonomics approaches

Depending on the product mix and demand, it may be easier to turn the mixed-model assembly line into a single-model case by joining the precedence graph of each model into a join precedence graph. A join precedence diagram implies that:

- there is a common subset of tasks among the considered models;
- some tasks may be required for one model but not for others;
- the same task may have different operating times for different models, implying that it must be performed at the same station.

The balancing of a mixed-model assembly line requires not only a joint precedence graph but also the concept of the VAM, which consists of a dummy average model representing all the products assembled on this line. The time for each activity of the VAM can be calculated based on:

- the maximum time required for this activity, considering all products;
- the average time required for this activity, considering all products;
- the weighted average time required for this activity, considering the mix of products.

In this chapter, the third approach to evaluating the VAM is applied, and it is integrated with the multi-objective problem based on energy expenditure.

In the multi-objective approach, we consider both the solution that optimises time and the one that optimises energy. The analysis of the Pareto frontiers allows us to evaluate the trade-off from one solution to the other. This gives the set of non-dominated solutions for a multi-objective system, where the solutions optimise one of the objectives of the problem.

In order to apply this kind of approach, it is necessary to know the task time and the energy expenditure for each task in each model. We denote t_{jm} as the time for task j in model m, e_{jm} as the relative energy expenditure, and d_m as the percentage demand of model m in the considered mix. The formulae for t_j and e_j for a VAM are as follows:

$$t_j = \sum_m t_{jm} d_m \tag{1}$$

$$e_j = \sum_m e_{jm} d_m \tag{2}$$

4.2. Time-SALBP and Energy-SALBP with VAM

The definition of t_j allows us to balance the mixed-model assembly line with the SALBP-2, which is the SALBP model that minimises the cycle time with a predefined number of stations, in order to increase the productivity. Based on the binary linear model in the single-model assembly line, the binary variable x_{jk} is used to indicate the assignment of task j to station k, and B_k is the set of tasks assignable to station k (within a set of workstations from 1 to K). To solve the SALBP-2, the following constraints need to be considered:

- Occurrence constraint:

$$\sum_k x_{jk} = 1 \qquad \forall j = 1,..,n \tag{3}$$

- Cycle time constraint:

$$\sum_j x_{jk} t_j \le c \; \forall \, k = 1,..,K \tag{4}$$

- Precedence constraint:

$$\sum_k k x_{hk} \le \sum_i i x_{ji} \qquad \forall \, (h, j) \in A \tag{5}$$

There may be many different balancing solutions, and each one needs to be evaluated. In this case, unlike traditional approaches, the objective functions considered are the time smoothness index (*SX-T*) and the energy smoothness index (*SX-E*), which measure the equality of workload distribution among the stations and the physical load on workers at different stations, respectively. They are defined as follows:

$$\min SX - T = \min \sqrt{\sum_{k=1}^{K} (c_r - \sum_j x_{jk} t_j)^2} \tag{6}$$

$$\min SX - E = \min \sqrt{\sum_{k=1}^{K} (e_r - \sum_j x_{jk} e_j)^2} \tag{7}$$

where c_r (resp. e_r) is the maximum station time (resp. energy expenditure) for all stations.

To evaluate the trade-off between the time-based and energy-based optimal solutions, the Pareto frontier (the set of non-dominated solutions of a multi-objective system) is defined using the following function:

$$\min \{SX - T; SX - E\} = \min \{\sqrt{\sum_{k=1}^{K} (c_r - \sum_j x_{jk} t_j)^2} ; \sqrt{\sum_{k=1}^{K} (e_r - \sum_j x_{jk} e_j)^2} \} \tag{8}$$

4.3. Time- and energy-MALBPs

In a mixed-model assembly line, the time-SALBP and energy-SALBP refer to the concept of VAM might not be enough to evaluate the changing properly in the Pareto frontier. When the same balancing solutions are evaluated knowing the number of stations and the cycle time (MALBP-F), the idle time and the workloads may be different depending on the distribution of work. To evaluate a balancing solution properly, it is necessary to include objective functions for the analysis of smoothed station loads. In a mixed-model assembly line, we can define T_{mk} and E_{mk} as the processing time and energy expenditure per unit of model m at station k.

S_k is the set of tasks assigned to station k, and T_{mk} and E_{mk} can be defined as follows:

$$T_{mk} = \sum_{j \in S_k} t_{jm} \quad (9)$$

$$E_{mk} = \sum_{j \in S_k} e_{jm} \quad (10)$$

Knowing the values of T_{mk} and E_{mk}, we can define c_{mr} and e_{mr} for the model m as:

$$c_{mr} = \max\{T_{mk} \mid m = 1,..,M\} \quad (11)$$

$$e_{mr} = \max\{E_{mk} \mid m = 1,..,M\} \quad (12)$$

Having defined these instances, the balancing solutions can be evaluated not only in terms of the operation time but also the operation energy.

The following functions express the maximal deviation of the operation time/operation energy of a model from the maximum station time/energy weighed on the demand of each model:

$$\Psi_t = \sum_{m=1}^{M} \sum_{k=1}^{K} | T_{mk} - c_{mr} | d_m \quad (13)$$

$$\Psi_e = \sum_{m=1}^{M} \sum_{k=1}^{K} | E_{mk} - e_{mr} | d_m \quad (14)$$

The multi-objective functions of this second approach are introduced to allow us to compare them with a time-based and energy-based approach applied to a virtual average product, in order to demonstrate how the Pareto frontier changes when one approach or the other is used for a mixed-model assembly line.

4.4. Numerical application

A numerical example is provided here to evaluate the effects that energy expenditure can have on the solution to the MALBP.

In the case study described here, there are three models, and the joint precedence graph contains 17 tasks that are denoted by A,..,Q (Figure 7). For each model and each task, the time and the energy expenditure are given in Table 1.

In this case, smartwatches are used to evaluate HR values while executing the tasks, and energy expenditure values are then obtained using regression models and general formulae.

Different kinds of VAM are also considered, and these are obtained by considering a different demand for each model weighted in the mix. The correlation index R between the time and energy expenditure for each model and VAM is known.

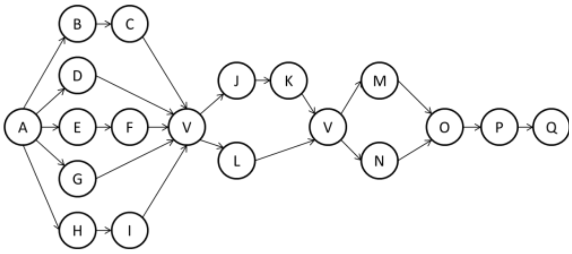

Figure 7: The joint precedence graph

This analysis aims to apply a multi-objective approach through the utilisation of the Pareto frontier in a MALBP, and to discover whether or not the traditional practice of evaluating a mixed model assembly line by approximating all the considerations to the concept of a VAM has a meaning, and in which cases.

This numerical example is calculated by computing different balancing solutions for each kind of VAM using the Patterson and Albracht algorithm, and evaluating each possible assignment of the task to each station in order to respect the occurrence, cycle time and precedence constraints.

For each feasible balancing solution for each VAM (whose values of t_j and e_j depend on the particular mix considered), *SX-T* (resp. *SX-E*) is calculated based on the concept that a mixed-model line can be transformed to a single-model one by producing a VAM. We then calculate Ψ_t and Ψ_e, based on which we derive the line efficiency in terms of time and energy, considering the effect that a particular mix might have.

							VAM SCENERIES							
							MIX A		MIX B		MIX C		MIX D	
	MODEL 1		MODEL 2		MODEL 3		33.3% - 33.3% - 33.3%		5.56% - 22.2% -72.2%		22.2% - 72.2% - 5.56%		72.2% - 5.56% - 22.2%	
R	0.559		0.729		0.678		0.662		0.684		0.696		0.598	
Task	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]	t_j [s]	e_j [kcal]
A	19.20	0.76	24.00	0.95	28.80	1.14	24.00	0.95	27.20	1.07	23.20	0.92	21.60	0.85
B	46.00	2.69	55.20	3.23	36.80	2.15	46.00	2.69	41.40	2.42	52.13	3.05	44.47	2.60
C	15.60	1.08	13.00	0.90	10.40	0.72	13.00	0.90	11.27	0.78	13.43	0.93	14.30	0.99
D	7.00	0.18	5.60	0.14	8.40	0.21	7.00	0.18	7.70	0.19	6.07	0.15	7.23	0.18
E	20.00	0.95	25.00	1.19	30.00	1.43	25.00	1.19	28.33	1.35	24.17	1.15	22.50	1.07
F	15.00	0.88	12.00	0.70	18.00	1.06	15.00	0.88	16.50	0.97	13.00	0.76	15.50	0.91
G	4.00	0.12	5.00	0.15	6.00	0.18	5.00	0.15	5.67	0.17	4.83	0.15	4.50	0.14
H	45.60	1.47	30.40	0.98	38.00	1.23	38.00	1.23	36.73	1.19	34.20	1.11	43.07	1.39
I	11.00	0.96	8.80	0.77	13.20	1.16	11.00	0.96	12.10	1.06	9.53	0.84	11.37	1.00
J	64.00	3.65	96.00	5.47	80.00	4.56	80.00	4.56	82.67	4.71	88.00	5.02	69.33	3.95
K	68.00	4.06	85.00	5.07	102.00	6.09	85.00	5.07	96.33	5.75	82.17	4.90	76.50	4.56
L	30.00	1.20	25.00	1.00	20.00	0.80	25.00	1.00	21.67	0.87	25.83	1.03	27.50	1.10
M	60.00	1.08	72.00	1.30	48.00	0.87	60.00	1.08	54.00	0.97	68.00	1.23	58.00	1.05
N	65.00	1.17	52.00	0.94	78.00	1.41	65.00	1.17	71.50	1.29	56.33	1.02	67.17	1.21
O	36.00	0.74	45.00	0.92	54.00	1.10	45.00	0.92	51.00	1.04	43.50	0.89	40.50	0.83
P	20.00	0.40	25.00	0.50	30.00	0.60	25.00	0.50	28.33	0.57	24.17	0.48	22.50	0.45
Q	19.20	0.76	12.80	0.50	16.00	0.63	16.00	0.63	15.47	0.61	14.40	0.57	18.13	0.72

Table 1: Input data for the numerical example

Using these functions, it is possible to define two different kinds of frontiers. The aim of obtaining the non-dominant solutions in terms of time and energy is the same, but the first considers *SX-E* and *SX-T*, and the second Ψ_e and Ψ_t .

These two approaches cannot have the same frontier, as can be seen in the example below, which involves a mix containing 33.3% of M1, 33.3% of M2, and 33.3% of M3. The numbers and types of scenarios are different (where each one implies a specific balancing solution within the frontier) (Figure 8).

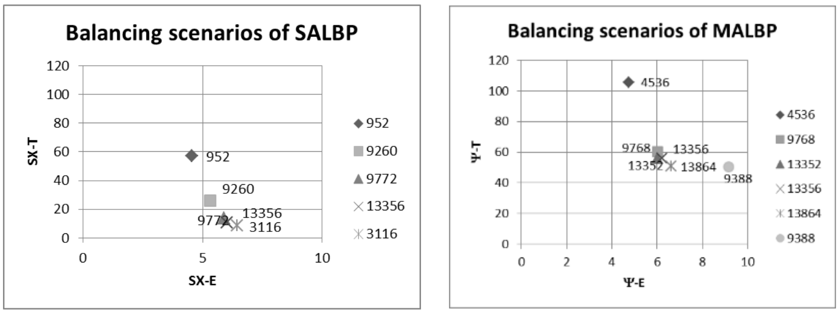

Figure 8: SALBP and MALBP frontiers for mix A

If the scenarios for the Pareto frontier are different between the two approaches, we need to evaluate whether the difference is more evident for some mixes than others. If this difference is substantial, the choice of the SALBP approximation is not the right way to evaluate a mixed-model line, or if used, the choice of one of the SALBP solutions would not correspond appropriately to the MALBP solution.

In Figure 9, the efficient frontier for the MALBP is compared with the frontier for the MALBP for each mix, the scenarios for the SALBP frontier are considered and the scenarios of the time-optimal solution and energy-optimal solution are highlighted.

The difference between the two frontiers is not the same in all mixes, but the frontier for the SALBP is always to the right of the real frontier for each mix considered. A frontier can move from left to right if the correlation index R (the relation between t_j and e_j) decreases; the more it increases, the more the frontier moves to the left and is reduced to a point.

In order to evaluate the deviation between the two frontiers ΔT_{opt} and ΔE_{opt} , it is necessary to consider the two-point of time-optimal and energy-optimal solutions of the two frontiers and to analyse the subsequent measures. We define Ψ_{T-VAM} and Ψ_{E-VAM} as the optimum points of the SALBP frontier for time and energy and Ψ_T^*, Ψ_E^* the optimum points for time and energy for the other frontier in the MALBP.

$$\Delta T_{opt} = \frac{\Psi_{T-VAM} - \Psi_T^*}{\Psi_T^*} \tag{15}$$

$$\Delta E_{opt} = \frac{\Psi_{E-VAM} - \Psi_E^*}{\Psi_E^*} \tag{16}$$

The results for the mixes considered here are as follows:

Mix	ΔT_{opt}	ΔE_{opt}
A	20.6%	1.7%
B	-	2.6%
C	11.9%	9.7%
D	29.7%	9.2%

Table 2. Results for the different mixes

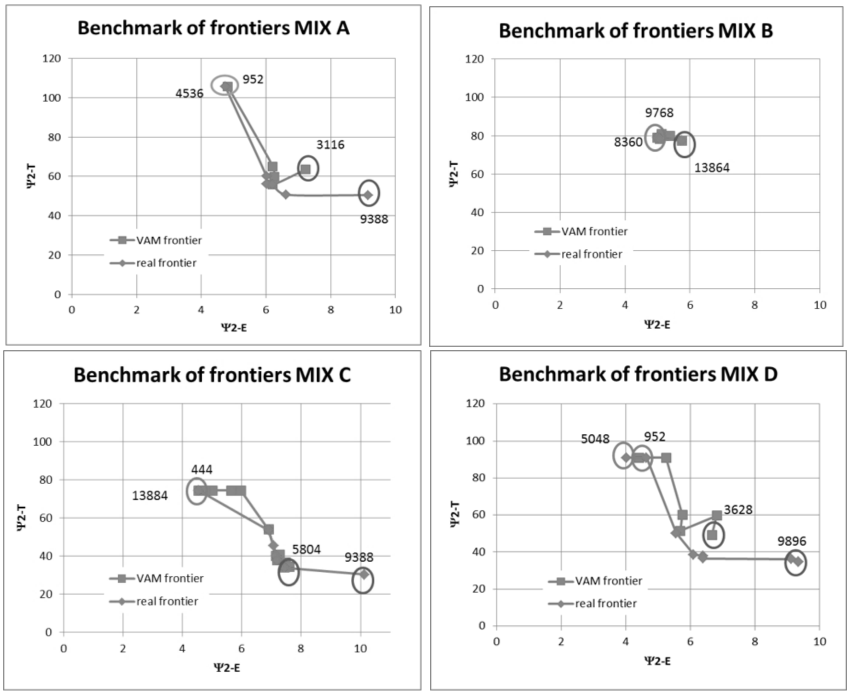

Figure 9: Comparison of SALBP and MALBP frontiers for all mixes

As it can be seen from the table above, the error in the points of the energy-optimal solutions is lower, since the feasible balancing solutions take into account only the time (cycle time). Conversely, there is a higher value of error for the time-optimal solutions.

5. Ergo-sequencing problem

As stated in Section 3, for mixed-model assembly systems, the balancing phase represents the long-term decision process. During the balancing phase, important decisions concerning the assembly system design are taken. Moreover, the assignment of tasks to stations is conducted based on the long-term demand for items and the VAM.

However, in the short-term, for mixed-model assembly systems, the main issue is to define the sequence of products to launch down the line in order to respect the short-term demand for products and to minimise certain objective functions such as the total work overload, the total idle time or the labor cost. In the short-term, the demand mix may be slightly different from the long-term one due to problems with material suppliers. Companies must therefore schedule the assembly process according to the availability of material, and the model mix may therefore change. Proper assembly sequencing can be used to cover inefficiencies.

In recent years, companies have solved the sequencing problem in several ways, but in most cases, ergonomics and working conditions have been neglected. However, in the same way as the balancing process, wearable devices, Industry 4.0 solutions, IoT or cloud platforms can be used to achieve good product sequencing, including workers' physical conditions. Dynamic scheduling can therefore be conducted, and real-time changes can be made based on the operators' fatigue level. In this way, a reduction in productivity can be avoided by assigning light tasks to more fatigued workers and heavier tasks to less fatigued ones.

Starting from balancing solutions provided with a multi-objective approach defined in the previous section, a sequencing model that evaluates energy expenditure inefficiencies is presented. Since the balancing methodology used above generates several solutions, the sequencing model is applied to each balancing scenario associated with the Pareto frontier. Finally, the model sequence that provides the best results in terms of both work overload and energy overload is chosen.

5.1. Sequencing model

Starting from the line balancing phase and considering the features of each model in terms of operating times than energy expenditure, Eq. (9) (resp. Eq. (10) can be used to evaluate the processing time (resp. energy expenditure) in model *m* at station *k*. The set of data acquired through Eqs. (9) and (10) forms the input data for the sequencing model. The following data are required to solve the problem. For each model, the short-term demand is known, and this is set to d'_m, while the sequence length *I* is equivalent to the sum of the demand in each model $I = \sum_m d'_m$.

The sequencing decision variable is introduced as follows:

$$y_{mi} = \begin{cases} 1, if\ m\ is\ assigned\ to\ the\ ith\ position\ of\ the\ sequence \\ 0, otherwise \end{cases}$$

The other variables that must be included are:

- $\Delta E^*_{ki} \quad \forall k,i$, defined as $\max\{0; \sum_m E_{mk} y_{m,i+1} - \sum_m E_{mk} y_{m,i}\}$. This represents the energy expenditure overload between two consecutive units processed. Only positive gaps are considered, since models that require higher ergonomic effort should be assessed before the lighter ones.
- $s_{ki} \quad \forall k,i$ represents the operator start position at station *k* for the *i-th* unit;
- $wo_{ki} \quad \forall k,i$ represents the work-overload at station *k* for the *i-th* unit. This is defined as $\max\{0; s_{ki} - \sum_m T_{mk} y_{mi} - c_r\}$

The objective function of the sequencing model is defined as follows:

$$\min EO = \min \sum_k \sum_i \Delta E^*_{ki} \tag{18}$$

This minimises ΔE^*_{ki} considering all stations and the sequence of the product. The following constraints then need to be considered:

- Only one model unit must be assigned to each position of the sequence, according to the following formula:

$$\sum_m y_{mi} = 1 \quad \forall i \tag{19}$$

- For each model, the short-term demand d'_m must be met, according to:

$$\sum_i y_{mi} = d'_m \qquad \forall m \tag{20}$$

- The processing of a model unit must start only when the previous unit has been completed, as defined by:

$$s_{k,i+1} \geq s_{ki} + \sum_m T_{mk} y_{mi} - c_r - wo_{ki} \quad \forall k,i \tag{21}$$

- The line must be in the initial state before and after unit production:

$$s_{k1} = s_{k,I+1} = 0 \qquad \forall k \tag{22}$$

- The objective function ΔE^*_{mi} is defined as the maximum value, and is nonlinear. To linearise this variable, the following additional constraints and an additional Boolean variable must be included in the final model:

$$\Delta E^*_{ki} \geq \sum_m E_{mk} y_{m,i+1} - \sum_m E_{mk} y_{m,i} \qquad \forall k; \forall i = 1,..,I-1 \tag{23}$$

$$\Delta E^*_{ki} \geq 0 \qquad \forall k; \forall i = 1,..,I-1 \tag{24}$$

$$\Delta E^*_{ki} \leq \sum_m E_{mk} y_{m,i+1} - \sum_m E_{mk} y_{m,i} + UB(1 - z_{ik}) \quad \forall k; \forall i = 1,..,I-1 \tag{25}$$

$$\Delta E^*_{ki} \leq 0 + UBz_{ik} \qquad \forall k; \forall i = 1,..,I-1 \qquad (26)$$

- While the following constraints set the type of variables:

$$s_{ki} \geq 0 \quad \forall k,i \qquad (27)$$

$$wo_{ki} \geq 0 \ \forall k,i \qquad (28)$$

$$y_{mi} \in \{0;1\} \qquad \forall m,i \qquad (29)$$

$$z_{ki} \in \{0;1\} \qquad \forall k; \forall i = 1,..,I-1 \qquad (30)$$

The sequencing model proposed here assigns a model unit in a point of the sequencing length to minimise the total energy overload of the assembly systems, based on the difference in energy expenditure between two consecutive product units. Moreover, the processing of each unit model starts only after the previous one has been completed. In this way, both the time and ergonomics aspects are considered simultaneously.

5.2. Numerical example

A numerical example is used to test the balancing approach and to evaluate the sequencing methodology. The balancing solutions obtained for mix A are used. In the short-term, the demand for each model and among models can change, and six scenarios are therefore analysed, as shown in Table 3.

Model	*Mix1*	*Mix2*	*Mix3*	*Mix4*	*Mix5*	*Mix6*
Model 1	6	4	7	5	7	7
Model 2	6	7	7	6	6	3
Model 3	6	7	4	7	5	8

Table 3. Short-term demand mix

The sequencing model is then applied for each mix, and each balancing solution is related to each point of the Pareto frontier (see Figure 8).
It is interesting to note from Table 4 that for the same point on the Pareto frontier, and thus the same balancing solution, the total energy overload is assumed to always have the same value. Conversely, Table 5 shows that the total work overload, defined as $WO = \sum_k \sum_i wo_{ki}$, varies between mixes for the same balancing solution. Moreover, the same model is used continuously until the short-term demand is achieved. In this way, the sequencing approach is closely linked to the differences in energy expenditure at each station between models.

SX-E	**SX-T**	**Energy overload**					
		Mix1	**Mix2**	**Mix3**	**Mix4**	**Mix5**	**Mix6**

4.56	57.16	0.86	0.86	0.86	0.86	0.86	0.86
5.31	25.79	0.96	0.96	0.96	0.96	0.96	0.96
5.91	13.96	0.93	0.93	0.93	0.93	0.93	0.93
6.01	10.82	0.89	0.89	0.89	0.89	0.89	0.89
6.45	8.77	1.02	1.02	1.02	1.02	1.02	1.02

Table 4. Energy overload results

SX-E	**SX-T**	**Work overload**					
		Mix1	**Mix2**	**Mix3**	**Mix4**	**Mix5**	**Mix6**
4.56	57.16	120	140	116	128	112	100
5.31	25.79	180	210	120	210	150	240
5.91	13.96	228	266	164	262	194	284
6.01	10.82	240	280	181	237	207	285
6.45	8.77	258	301	211	288	228	279

Table 5. Work overload results

Figure 10 provides information that is valuable for identifying which point on the Pareto frontier is preferable compared to the others, and this can help in the selection of the mix. For each point on the Pareto front, both the EO and WO for each mix are illustrated.

The point on the Pareto front that provides acceptable results in terms of EO that WO is the one at which the value of SX-E is minimised, while the point that minimises SX-T provides a higher EO and WO.

It is interesting to compare the ergo-sequencing results with those of the traditional sequencing model (EO* and WO*) that minimises the work overload. We define $\Delta EO_{mix(i)}$ and $\Delta WO_{mix(i)}$ for a generic mix *i-th* as:

$$\Delta EO_{mix(i)} = \frac{EO_{mix(i)} - EO*_{mix(i)}}{EO*_{mix(i)}} \tag{31}$$

$$\Delta WO_{mix(i)} = \frac{WO_{mix(i)} - WO*_{mix(i)}}{WO*_{mix(i)}} \tag{32}$$

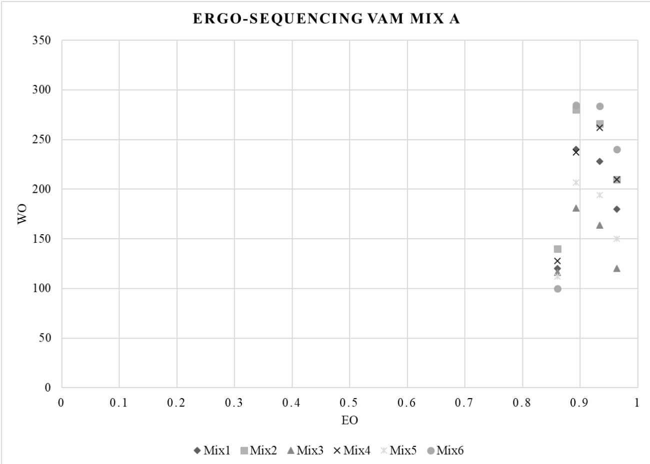

Figure 10. Graph of energy and work overload

Table 6 shows the deviation between the results of the ergo and traditional sequencing models. The mean value of the mix is shown.
These results are very interesting, and confirm that the point on the Pareto front that minimises SX-E is preferable over the others for two main reasons.
Firstly, WO is higher than WO*, but it is closer to WO* than the other points. Its ΔEO is −80.21%, meaning that the solution provided by the ergo-sequencing model can achieve the minimum EO and at the same time can provide correct solutions in terms of WO.

Moreover, the higher the value of SX-T, the lower the value of WO, since the work load is not well balanced between workstations, and idle time can occur in support of work-overload. Good sequencing results can therefore be achieved.

SX-E	SX-T	ΔEO	ΔWO
4.56	57.16	−80.21%	11.33%
5.31	25.79	−76.71%	24.31%
5.91	13.96	−78.92%	28.47%
6.01	10.82	−79.64%	16.34%
6.45	8.77	−79.82%	13.87%

Table 6. Results for energy and work overload

6. Conclusion

The design of efficient assembly systems requires the integration of ergonomics aspects, since the wellbeing and safety of operators implies an improvement in the final product quality and a reduction in costs related to absenteeism and employee turnover caused by accidents or injuries. Moreover, an ergonomics evaluation can be quickly conducted using smart solutions such as smartwatches, which can provide several forms of information about a worker's physical condition. Since many types of data can be collected with wearable devices, the cloud platform represents the best solution for collecting all of these data, which will be used to modify or improve the assignment of tasks to each workstation.

In this chapter, a balancing and sequencing model for a mixed-model assembly line has been described and discussed. The ergonomics level related to each task is defined based on the energy expenditure, since this can be easily quantified with smartwatches or HR monitoring systems. Using a multi-objective balancing model, SX-E and SX-T are minimised, and an in-depth analysis has been performed using a numerical example.

For each balancing solution belonging to the Pareto front, the ergo-sequencing model was applied to minimise the total energy overload. In this phase and the balancing phase, smartwatches can be used to monitor and quantify the physical effort required to execute the set of tasks assigned to each station according to the mix used.

Positive results are obtained since the optimal ergo-sequencing solution means that both energy and time overload can be minimised.

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