Including rest allowance in mixed-model assembly lines

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Abstract Ergonomics has a significant impact on productivity and human safety in manual assembly lines. For this reason, several studies in recent years have proposed including ergonomics in assembly lines. However, most works are focused on simple assembly lines, while only a few studies exist for mixed-model assembly lines (MMALs). Thus, in this paper, we propose a new methodological approach to include physical fatigue and rest allowance (*RA*) as ergonomic parameters in MMAL problems. For the balancing problem, we propose a linear mathematical model that minimises the cycle time by including *RA*. For the sequencing decision, we develop a heuristic approach that assigns workers to workstations according to the workers' age and their related maximum physical capacity. Then, we propose a linear sequencing model that minimises the work-overload by also evaluating *RA* to assign each worker according to her or his features. Finally, to complete the study, we test the mathematical models in a real case application and provide a detailed discussion of the results to highlight the benefits we can achieve with this approach.

Keywords: Mixed-model assembly line; Human factor; Recovery time; Ageing; Mathematical model; Case study

1. Introduction

Even if Industry 4.0 solutions and automation in industrial systems have been playing a crucial role in recent years, some high-value activities are still performed manually. This is the case for manual assembly lines (MALs), which are generally the last phase of the entire production process. In general, assembly lines comprise several workstations, paced or un-paced, and in each of them, several activities, called tasks, are performed by operators to obtain the final product (Scholl, 1999). Mixed-model assembly lines (MMALs) are currently used due to the increase in product variety aiming to satisfy customers' needs, (Sivasankaran and Shahabudeen, 2014). In MMALs, it is assumed that all models of the same family, represented by the virtual average model (VAM), are variations of a base product, and they only differ in some customised options that customers can choose. Some products can require additional assembly tasks compared with others or more or less time for the same tasks.

There are several options that lead to variable processing times and, for this reason, tactical and operational decisions must be made. Scholl (1999) stated that tactical decisions refer to a long-term period, generally one or more years, and define line balancing, which is the tasks assignment to workstations. Operational decisions are linked to a medium- or short-term period, such as a day, a week or a month, and they set the sequence to process the products in a fixed period. In addition, while the balancing phase defines the workload in each workstation by assigning tasks and achieving one or more objective functions, the sequencing phase permits minimizing the total overload of a fixed period. In fact, due to the variability among products of the same family, the cycle time, that is the maximum workstation time obtained by assigning tasks to workstations, could be exceeded and, consequently, overloads could occur.

However, in both decision processes, task time and cycle time might not be enough to ensure a balanced workload among workers. Even if the workload is balanced in terms of time, it might not balance well when the posture, the physical effort or the general fatigue of each worker are considered. In such a context, academics and practitioners should provide each worker with the right working conditions, preventing ergonomic risks, injuries, musculoskeletal disorders, or excessive fatigue levels. For this reason, with an aim to design safe and comfortable workplaces, Battini et al. (2011) suggested incorporating both technological and ergonomic variables during the design or the re-design of MMALs.

In the literature review provided by Otto and Battaia (2017), the studies focused on integrating ergonomics into balancing and job rotation problems were investigated. As also highlighted by the authors, almost all works are focused on evaluating the main ergonomic indexes such as OCRA, RULA, REBA or NIOSH, while only a few articles have evaluated the fatigue effects of the workers' efficiency in manual assembly systems (Adbous et al., 2018; Finco et al., 2019a). This is a limit of the current literature because, as defined by Kolus et al. (2018), physical fatigue can negatively impact final product quality. Therefore, it should be integrated into traditional decision problems such as balancing or sequencing by assigning, for example, the adequate recovery time to each worker, as demonstrated by Calzavara et al. (2018).

To better fit workstations to workers, physical and anthropometric data, such as height, body mass index, age, gender and sedentary level, should be incorporated in the design phase (Romero et al. 2016). As defined by Shepard (1999), postures and fatigue can change according to the worker involved in the activity and, in particular, they are strongly affected by the age of the worker involved (Sgarbossa et al., 2020). Consequently, if acceptable ergonomic levels must be achieved, workers' features must be included by giving, for example, more rest time to elderly workers compared with younger ones due to their lowered physical capacity.

In this paper, starting from these initial considerations and aiming to reduce the existing gap between practitioners and academics, we want to answer two research questions:

RQ1: How does the workers' age influence the balancing and sequencing problems in MMALs?

RQ2: How can we avoid excessive fatigue levels by including workers' physical features during tactical and operational decisions?

To answer to these questions, we propose a global approach in which the physical fatigue required to perform manual tasks is included in long-, medium- and short-term decisions for MMALs. Moreover, we also include the age of each worker during medium- and short-term decisions to fit the workload to workers according to their physical capacity. In this way, we demonstrate how a reduction of work overload (WO) can be achieved during the sequencing process.

We use the energy expenditure concept to evaluate physical fatigue, as previously used by Battini et al. (2016) and Finco et al. (2018; 2020b). For the balancing problem, which represents the tactical decision, we minimise cycle time by including the recovery time and we propose a linear mathematical model optimally solved by considering the VAM. For the sequencing problem, which refers to the operational decisions, we include workers' features as well as the type of models and we provide a two-step approach to define the sequence of products to assembly. Firstly, we assign workers to workstations according to their physical capacity, which is strongly related to age. Then, we define the sequence of products to the assembly line during a fixed period minimizing the work-overload. As for the balancing phase, we propose a linear mathematical model optimally solved. Finally, we evaluate the benefits we can achieve by applying this approach through a case study.

The main contributions of this paper can be summarized as follows:

- A new methodological approach for tactical and operational decisions in MMALs.
- The integration of physical fatigue during balancing and sequencing decisions.
- The proposal of workforce assignment before sequencing, aiming to avoid excessive fatigue levels and to consider the related recovery time for older workers.
- A detailed analysis of benefits we can achieve with this innovative approach, by applying the whole procedure to a case study.

This paper is organised as follows. Section 2 provides a general overview of papers related to MMALs in which ergonomics is considered. Moreover, we provide details about fatigue and recovery time. In Section 3, we propose a methodological structure aiming to include workers' features in Mixed Model Assembly Line Balancing (MMALB) tactical and operational decisions. Section 4 describes the mathematical model related to balancing, workforce assignment and sequencing. In Section 5, we describe a case study, and discuss the results. Finally, in Section 6, we provide conclusions and future perspectives.

2. State of the art

2.1. Mixed-model assembly line

In their recent literature review, Razali et al. (2019) analysed 59 papers related to MMALB, which were categorised into homogenous categories according to the adopted optimisation algorithm, the objective function and the utilised constraints. For the authors, the integration of human factors into balancing and sequencing for this type of assembly systems represented a future requirement and a sustainable issue in problem modelling. According to the authors, there is a relatively small number of papers concerning MMALB that also includes human factors or ergonomics, as summarized in Table 1.

Reference	Methodology	Human factor evaluated	Type of decision	Objective	Algorithm used
Celano et al. (2004)	Mathematical model	Workers' competences profile (skilled vs. unskilled)	Operational	Minimise the total conveyor stoppage	Genetic Algorithm
Shaikh et al. (2012)	Empirical study	Workload, stress, fatigue, posture	Tactical and operational	Minimise the number of error and quality problems	-
Barathwaj et al. (2015)	Mathematical model	RULA	Tactical	Minimise the workstation number and the workload among workstations	Genetic Algorithm
Cortez and Costa (2015)	Mathematical model	Heterogeneous workers, the effect of disability	Operational	Minimise the utility work needed	Heuristics, local search procedures and a metaheuristic
Dollinger and Reinhart (2016)	Empirical study	Learning and forgetting, skills and competence profiles	Tactical	Minimise productivity losses and quality defects	-
Sgarbossa et al. (2016)	Mathematical model	Physical fatigue	Tactical	Minimise smoothness index among workstations and energy expenditure among workers	Linear programming
Al-Zuheri et al. (2016)	Mathematical model	Ergonomic workload with an in-house approach	Tactical	Minimise total production cost and ergonomic workload	Genetic Algorithm
Bautista et al. (2016)	Mathematical model	OCRA, RULA, REBA	Tactical	Minimise the maximum ergonomic risk among workers and the average absolute deviation	Greedy randomized adaptive search procedure
Carrasquillo et al. (2017)	Simulation	Ergonomic risk in the upper body, lower back exertion and recovery time	Tactical	Investigate the effects on ergonomic risks due to the product sequence and conveyor type	-
Bautista-Valhondo and Alfaro-Pozo (2018)	Mathematical model	Ergonomic risk	Tactical and operational	Minimise the maximum ergonomic risk of the assembly line, and the standard deviation of risk among workstations	Greedy randomized adaptive search procedure
Alghazi and Kurz (2018)	Mathematical model	Ergonomic risk	Tactical	Maximise productivity	Constrained programming
Tiacci and Mimmi (2018)	Mathematical model	OCRA index	Tactical and operational	Minimise OCRA index	Genetic Algorithm
Ostermeier (2020)	Simulation	Learning and forgetting, muscular fatigue and recovery time	Operational	Evaluate the effect of human factors in scheduling process for MMALs	-
Çil et al. (2020)	Mathematical model	Interaction between human and collaborative robots	Tactical	Minimise cycle time	Linear programming and bees algorithm

Table 1. The main works focused on MMALs and human factors.

Celano et al. (2004) made one of the first attempts to include human factors in MMALB. They used human factors, expressed as competences profiles, to evaluate their effects on the sequencing process for mixed-model U-Shaped assembly lines. The authors proposed a genetic algorithm that could minimise the total conveyor stoppage to maximise line efficiency. Shaikh et al. (2012) evaluated the effects of variability in MMALB on the quality of performance and subjective assessments of workload, stress, physical fatigue, and general discomfort. They found an improvement in errors and widespread quality problems each time mixed-model assembly systems occurred. Consequently, they proposed an improved task design that could reduce the global complexity of these assembly systems. Barathwaj et al. (2015) proposed a genetic algorithm (GA) aiming to minimise the number of workstations and the workload index among stations and within each station in a MMAL. They evaluated the ergonomic load with a parameter called accumulated risk posture, calculated using the RULA sheet. Finally, they applied the GA to a real industrial application with promising results because they minimised the cycle time, required space, and the ergonomic hazards of each workstation. Cortez and Costa (2015) focused their attention on the sequencing problem by considering a heterogeneous workforce and the presence of disable workers in some workstations. In their sequencing model, the time of each task is both model and worker dependent. They solved the two mixed-integer model with constructive heuristics, two local search procedures and a metaheuristic. Dollinger and Reinhart (2016) provided an innovative approach for mixed-model assembly systems to increase efficiency and reduce productivity losses and quality defects by using auxiliary workers according to their competence profiles. Moreover, they evaluated the effect of this approach by analysing the learning curves in an empirical study. Sgarbossa et al. (2016) assessed the impact of human energy consumption in a MMAL with a multi-objective model that aimed to minimise both the smoothness index related to workstation time and the workstation energy expenditure. Moreover, with a case study, they compared the results obtained for the virtual average model with those obtained with two new functions that also integrate the demand of each type of product and they found significant differences. However, as also highlighted by the authors, an additional analysis is required and a sequencing method should be given. Al-Zuheri et al. (2016) developed a GA for a mixed-model walking worker assembly line aiming to minimise the total production cost and the ergonomic workload of each workstation. They tested the developed method in plastic electrical box assembly systems that produce two types of models and they evaluated the ergonomic workload with an in-house approach. Bautista et al. (2016) aimed to improve the comfort of operators by minimising the maximum ergonomic risk and minimising the average absolute deviations of it. They analysed several ergonomics indexes and developed a greedy randomized adaptive search procedure and compared it with exact models. Carrasquillo et al. (2017) conducted a simulation analysis to investigate the effect of conveyor type and product sequence on the ergonomic risks to workers' upper body and lower back exertions and total recovery time. Bautista-Valhondo and Alfaro-Pozo (2018) proposed a greedy randomised adaptive search procedure to jointly minimise the ergonomic risk dispersion and the maximum ergonomic risk level. They compared results obtained using the developed procedure with two mixed-integer linear models by applying them to a real industrial application, an automotive engine assembly line. Alghazi and Kurz (2018), starting from the model proposed by Becker and Scholl (2006), proposed a scheduling constrained programming that could solve an industrial-sized assembly line problem. Moreover, they evaluated mixed-model assembly systems with parallel stations, zoning constraints and ergonomics risks. They performed two sensitivity analyses to assess the effects of changing the maximum ergonomic score limit and the zoning constraints in terms of solution quality and processing time. Both yielded significant results because they strongly influenced outcomes if they increased. Tiacci and Mimmi (2018) proposed a GA that could minimise the OCRA index in mixed-model and asynchronous assembly lines by also integrating some other characteristics of complex industrial assembly systems, such as stochastic task times, precedence constraints, equipment, line feeding costs and, finally, blocking and starvation phenomena related to cycle time and workers' ergonomic workload. The application of their algorithm to an industrial use suggested that ergonomics could be achieved with limited additional investment. Recently, Ostermeier (2020) used simulation to evaluate the effect of schedule types, product mix and human consideration (learning and forgetting, muscular fatigue and recovery time) on the scheduling process for unpaced mixed-models assembly lines. Finally, Çil et al. (2020) proposed a mixed-integer mathematical model to solve MMALB by considering physical human-robot collaboration. They optimally solved the problem for small size instances, while for large size instances, they proposed a bees algorithm.

2.2.Physical fatigue and recovery time

Energy expenditure is a good ergonomic assessment measurement, especially for evaluating tasks for which the whole body is used and various levels of effort are required (Garg et al., 1978). It permits evaluating the physical stress necessary to perform several activities and identifies the cases that exceed the workers' capabilities (Åstrand, 1967; Garg et al., 1978; Ilmarinen, 1992). Moreover, thanks to smart or heart rate devices, workers' effort in terms of energy expenditure can be quickly evaluated and monitored in real-time (Wu and Wang, 2002; Calzavara et al., 2018).

The energy expenditure spent in executing tasks can be compared with the maximum acceptable energy expenditure (MAEE), which is the maximum level for which an individual can work without fatigue effects (Åstrand, 1967). Initially, it has been defined as 33% of the individual maximum aerobic capacity, which is the maximum energy expenditure that a human can spend in executing an activity. However, during the years, ad hoc models have been developed thanks to the technological devices we can easily find and use to track and monitor our body. Moreover, it has been demonstrated that MAEE is affected by sex, age, body weight, and body height (Wu and Wang, 2002). Consequently, nowadays, MAEE can be easily adapted to each worker according to his or her personal features.

When MAEE is exceeded, objective and subjective indications of fatigue arise (Konz, 1998) and physical stress occurs. Aiming to avoid a decrease in physical capacity, breaks can be a good compromise to store the fatigue. For this reason, some models have been created to evaluate the so-called rest allowance (*RA*), which is the time needed for adequate rest after executing static or dynamic exertion (Rohmert, 1973). In the literature, there are several ways to evaluate the *RA* (Imbeau, 2009). However, some of these models require input data concerning maximum voluntary contraction or endurance time, which need ad hoc tools and specific competencies to be measured. Moreover, they cannot be easily measured in an industrial context and, generally, laboratory measures are taken. However, to the best of our knowledge, the *RA* concept, as defined in Price (1990), could be a good tool to evaluate how much time each worker should rest after executing some tasks. In Price (1990), the MAEE is assumed to be 4.3 kcal/min, and it represents 33% of the maximum aerobic capacity of a healthy man (40 years old, 1.75 m and 70 kg). According to Price (1990), we can define *RA* as follows:

$$RA = \max\{0; \frac{EE - ET_{max}}{ET_{max} - ET_R}\} \quad (1)$$

where:

- EE represents the mean work rate that can be considered as energy expenditure during a defined period. It is defined as the ratio between the total energy required in executing a task and its execution time;
- ET_{max} is the MAEE, which is assumed equal to 4.3 kcal/min for a mean worker 40 years old that works for 8 hours continuously;
- ET_R represents the relaxation rate and is 1.86 kcal/min if the worker is in a standing position or 1.64 kcal/min if the worker is sitting.

Note that *RA* is a percentage, while the *RA* time can be calculated as the product of *RA* and of the working time. Compared with other *RA* formulations, the Price one is simpler. Consequently, it can be very useful for managers and practitioners who want to evaluate the required recovery time to give to workers. Following this formulation, *RA* occurs if the *EE* exceeds the threshold value of 4.3 kcal/min.

Aiming to better fit the *RA* to the physical features of each worker, in Finco et al. (2019b) the Price formulation has been modified as follows:

$$RA = \max\{0; \frac{EE - MAEE}{MAEE - ET_R}\} \tag{2}$$

where MAEE varies according to the age and the bodyweight of the worker as defined in the formula provided by eSilva et al. (2016):

$$MAEE = 0.0016[(60 - 0.55AGE)BW] \tag{3}$$

In order to explain the effect that *MAEE* can have on *RA*, we propose an example. We apply both formulations (1) and (2) and we compare them to demonstrate how Eq. (1) can over- or underestimate the *RA* time. We assume that a healthy man 50 years old must perform a task that requires 4 kcal/min which is continuously performed for 1 hour. The worker weighs 70 kg. By applying the Price formulation (1990), the *RA* should be equal to 0 since we assume a MAEE equal to 4.3 kcal/min. However, this is not realistic, since the worker is older than 40 years. Moreover, in Price, no information is given about the workers' features. On the other hand, by applying Eq. (3), a worker 50 years old should have a MAEE equal to 3.64 kcal/min and, consequently, *RA* is necessary, since his MAEE is lower than the energy expenditure rate required to perform the task. Therefore, the *RA* time needed after completing the activity should be more than 12 minutes. In this case, Price (1990) underestimates the *RA* to assign to the worker since he is older than 40 years. On the contrary, if we assume a worker 25 years old, the MAEE is higher than 4.3 kcal/min and, consequently, the result provided by Price is the same as the one provided by Eq. (2) considering the exact MAEE value.

To sum up, starting from the current state of the art and focusing on general physical fatigue in MMALB, to the best of our knowledge, only Sgarbossa et al. (2016) studied the effects of fatigue on the balancing process for MMALs. However, they considered a multi-objective function for only the balancing phase; they did not provide a model for integrating fatigue during the sequencing phase. Furthermore, they did not apply the *RA* concept. Moreover, according to Table 1, only three papers evaluated human factors on tactical and operational decisions jointly but, in all cases, no focus on workers' features had been given. Thus, to improve the existing literature by providing an easy-to-use approach to practitioners, we propose a methodological approach for MMAL by including *RA* and workers' features to evaluate the MAEE. We consider both tactical and operational decisions. For the tactical decisions, we aim to balance the assembly system by minimizing cycle time for the VAM by including physical fatigue through *RA* according to Equation (1). For the operational decisions, we assign workers to stations according to their MAEE and, consequently, we evaluate *RA* according to Eq. (2). Finally, we apply the sequencing phase by minimising the WO that occurs each time a worker has insufficient time to complete the assembly process of a model.

3. Methodological approach

As defined by Scholl (1999), in mixed-model assembly systems, the balancing and sequencing problems are related to different planning horizons. Moreover, they lead to different decision processes. Of note, the balancing problem considers a long-term planning horizon, generally more than one year, and it is a tactical decision. The balancing phase of an assembly line is made only a few times or only when the task precedence diagram or product demands drastically change. On the other hand, the sequencing problem refers to a short-term decision problem and it can be related to monthly, weekly or daily product demands. It leads to operational decisions and, for this reason, it must be evaluated each time the operational scenario is facing changes. Figure 1 shows a scheme that includes the two primary decision levels and the related four steps of the proposed method. For each stage, the input data and the outputs are described; the points written in bold refer to the innovative contribution of the paper. In the next subsections, we discuss tactical and operational decisions in MMALB and we highlight the novelties compared with traditional approaches.

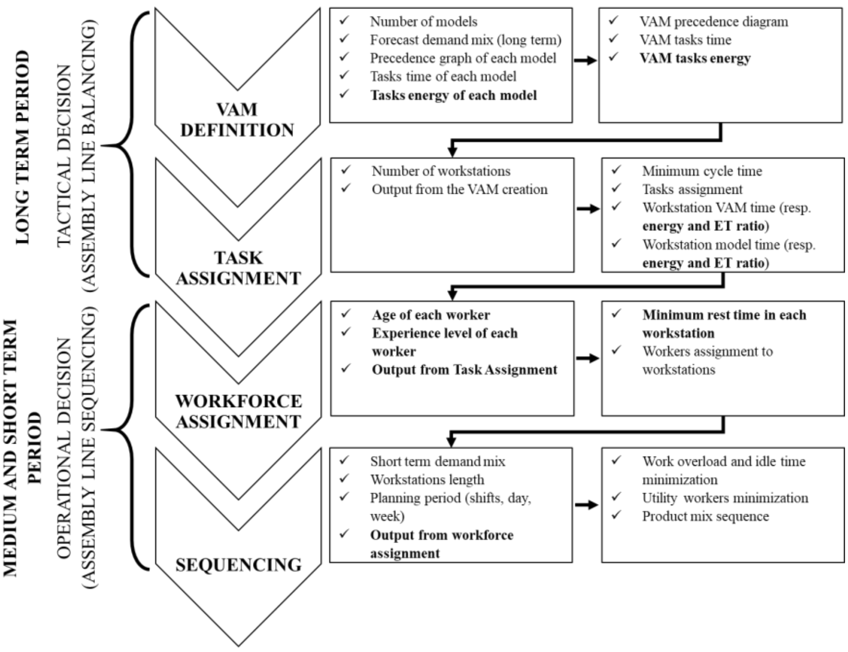

Figure 1. The methodological approach to include physical fatigue and related rest allowance in MMALs

3.1. Tactical decisions

According to Battini et al. (2009), in the long-term planning horizon, tactical decisions are taken concerning task assignments to stations. In MMAL, the balancing procedure starts from the VAM creation; then, the task assignment phase can be completed.

For VAM, the number of models, notated as M, that can be assembled in the same assembly system and the long-term demand forecast for each model *m*, denoted as D_m, must be known. Then, for each model, and each task *i*, the time t_i^m, and the human energy expenditure e_i^m, must be collected, and finally, the precedence diagram must be defined. In this first step, we manage all data by considering a general worker, middle-aged and physically active. This assumption is made because, in the long-term period, managers would not know the assembly workers' features. Thus, a general worker is a good compromise during the balancing procedure and for this reason, a MAEE value equal to 4.3 kcal/min as defined in Equation (1) could be used.

Once the VAM and the technological and ergonomics input data are defined, the balancing process can start. In this paper, we aim to minimize the cycle time, *c*. Consequently, we consider the MALBP type 2. Despite traditional approaches, we propose a new mathematical formulation, aiming to minimise both time and human energy expenditure using *RA* formulation as defined in Eq. (1). Moreover, unlike Sgarbossa et al. (2016), we propose a single-objective function, and this represents one of the first novelties of our methodological approach, despite the existing ones. In Figure 1, we divide the entire balancing process into two steps, namely the VAM creation and the task assignment to workstations.

3.2. Operational decisions

In medium- and short-term periods, managers know the assembly team as well as the short-term demands of each model d_m. In MMALB, the main operational decision is the definition of the sequence of products for short-term assembly. The workload is generally minimised as well as the employment of utility workers who are involved in the assembly process each time an assembly worker cannot complete all tasks in the assigned workstation (Matanachai and Yano, 2001). Utility workers, also called floaters, are generally multi-skilled and have a high experience level. Therefore, their salary is usually higher than their colleagues; thus, by minimising WO, companies also achieve labor cost minimization. Finally, due to their strategic importance in this type of assembly system, they are cross-trained and they move from a workstation to another each time workers directly involved in the workstation are not able to complete the task by respecting the cycle time. Since they continuously move among workstations, they can be considered as walking workers, as defined in Al-Zuheri et al. (2016). Consequently, by minimizing the WO, we also minimize their physical fatigue that, in their case, depends on the tasks they are called to perform and the fatigue associated with the walking time.

By knowing the workers' features and by assuming that assembly workers are equally skilled, we can assign workers to workstations according to their maximum physical fatigue (MAEE). In this way, we avoid assigning elderly workers to stations that require higher physical fatigue levels and, consequently, we also minimise *RA* defined through Eq. (2). With lower *RA*, we can also reduce the total WO. Moreover, MAEE decreases when age increases; thus, to minimise *RA* for high physical effort, a younger worker is preferable to an older one. Consequently, in our methodology, we introduce the workforce assignment process before the sequencing procedure, and we adjust workstation time, recovery time and cycle time to fit workstations to workers.

Once the workers are assigned to workstations, the sequencing problem can be solved, and, finally, the order in which products must be assembled is obtained by minimising WO. The required input data, in this case, are derived from balancing and workforce assignment steps. We adjust the cycle time obtained from the assembly line balancing problem by evaluating the correct *RA* to assign to each worker according to the workforce assignment. Additional data about the short-term demand mix, the planning period on which products must be sequenced and the workstation length (i.e. the maximum available time to make operations in a workstation, Scholl et al. 1999) must be collected. In Section 4.3, we propose a mathematical formulation to jointly minimise no value-added activities that are linked to WO. Furthermore, in these last steps, we include human factors to achieve a trade-off between line efficiency and human well-being. In this paper, we apply this approach to MMAL systems. However, it might be easily implemented in other types of production systems, such as the hybrid production systems or the multi-hybrid cell production systems (Yılmaz and Durmuşoğlu, 2018a; Yılmaz and Durmuşoğlu, 2018b). In fact, for these production systems, workers represent a critical resource (Yılmaz, 2020) since they are highly skilled and, consequently, inefficiency should be avoided. For this reason, fatigue effects and the related RA should be integrated during the order release or the sequencing process or the workforce assignment that represents the three main problems than impact on performances of these production systems.

The next section presents the mathematical models related to assembly line balancing and workforce assignment, as well as the sequencing problems.

4. Mathematical models and notations

In this section, the mathematical models leading to tactical and operational decisions, according to Figure 1, are presented. Table 2 lists all indexes, parameters and decision variables we will use in the sequel.

Indexes	
i	Index for tasks
j	Index for workstations
m	Index for models
k	Index for sequence
Parameters	
M	Number of models
O	Number of tasks related to the VAM
N	Number of workstations
K	Length of the sequence in the short-term period
D_m	Long-term demand for model *m*
d_m	Short-term demand for model *m*
t_i^m	Time required to process task *i* for model *m*
e_i^m	Energy required to process task *i* for model *m*
ET_{MAX}	Maximum Energy-Time ratio (4.3 kcal/min)
ET_{REST}	Rest Energy-Time ratio (1.86 kcal/min)
$MAEE_j$	Maximum Acceptable Energy Expenditure for workstation *j*
t_i^{VAM}	Time required to process task *i* for VAM
e_i^{VAM}	Energy required to process task *i* for VAM
l_j	Length of workstation *j*
A	Set of all direct precedence among tasks
UB	Big-M
Variables	
c	Cycle time
T_j^m	Total time required to process model *m* in workstation *j*
E_j^m	Total energy required to process model *m* in workstation *j*
ET_j^m	Energy-Time ratio required to process model *m* in workstation *j*
T_j^{*VAM}	Total time required to process the VAM in workstation *j* in the short-term period
E_j^{*VAM}	Total energy required to process the VAM in workstation *j* in the short-term period
ET_j^*	Energy-Time ratio we can have in workstation *j* in the short-term period
T_j^{*m}	Total time required to process model *m* in workstation *j* by also including rest allowance
RA_j	Rest allowance for workstation *j* (expressed as a percentage of the total workstation time)
TRA_j	Rest allowance time for workstation *j*
c'	Adjusted cycle time obtained by considering workers' age and the related MAEE
WO	Total work-overload
ω_{jk}	Work-overload in station *j* and position *k* of the sequence
s_{jk}	Stating assembly time for station *j* and position *k* of the sequence
Decision variables	
x_{ij}	Boolean variable that assumes a value 1 if task *i* is assigned to workstation *j*, 0 otherwise

φ_j	Boolean variable that is equal to 1 if worker employed in workstation *j* needs rest, 0 otherwise
∂_{mk}	Boolean variable that is equal to 1 if model m is assembled in the position k of the sequence, 0 otherwise
β_{jk}	Boolean variable that is equal to 1 if work-overload occurs in station *j* in the position *k* of the sequence, 0 otherwise

Table 2. List of all indexes, parameters, variables and decision variables

4.1. Tactical decision problems

4.1.1. VAM definition

Balancing a MMAL implies not only a joint precedence graph but also the concept of VAM, which is a dummy average model representing all the products assembled in the assembly line.

The time (resp. the energy expenditure) of each task in the VAM can be calculated as:

• The maximum time (resp. energy expenditure) required for this activity considering all the products;

• The average time (resp. energy expenditure) required for this activity considering all the products;

• The weighted average time (resp. energy expenditure) required for this activity considering the mix of products.

According to Sgarbossa et al. (2018), we use the weighted average time (resp. energy expenditure) and, consequently, by knowing D_m, t_i^m and e_i^m for each model, we can define the VAM time of each task, notated as t_i^{VAM}, and the VAM energy of each task, notated as e_i^{VAM}, as follows:

$$t_i^{VAM} = \frac{\sum_m D_m t_i^m}{\sum_m D_m} \tag{4}$$

$$e_i^{VAM} = \frac{\sum_m D_m e_i^m}{\sum_m D_m} \tag{5}$$

4.1.2. Assembly line balancing problem

According to the VAM, t_i^{VAM} and e_i^{VAM} are known, as well as the precedence constraints that exist among tasks. Given that a MALBP-2 is considered, the number of workstations *N* is known, while the cycle time, denoted as *c*, represents the objective function to minimise. Finco et al. (2018) demonstrated that a lower cycle time could be achieved if *RA* is computed during the balancing phase in Simple Assembly Line Balancing Problem (SALBP). Thus, for the MMALB problem, we include *RA* jointly with the balancing problem. Using the VAM concept, the MALBP-2 becomes a SALBP-2 that is an NP-hard problem (Scholl, 1999).

The main assumptions of the assembly line balancing model can be summarized as follows:

- There are N workstations;
- There are O manual tasks;
- Each task *i* has deterministic time and energy values;
- Each task *i* can be assigned only if its predecessors have already assigned;
- Tasks are assigned to the workstation by assuming that workers have a MAEE equal to 4.3 kcal/min.
- *RA* in each workstation *j* is computed in an integrated way with balancing procedure according to Finco et al. (2018).

The mathematical model can be defined as:

$$O.F.1\text{: Minimize } c \tag{6}$$

Subject to:

$$\sum_j x_{ij} = 1 \; \forall \; i = 1,..,O \tag{7}$$

$$\left(1 + RA_j\right)\sum_i x_{ij} t_i^{VAM} \le c \; \forall \; j = 1,..,N \tag{8}$$

$$\sum_k x_{hk} k \le \sum_j x_{ij} j \;\; \forall \; (h,i) \in A \tag{9}$$

$$c \in \mathbb{R} \tag{10}$$

$$x_{ij} \in \{0;1\} \; \forall \; i = 1,..,K; j = 1,..,N \tag{11}$$

Where *O.F.1* minimises the cycle time. Constraint (7) assures that each task i is assigned to only one workstation j. Constraint (8) evaluates the cycle time by considering a task's time and energy jointly, while Constraint (9) assures that precedence relations among tasks are not violated. Finally, Constraints (10) and (11) define the type of variable that are respectively real and Boolean variables. Please note that in Constraint (8), time and energy are linked through the *RA* formulation as in Eq. (1).

However, the mathematical model presented here is not linear due to the presence of RA_j in Constraint (8), which is defined as:

$$RA_j = \max\left\{0; \frac{\frac{\sum_i x_{ij} e_i^{VAM}}{\sum_i x_{ij} t_i^{VAM}} - ET_{max}}{ET_{max} - ET_R}\right\} \forall \; j = 1,..,N \tag{12}$$

Therefore, it is necessary to linearise the model. Thus, starting from the mathematical approach adopted in Finco et al. (2020), the following additional equations that lead to a linearised formulation are required. Constraint (8) can be written as:

$$TRA_j + \sum_i x_{ij} t_i^{VAM} \leq c \ \forall \ j = 1, .., N \tag{13}$$

where TRA_j is *RA* expressed in term of time for workstation *j* and is defined as:

$$TRA_j = \max\{0; \sum_i x_{ij} \frac{e_i^{VAM} - ET_{MAX} t_i^{VAM}}{ET_{MAX} - ET_{REST}}\} \forall \ j = 1, .., N \tag{14}$$

The following additional constraints must be added in the final model to linearize Eq. (14):

$$TRA_j \geq 0 \ \forall \ j = 1, .., N \tag{15}$$

$$TRA_j \geq \sum_i x_{ij} \frac{e_i^{VAM} - ET_{MAX} t_i^{VAM}}{ET_{MAX} - ET_{REST}} \ \forall \ j = 1, .., N \tag{16}$$

$$TRA_j \leq 0 + UB\varphi_j \ \forall \ j = 1, .., N \tag{17}$$

$$TRA_j \leq \sum_i x_{ij} \frac{e_i^{VAM} - ET_{MAX} t_i^{VAM}}{ET_{MAX} - ET_{REST}} + UB(1 - \varphi_j) \ \forall \ j = 1, .., N \tag{18}$$

$$\varphi_j \ \in \{0; 1\} \ \forall \ j = 1, .., N \tag{19}$$

Constraints set (15) to (19) allows selecting the maximum value. UB corresponds to the big-M, while φ_j is the additional Boolean variable that leads to choosing the higher value that TRA_j can assume.

In conclusion, *O.F.1* and Constraints (7), (9)–(11), (13) and (15)–(19) lead us to define the minimum cycle time related to the assembly process of the VAM.

4.2. Operational decision problems

4.2.1. Workforce assignment problem

Once the balancing problem is solved, the tasks are assigned to the stations and the cycle time is defined. However, for each workstation, its load depends on the model that needs to be processed since we are in MMALs. Moreover, for the short-term period, the demand for each model could differ from the long-term one. Consequently, it is necessary to take into account all these aspects. Moreover, aiming to correctly assign the right worker to each workstation, for each workstation *j* it is necessary to define the following data about each model and the VAM:

$$T_j^m = \sum_i x_{ij} t_i^m \ \forall \ j = 1, .., N; m = 1, .., M \tag{20}$$

$$E_j^m = \sum_i x_{ij} e_i^m \ \forall \ j = 1, .., N; m = 1, .., M \tag{21}$$

$$ET_j^m = \frac{E_j^m}{T_j^m} \ \forall\, j = 1,..,N; m = 1,..,M \tag{22}$$

$$T_j^{*VAM} = \frac{\sum_m T_j^m d_m}{\sum_m d_m} \ \forall\, j = 1,..,N \tag{23}$$

$$E_j^{*VAM} = \frac{\sum_m E_j^m d_m}{\sum_m d_m} \ \forall\, j = 1,..,N \tag{24}$$

$$ET_j^* = \frac{E_j^{VAM}}{T_j^{VAM}} \ \forall\, j = 1,..,N \tag{25}$$

where T_j^m, E_j^m and ET_j^m are respectively the time, human energy, and energy-time ratio required to assemble model *m* in workstation *j* while T_j^{*VAM}, E_j^{*VAM} and ET_j^{*VAM} are the updated values concerning VAM which take into account the short term demand.

As described in Section 3.2., during the workforce assignment, we assume the assembly staff is known. Consequently, the Price (1990) formulation can be modified according to Finco et al. (2019b), by replacing the ET_{MAX} that is 4.3 kcal/min with the MAEE related to the worker. In this way, workers can be assigned to the workstations by also including their features. We assume that all workers are equally skilled while they differ in age. Moreover, the number of available workers is equal to the number of workstations and each worker must be assigned to only one workstation and vice versa.

For this type of problem, we develop an easy heuristic approach, as reported in Figure 2. This approach aims to assign workers with a higher MAEE to workstations that require a higher physical effort according to the ET_j^*, as defined in Eq. (25). In this way, we avoid having high *RA* values and we reach both employees' and employers' needs. Moreover, we can prevent an increase in cycle time due to excessive *RA* time. In fact, in short term period, since we assume to know workers' features, we can adjust the cycle time by including them on it as defined as follows:

$$c' = \max\{T_j^{*VAM}(1 + \max\left\{0; \frac{ET_j^m - MAEE_j}{MAEE_j - ET_R}\right\}\} \tag{26}$$

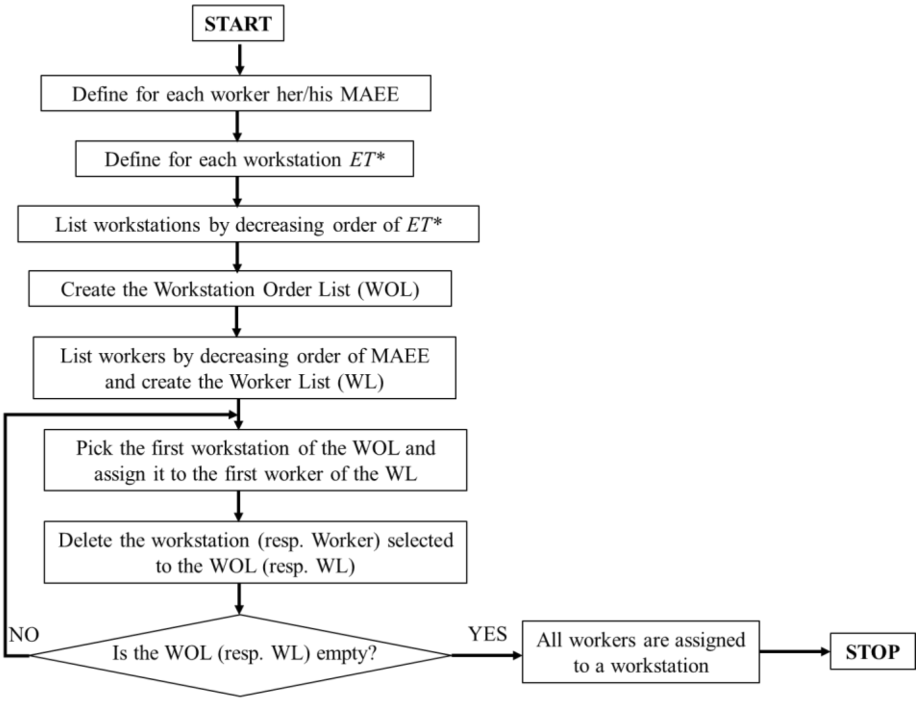

Figure 2. Workforce assignment heuristic approach.

<u>Numerical example</u>

There are two workstations, with a weighted ET value of ET_1^*=4.40 kcal/min and ET_2^*=3.95 kcal/min. The available workers have a MAEE of 4.10 kcal/min (Worker 1) and 4.30 kcal/min (Worker 2). Following the heuristic procedure, we assign Worker 2 to Workstation 1 and Worker 1 to Workstation 2. In this way, we obtain a maximum *RA* of 3.94% in Workstation 1 and 0% in Workstation 2 because ET_2^*<MAEE. However, if we assign Workstation 1 to Worker 1 and Workstation 2 to Worker 2, *RA* becomes 13.39% and 0%.

4.2.2. Sequencing model

The sequencing problem defines the optimal sequence that allows satisfying the demand of all models in a short-term period and minimizing or maximizing an objective function that can be expressed as cost, time or productivity (Scholl, 1999). In our case, the objective function is to minimise the WO.

In our case, from Section 4.2.1, workers involved in the assembly process have distinctive features. Consequently, we need to adjust the total time required to assemble each model *m* in each workstation *j* according to their characteristics as follows:

$$T_j^{*m} = T_j^m(1 + \max\left\{0; \frac{ET_j^m - MAEE_j}{MAEE_j - ET_R}\right\}) \tag{27}$$

where $MAEE_j$ is the maximum acceptable energy expenditure of the worker assigned to workstation *j*. Through Eq. (27), the total process time for model *m* in workstation *j* also includes the specific rest time to give to each worker. Equation (27) also represents the relationship between the workforce assignment problem and the sequencing one, since the assignment strongly influences the workstation time and, consequently, it could affect the total WO.

In the short-term period, the demand of each model, denoted as d_m, is known. Consequently, we can set the length of the sequence, K, as the sum of the short-term demands of all models.

For the sequencing model, the following assumptions need to be considered:

- Each model *m* requires a processing time in each workstation *j* that is influenced by the features of the workers selected during the workforce assignment phase.
- The demand for each model *m* must be reached.
- Only a model can be processed in a workstation at the same time
- Utility workers are involved only if assembly workers are not able to complete the model in the available time.

Finally, the sequencing mathematical model can be defined as follows:

$$\textit{O.F.2.}\ \text{Minimize WO} \tag{28}$$

Subject to:

$$WO = \sum_j \sum_k \omega_{jk} \tag{29}$$

$$\sum_m \partial_{mk} = 1 \ \forall\ k = 1,..,K \tag{30}$$

$$\sum_k \partial_{mk} = d_m \ \forall\ m = 1,..,M \tag{31}$$

$$s_{j,k+1} \geq s_{j,k} + \sum_m T_j^{*m} \partial_{mk} - w_{jk} - c' \ \forall\ j = 1,..,N; k = 1,..,K \tag{32}$$

$$s_{jk} + \sum_m T_j^{*m} \partial_{mk} - w_{jk} \leq l_j \ \forall\ j = 1,..,N; k = 1,..,K \tag{33}$$

$$\omega_{jk} \geq w_{jk} - \sum_m TRA_j^{*m} \partial_{mk} \ \forall\ j = 1,..,N; k = 1,..,K \tag{34}$$

$$\omega_{jk} \geq 0 \ \forall\ j = 1,..,N; k = 1,..,K \tag{35}$$

$$\omega_{jk} \leq w_{jk} - \sum_m TRA_j^{*m} \partial_{mk} + UB(1 - \beta_{jk}) \forall\ j = 1,..,N; k = 1,..,K \tag{36}$$

$$\omega_{jk} \leq UB\beta_{jk} \forall\ j = 1,..,N; k = 1,..,K \tag{37}$$

$$s_{j,1} = s_{j,K+1} = 0 \ \forall\ j = 1,..,N \tag{38}$$

$$\partial_{mk} \in \{0; 1\} \ \forall\ m = 1,..,M; k = 1,..,K \tag{39}$$

$$\omega_{jk}, w_{jk}, s_{jk} \in \mathbb{R}^+ \ \forall\ j = 1,..,N; k = 1,..,K \tag{40}$$

Where *O.F.2* (28) minimises the total WO as defined in Constraint (29). ω_{jk} is defined as follows:

$$\omega_{jk} = \max\left\{0; w_{jk} - \sum_{m} TRA_j^{*m} \partial_{mk}\right\} \ \forall\, j = 1,..,N; k = 1,..,K \quad (41)$$

and, due to its no linearity formulation, Constraints (36) and (37) must be introduced in the model.

In the objective function, we consider the maximum value between zero and the difference between the workload and the rest time required to process the product. In this way, we avoid assigning utility workers when the WO is equivalent to or lower than rest time. Moreover, we assume that *RA* could also be used by workers to complete the task.

Finally, Constraint (30) assures that each unit product is assigned to exactly one position of the sequence. Constraint (31) guarantees the respect of the demand required for each model. Constraint (32) assures that the assembly of an item cannot start before the preceding item has been completed by using regular workers, while Constraint (33) guarantees the respect of the maximum available time, l_j, of the station. Finally, Constraints (39) and (40) set the type of variables.

5. Case study and discussion

To evaluate the benefits we can achieve by applying the methodological approach developed, we present and discuss a real case application. We have used Cplex V12.8 as a solver to compute the optimal solution for each mathematical model proposed. Since both balancing and sequencing problems are NP-hard problems, only small- and medium-size instances can be optimally solved in a reasonable amount of time. For large size instances, a suboptimal solution can be achieved.

However, in our case, since the aim of this study is related to the effect of workers' features, we have considered a medium-size instance and optimal results have been obtained. The company produces truck trailers in a mixed-model assembly system. Some tasks require considerable physical effort because some parts or components are very large and bulky. Five models are assembled in the assembly line, composed of five workstations. For each model, we evaluated the task time and energy expenditure. The precedence graph, VAM task time and task energy have been obtained by considering the long-term demand. According to the approach developed in Section 3 and to Figure 1, we divide the case study into two parts.

5.1. Tactical decision analysis

The long-term period demand for each model is equal to 32% of the demand for Model 1, 27% for Model 2, 19% for Model 3, 13% for Model 4 and, finally, 9% for Model 5. We know the time and energy expenditure of each task for each model. Consequently, the time and energy values for each task in the VAM can be calculated according to Eq. (4) and (5). In Table 3, VAM values for task time and energy are reported. Moreover, Figure 3 shows the VAM precedence graph. Details about the task times and energy expenditures of each model, as well as each precedence graph and the VAM precedence graph, are reported in Appendix 1.

Task	Time [s]	Energy [kcal]	Task	Time [s]	Energy [kcal]	Task	Time [s]	Energy [kcal]	Task	Time [s]	Energy [kcal]
1	144.82	10.13	22	33.92	2.41	43	163.8	12.87	64	33.91	2.44
2	10.8	0.87	23	147.82	11.42	44	228.2	15.91	65	147.42	10.94
3	118.12	8.47	24	114.53	7.27	45	370.42	27.2	66	236	16.13
4	101.36	7.43	25	69	4.59	46	105	8.32	67	181.51	13.47
5	113.38	8.81	26	188.41	14.59	47	57.64	4.15	68	213.05	17
6	431.6	34.42	27	341.36	21.8	48	29.75	2.02	69	447.88	29.27
7	139.68	10.58	28	160.8	12.83	49	206.39	12.8	70	77.88	5.22
8	110.69	7.43	29	1347.2	106.49	50	52.08	4.01	71	67.46	5.19
9	156.68	9.6	30	158.12	9.53	51	125.15	9.06	72	88.92	7.44
10	282.42	17.4	31	537.62	39.36	52	119.58	8.65	73	134.05	10.32
11	214.48	17.16	32	184.41	12.66	53	253.19	18.27	74	33.29	2.59
12	36.7	2.75	33	40.5	2.91	54	96.46	6.02	75	131.24	8.22
13	317.17	22.08	34	211.39	15.71	55	196.36	12.06	76	304.34	21.82
14	156.78	11.18	35	100.44	7.97	56	104.16	7.43	77	67.54	5.02
15	309.81	19.6	36	68.66	5.26	57	164.8	11.54	78	218.83	18.78
16	258.75	18.86	37	202.39	14.09	58	113.65	8.74	79	125.93	8.77
17	255.1	16.59	38	382.29	27.9	59	100.44	7.51	80	205.18	15.08
18	134.14	10.16	39	468.46	34.24	60	260.75	17.36	81	120.3	7.17
19	182.68	12.27	40	187.77	13.21	61	61.26	4.26	82	49.84	3.26
20	1067.38	70.63	41	134.05	10.57	62	409.29	29.25			
21	488.26	38.06	42	189.41	13.99	63	130.29	9.37			

Table 3. Task time and energy values for VAM

By applying the line balancing model defined in Section 4.1, the minimum cycle time for VAM is 3,330 s and it is well distributed among stations, as shown in Figure 3. Table 4 provides the tasks to stations assignment.

Workstation	Tasks assigned
Station 1	1, 5, 6, 7, 11, 12, 13, 14, 15, 16, 17, 44, 48, 52, 63, 64, 65, 66
Station 2	3, 4, 18, 19, 20, 21, 38, 39, 53, 73
Station 3	2, 8, 9, 10, 23, 24, 26, 27, 29, 33, 40, 54, 55, 56
Station 4	22, 25, 28, 30, 31, 32, 34, 35, 36, 37, 41, 42, 43, 45, 51, 69, 70, 71
Station 5	46, 47, 49, 50, 57, 58, 59, 60, 61, 62, 67, 68, 72, 74, 75, 76, 77, 78, 79, 80, 81, 82

Table 4. Task to station assignment obtained for the case study.

According to the mathematical model, the cycle time also includes recovery time by considering a middle-aged worker in a healthy status (MAEE equals to 4.3 kcal/min). Moreover, the energy expenditure is well distributed among stations if VAM is evaluated and its maximum value is 238.5 kcal, reached in station 3. However, if each model is considered separately, we can say that workstation time and energy are not well balanced. By examining the same workstation, some models require a higher time to be processed compared with the VAM, while others require a lower time. This is particularly true if workstations 1, 2 and 3 are considered. Finally, by considering the same model, the workload among workstations is unbalanced, especially for Models 3, 4 and 5.

Going in-depth in this study and evaluating the physical fatigue belonging to each station, Figure 3 reports also the ET ratio required to assemble respectively the VAM and each model in each workstation. If the VAM is considered, the maximum ET value is reached in Station 5 with a value of 4.34 kcal/min, which implies a rest of a couple of seconds since 4.34 kcal/min is very close to 4.3 kcal/min. However, likewise to time and energy distribution, if we consider each model separately, the ET ratio reaches higher values than 4.34 kcal/min. Consequently, when some models are assembled, a higher rest could be required. In fact, according to Figure 3, we can see an ET ratio peak for model 3 in Station 1. In this case, the ET ratio is equal to 5.33 kcal/min and it implies a higher rest time despite the one required for the VAM. Moreover, also for all other models, the ET ratio maximum value in some workstations is higher than the VAM one. Consequently, some models in some stations could require a higher RA while others, which are physically lighter, have a RA equal to zero because fatigue does not arise.

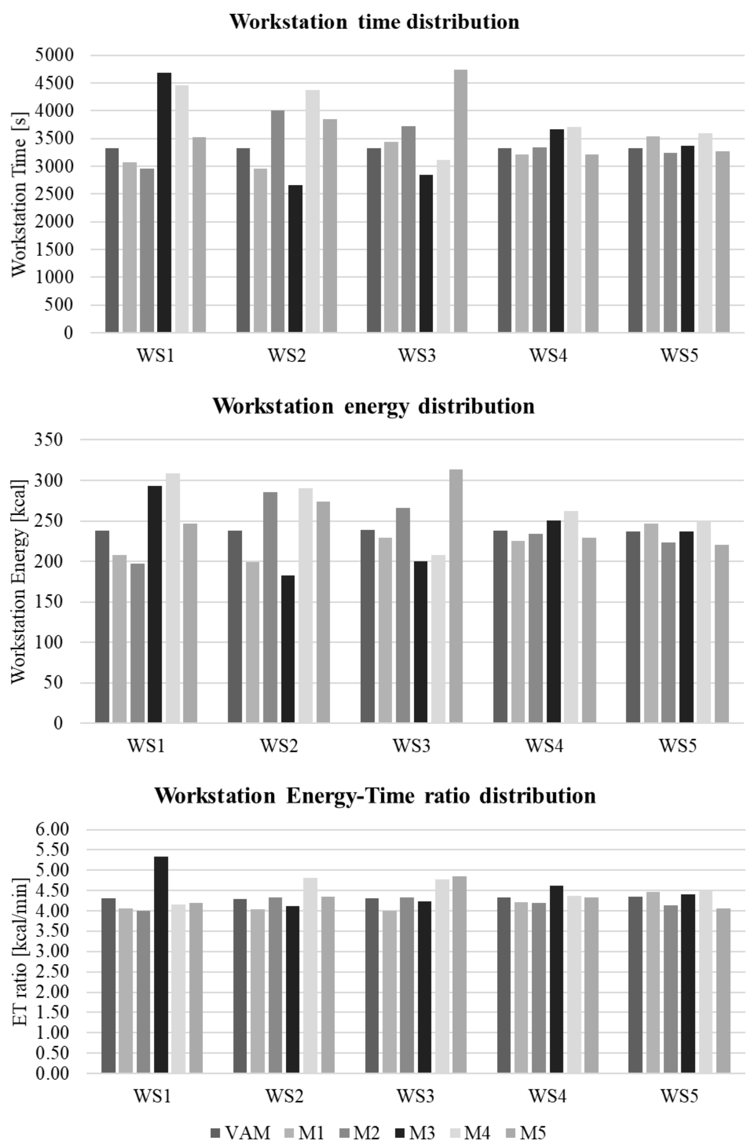

Figure 3. Workstation time, energy and energy-time ratio by considering the VAM and each model separately

5.2.Operational decision analysis

Once the balancing phase is completed, tasks are assigned to workstations and short-term decisions can be taken. In this case, we know the age of the five workers involved in the assembly process. Moreover, we assume they are male workers with a body weight, denoted as BW, of 70 kg.

We evaluate the MAEE starting from the Equation provided by eSilva et al. (2016), as defined in Eq. (3). Once the MAEE is calculated, as we can see in Table 5, the workforce assignment process can start.

Worker	Age	MAEE [kcal/min]
W1	32	4.74
W2	34	4.61
W3	42	4.12
W4	44	4.01
W5	46	3.92

Table 5. Workers' features

The short-term demand, in this case, is equal to 12 items for Model 1, 7 for Model 2, 6 for Model 3, 3 for Model 4 and, finally, 2 for Model 5. The ET_j^* can be defined according to the assembly time and energy values related to each model in each workstation. In this case, Eq. (23)-(26) need to be applied. Results are available in Table 6 that reports the assembly time (without recovery time) and the total energy required to assembly each model in each workstation.

		Time [s]					Energy [kcal]				
Model	d	WS1	WS2	WS3	WS4	WS5	WS1	WS2	WS3	WS4	WS5
VAM		3256.87	3251.43	3324.50	3287.17	3273.70	234.82	229.87	235.52	236.42	237.74
M1	12	3066.00	2957.00	3439.00	3209.00	3307.00	207.61	198.79	229.46	225.45	246.53
M2	7	2957.00	3957.00	3690.00	3348.00	3238.00	196.77	285.35	265.67	234.50	223.12
M3	6	3293.00	2660.00	2840.00	3253.00	3230.00	292.78	182.62	200.44	250.14	237.30
M4	3	4465.00	3620.00	2617.00	3599.00	3315.00	308.62	290.22	207.82	262.20	248.91
M5	2	3531.00	3770.00	3873.00	3178.00	3268.00	246.71	273.40	313.12	229.15	220.80

Table 6. Short-term demand for each model and the related assembly time and energy values.

According to Table 6 and Equation 26, ET_j^* can be defined since we know all data about each model in each workstation and, finally, also the heuristic approach as proposed in Section 4.2.1 can be applied. According to Table 7, since Station 3 has the higher ET*, we assign Worker 1 (W1) who is the youngest one and has a higher MAEE. Then, we continue to assign workers by comparing the ET with the MAEE. Finally, we obtain the assignments shown in Table 7. Please note that this scenario represents only one of the 120 possible workers' assignments to workstations.

Station	ET* [kcal/min]	Worker assigned	MAEE [kcal/min]	RA [%]	Total station time [s]
WS1	4.32	W3	4.12	8.85%	3545.08
WS2	4.24	W5	3.92	15.53%	3756.51
WS3	4.25	W4	4.01	11.16%	3695.61
WS4	4.32	W2	4.61	0.00%	3287.17
WS5	4.35	W1	4.74	0.00%	3273.70

Table 7. Workforce assignment and update station time.

By knowing the MAEE of each worker assigned to each station, the VAM time can be adjusted according also to the short-term demand. As an example, we take station 1. In this case, the ET* value is the same as the one obtained by applying the balancing. However, by using the workforce assignment, the worker's MAEE is lower than 4.3 kcal/min and, consequently, RA is necessary. We can say the same also for workstations 2 and 3, since workers older than 40 years are involved in the assembly. Consequently, we need to adjust also the cycle time by including the right RA. In this way, according to Table 7, the cycle time becomes 3765.51 s, which is 12.81% higher than the cycle time we have obtained during balancing. However, the increase in the cycle time allows elderly workers to complete tasks with a higher time by using the RA.

By considering this initial scenario, the model sequence definition can start. By applying the mathematical model described in Section 4.2.2, we obtain a WO equal to 3,090.44 s.

To evaluate the benefits of the applied approach and assess the age effects on sequencing, we perform a comparative analysis. For the case study analysed here, if no constraints related to ET values are assumed, there are 120 possible combinations (5!) to assign workers to workstations. Thus, we take into account all possible feasible solutions we can have by setting workers to workstations without evaluating the energy expenditure aspects, then we apply the sequencing model. This first method of analysis is called Scenario A (Workers Assignment, then Sequencing, WA-S). Then, we make another analysis. Firstly, we apply the sequencing model by assuming that all workers have the same features and the same cycle time obtained during balancing; then, we apply workforce assignment as a post-processing phase and consequently, we adjust the WO by also including the RA time. We call this second analysis as Scenario S-WA (Sequencing, then Workers Assignment).

Figure 4 reports the results we have obtained. Using the box-plots, we can summarize and quickly compare the results provided with the developed approach and the ones given by Scenario WA-S and Scenario S-WA. The whiskers represent, respectively, the minimum and the maximum value we have obtained by applying the model for all the possible workforce assignments. At the same time, the boxes indicate one standard deviation from the average (center line). As we can see, the minimum value we obtain with Scenario WA-S overlaps the WO value we got by considering the methodology we have proposed. With all other possible workforce assignment solutions, WO is always higher. Thus, it is not efficient since utility workers are employed for more time and fatigue could also arise on them.

Moreover, the WO median value is 6548.23 s, while the maximum value we reach is 9957.99 s that corresponds to the opposite workforce assignment we have proposed in Section 4.2.1. Hence, older workers are assigned to higher physical effort workstations, while youngest to the lighter ones. Scenario S-WA always provides higher WO compared to the methodology we propose. Furthermore, there is still a higher WO since sequencing does not integrate the *RA* and it considers only the time required to assemble a task without fatigue consideration, which is made during the post-processing. Scenario S-WA has a median value that is more than double than that one of Scenario WA-S and it reaches a maximum value equal to 19784.21 s. Moreover, the WO distribution is wider than the one of scenario WA-S. Finally, by applying Scenario S-WA, inefficiencies on the assembly systems could occur, since utility workers need to be continuously employed to smooth the delays in each workstation, due to the higher physical fatigue and the related *RA* time that has to be assigned to workers.

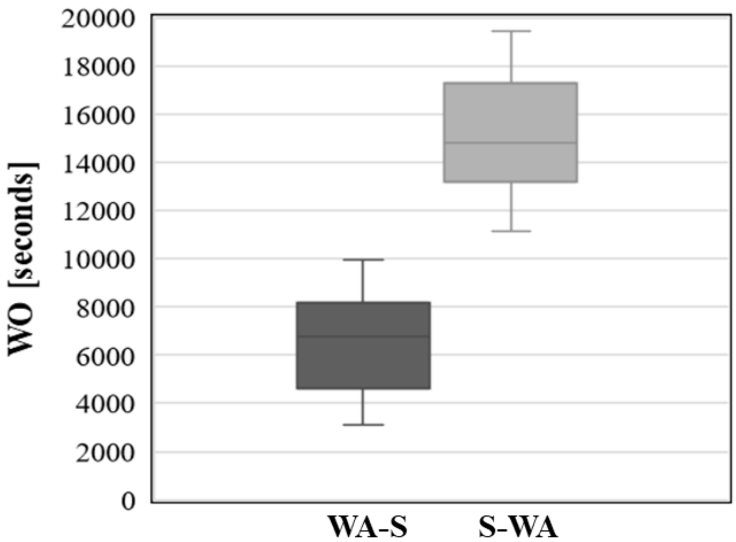

Figure 4. Box-plot about the WO distribution by applying Scenario WA-S and Scenario S-WA.

5.3.The influence of MAEE during operational decisions

Given that MAEE strongly influences the RA time to assign to each worker, in this section, we evaluate its effect by considering several instances with a different team of workers with different ages and, consequently, with different MAEE.

Category	Sub-category	Team age (years)	Mean MAEE	MAEE Variation
30	30-1	[30;30;30;30;30]	4.86	0.00
	30-2	[26;28;30;32;34]	4.86	0.03
	30-3	[24;27;30;33;36]	4.86	0.07
40	40-1	[40;40;40;40;40]	4.24	0.00
	40-2	[36;38;40;42;44]	4.24	0.03
	40-3	[34;37;40;43;46]	4.24	0.07
50	50-1	[50;50;50;50;50]	3.63	0.00
	50-2	[46;48;50;52;54]	3.63	0.03
	50-3	[44;47;50;53;56]	3.63	0.07

Table 8. Groups of workers

We consider nine teams of workers, reported in Table 8. They can be clustered into three main categories, respectively named 30, 40 and 50 according to their average age. In each category, there are three subgroups and, for each of them, we know their MAEE. Table 8 also shows the mean MAEE value and its variation. For each category, we assume that one group has five workers, all with the same features, thus, with the same MAEE. Hence, for this kind of group, workforce assignment is not required. For the remaining two groups of each category, workforce assignment can significatively change both the cycle time for the short-term period and WO. According to Section 4.2.2., each time workers change, cycle time changes too, since we need to adjust RA time according to the right MAEE of each worker. In this way, by considering each category, the cycle time needs to be adjusted according to Eq. (26).

In the same way as before, we compare the WO result by applying the methodology we have previously described with the two scenarios, Scenario WA-S and Scenario S-WA. Figures 5, 6 and 7 provide box-plot graphs about the WO we have obtained for each group of workers belonging to each category.

As we can see in Figures 5, 6 and 7 when all workers have the same age, the workforce assignment does not influence the optimal sequencing; thus, we have only a value of WO. However, Scenario WA-S performs better for Category 30 and Category 50. At the same time, it gives very close results for Category 40, since, in this last case, the cycle time for both scenarios changes only for a couple of seconds. In fact, in this previous case, the MAEE we use is very close to 4.3 kcal/min. In other cases, the cycle time used for Scenario WA-S is respectively lower for Category 30 and higher for Category 50 since workers have a MAEE that differs from the 4.3 kcal/min used during the balancing phase. Consequently, the RA time can be lower (it is the case for Category 30) or higher (as in Category 50). For Category 30, the mean MAEE equals 4.86 kcal/min, thus higher than 4.3 kcal/min. This implies that, according to the balancing that considers as a threshold value 4.3 kcal/min, RA is not required for all workers and, consequently, the cycle time is lower than the one obtained during the tactical decisions. On average, the cycle time we get is 12.52% lower than the cycle time obtained during the balancing phase. Finally, for Category 50, the mean MAEE is 3.63 kcal/min and, consequently, higher rest is necessary on average. This aspect strongly impacts on cycle time c', that is on average up to 35% higher than the cycle time obtained during balancing.

By analysing each category separately, we can say that, in general, WO is smoothed when workforce assignment and RA are introduced before the sequencing problem. However, the gap between Scenario WA-S and Scenario S-WA is closer for Category 30 compared to Category 40 and 50 (Figures 5, 6 and 7).

For Scenario WA-S and Scenario S-WA concerning Category 30 (Figure 5), we can say that, among separate groups, the WO differences we can obtain are smoothed with respect to the other categories. In fact, for Category 30, the WO varies from 6598.25 s to 7212.32 s for Scenario WA-S and from 6995.36 s to 7445.64 s for Scenario S-WA. Moreover, the median value we have obtained for Scenario WA-S is always lower than the one of Scenario S-WA, while the value distributions are larger for Scenario WA-S than for Scenario S-WA. Moreover, if we investigate the results obtained by applying sequencing and then workforce assignment (Scenario S-WA), we get a higher WO since workers cannot use the RA to complete the tasks assigned to their workstation.

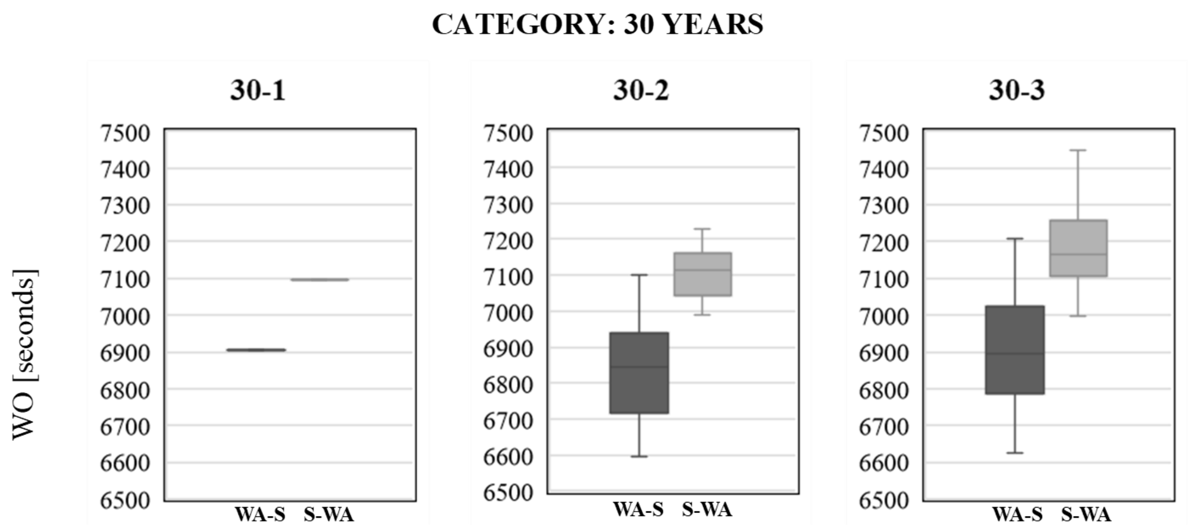

Figure 5. WO distribution for Category 30, comparison among groups of workers and different scenarios

For Category 40 and 50 (Figure 6 and Figure 7, respectively), the higher the age variation, the higher the WO. Furthermore, when all workers are 40 years old, the WO is the minimum value we can obtain; this is due to the value adopted by MAEE, which is very close to the ET_{MAX} defined by Price (1990). Category 50 represents the elderly worker category and, in this context, RA can assume high values that imply a higher cycle time. On average, the cycle time we obtain is up to 35% higher than the initial cycle time. According to Figure 7, the WO we reach by applying Scenario WA-S is always lower than the one of Categories 30 and 40. In fact, they can use RA time to complete the task by avoiding utility workers. However, it implies more fatigued workers. Moreover, the cycle time, c', is higher than the one of Categories 30 and 40. Moreover, by applying Scenario S-WA, WO increases if sequencing is applied before the workforce assignment.

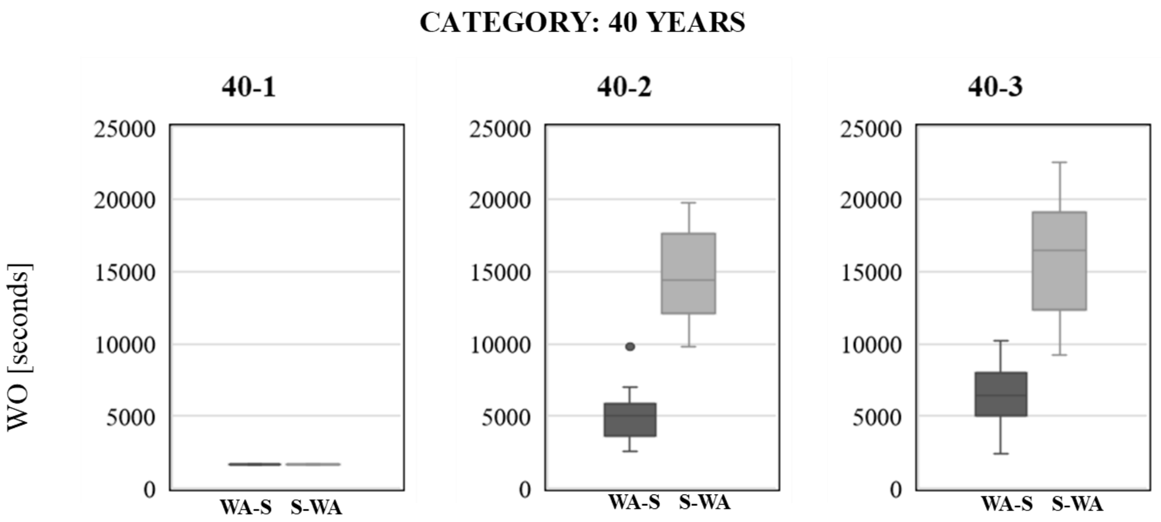

Figure 6. WO distribution for Category 40, comparison among groups of workers and different scenarios

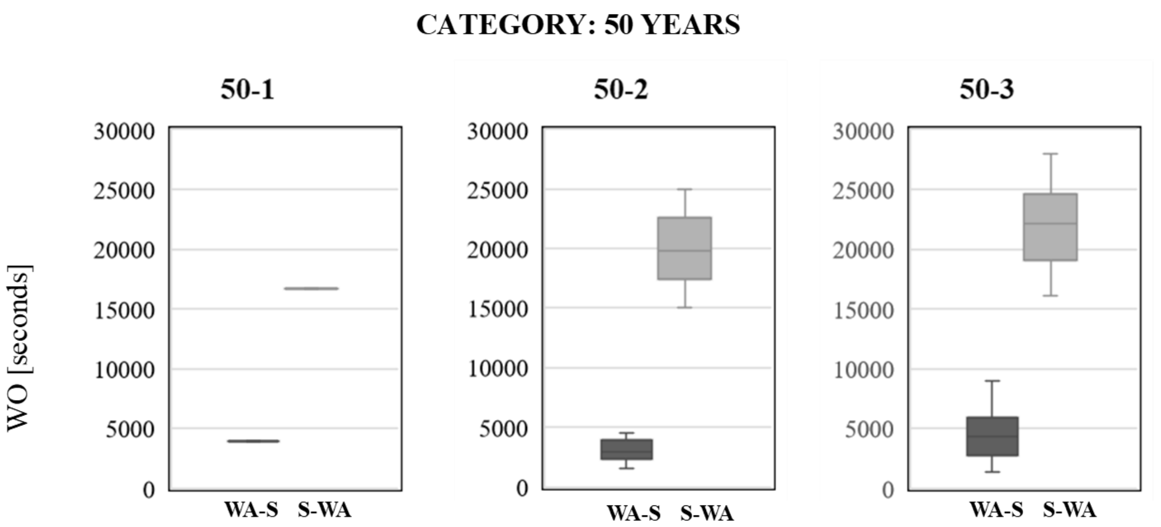

Figure 7. WO distribution for Category 50, comparison among groups of workers and different scenarios

Finally, by comparing groups with the same age variation, we can say that the higher the age, the lower the WO if Scenario WA-S is applied. On the contrary, the higher the age, the higher the WO if Scenario S-WA is applied and RA consideration is made as post-processing phase.

6. Concluding remarks

In this paper, we have considered the impact that workers' features can have on MMALs. Despite the existing work that investigates the fatigue effects on the same way as here (Sgarbossa et al., 2018), we have evaluated both tactical and operational decisions, referring to the long-, medium- and short-term planning horizons and we have proposed an integrated approach to include workers' physical fatigue. Moreover, we have included workers' physical features into production decisions. Since fatigue is strongly affected by the age of each worker, we have focused our analysis on the effects that age could have on system performances. For the tactical decision, which is the balancing problem, the workers' fatigue has been evaluated through the RA (Price, 1990). For the operational decisions, which is sequencing, RA has been set according to Finco et al. (2019b) and, consequently, workers' features have been included in the workforce assignment and sequencing procedure. The analysis highlights that the proposed method turns out to be preferable compared to traditional approaches, with an overall reduction in both the cycle time and the work overload.

The results obtained in the case study show that age impacts assembly line performances, for both cycle time and WO. In fact, for workers with age lower than 40 years, the MAEE is higher than 4.3 kcal/min and, consequently, physical fatigue arises only for higher intensity physical tasks. Moreover, the cycle time obtained during balancing can be overestimated and, for this reason, the cycle time adjustment during short-term decision processes could avoid assembly line inefficiencies. On the other side, when the average age of the workers exceeds 40 years, cycle time increases, since more rest is required. However, in this case, RA could be used to complete the product and, consequently, the WO decreases by avoiding utility workers and the corresponding increase in labor costs. Therefore, applying the presented method turns out to be particularly useful in the case of an heterogenous workforce.

From an industrial point of view, managers should consider the age of workers during medium and short-term decisions. In this way, both employees' and employers' benefits can be jointly achieved. First, workers are less fatigued if adequate recovery time is given. Then, employers can reduce costs related to utility workers and the product quality can increase, as defined in Kolus et al. (2018).

One limit of the methodology presented here is the assumption that all workers are equally skilled. Moreover, the experience could be related to workers' age, with a further reverse impact on task times. Consequently, for future research, integrating workers' experience into the model could be investigated, as well as other physical factors not considered here.

By a computational point of view the problems here presented can be optimally solved only for small and medium size instances in a reasonable amount of time. For large size instances the problems become difficult to solve optimally, thus, heuristics or meta-heuristics approaches could be implemented aiming to reduce the computational time. Finally, a sensitivity analysis might be carried out aiming to investigate the effects that tasks time and energy, precedence constraints, the number of assembled models and the demand of each model can have on the results according to the workers' features.

Appendix 1

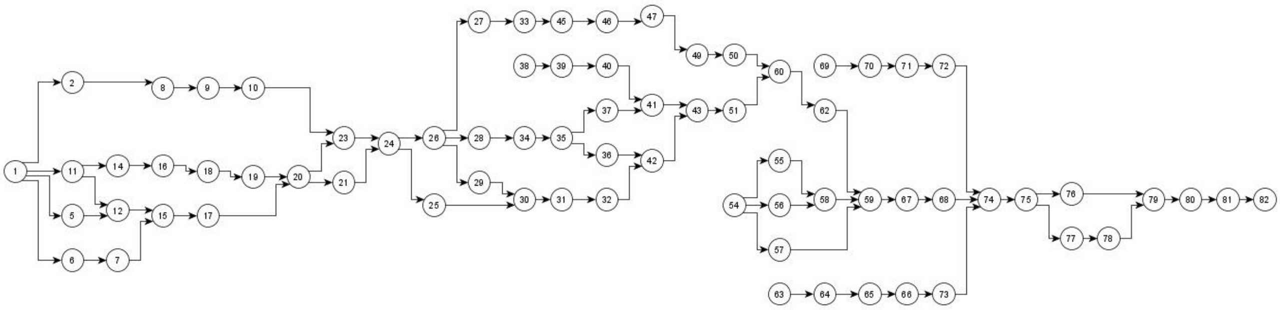

Figure A-1. Precedence graph for Model 1.

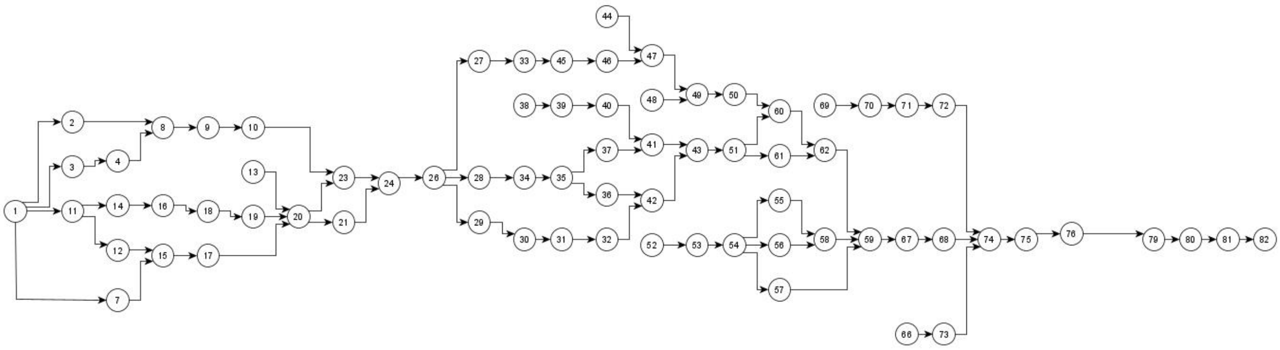

Figure A-2. Precedence graph for Model 2.

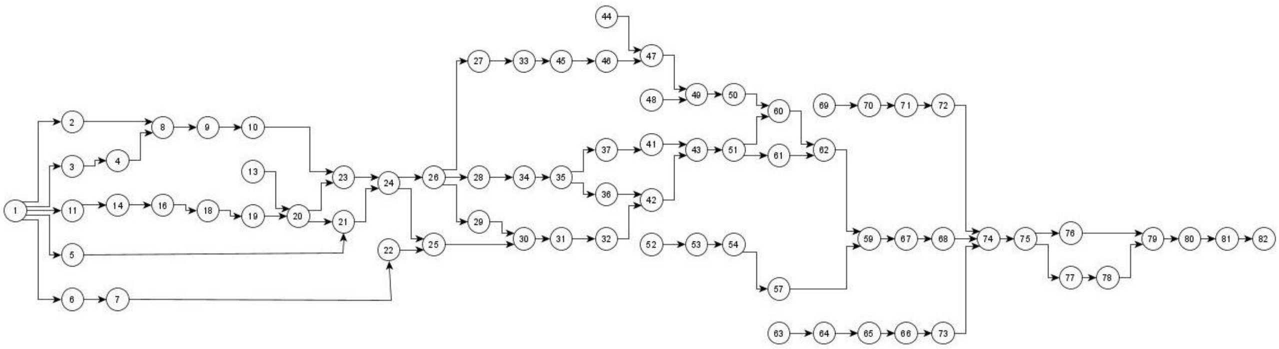

Figure A-3. Precedence graph for Model 3.

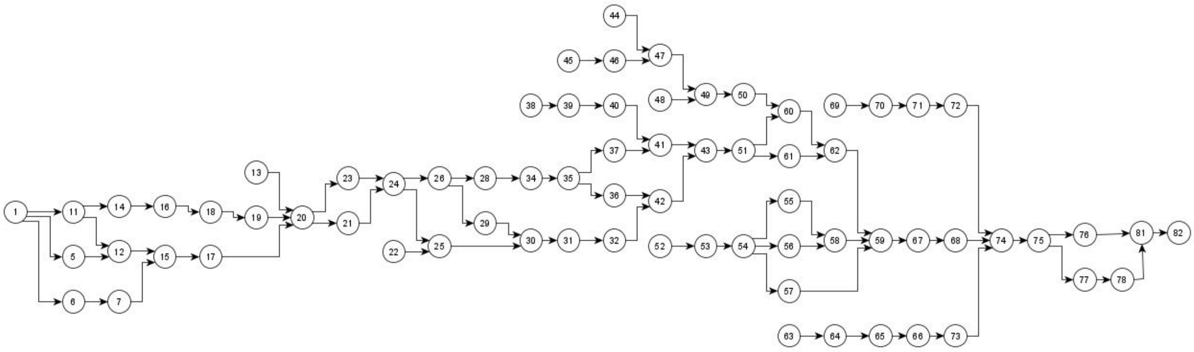

Figure A-4. Precedence graph for Model 4.

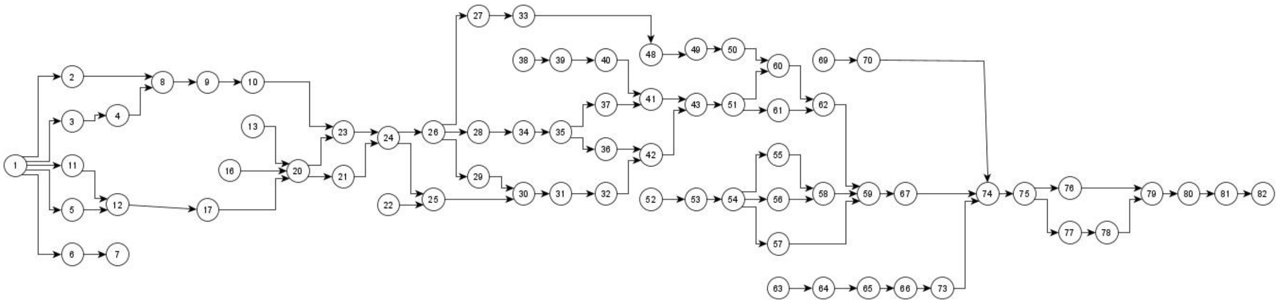

Figure A-5. Precedence graph for Model 5.

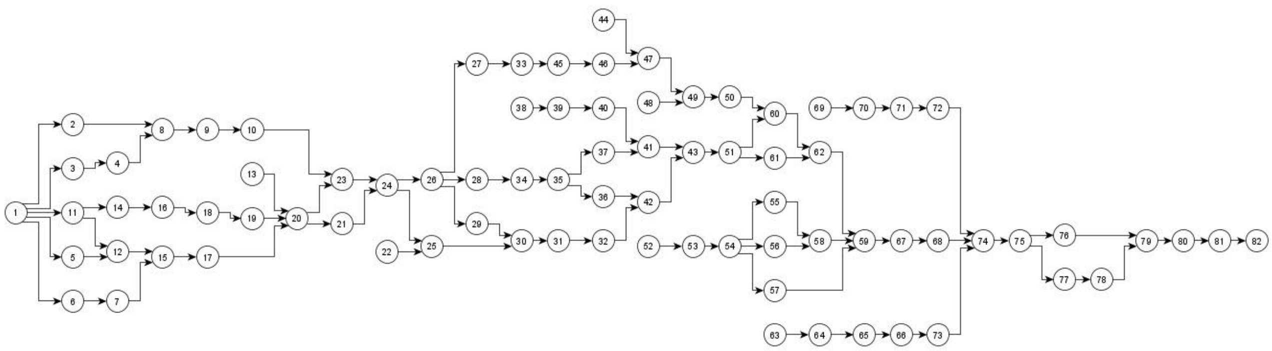

Figure A-6. Precedence graph for VAM

TA	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5

	TIME [s]	ENERGY [kcal]	TIME [s]	ENERGY [kcal]	TIME [s]	ENERGY [kcal]	TIME [s]	ENERGY [kcal]	TIME [s]	ENERGY [kcal]
1	139.00	7.46	149.00	10.63	138.00	11.64	152.00	11.40	157.00	13.06
2	12.00	1.06	13.00	1.19	12.00	0.69	0.00	0.00	13.00	0.84
3	0.00	0.00	219.00	13.25	202.00	20.10	0.00	0.00	229.00	11.83
4	0.00	0.00	188.00	16.79	173.00	10.12	0.00	0.00	197.00	10.77
5	151.00	12.89	0.00	0.00	149.00	13.81	165.00	8.58	170.00	10.43
6	574.00	47.45	0.00	0.00	568.00	51.31	629.00	36.48	647.00	52.62
7	186.00	11.63	0.00	0.00	184.00	16.77	203.00	17.59	209.00	15.40
8	123.00	8.98	132.00	8.10	122.00	8.11	0.00	0.00	139.00	9.17
9	174.00	9.02	187.00	14.80	173.00	9.11	0.00	0.00	196.00	10.94
10	314.00	16.17	337.00	20.39	311.00	20.06	0.00	0.00	354.00	32.21
11	206.00	15.35	221.00	15.91	204.00	20.40	225.00	20.36	232.00	15.78
12	43.00	3.18	46.00	3.35	0.00	0.00	47.00	3.96	49.00	3.41
13	0.00	0.00	472.00	25.02	435.00	41.83	481.00	36.64	495.00	28.96
14	167.00	8.85	179.00	15.66	165.00	14.08	182.00	11.07	0.00	0.00
15	412.00	24.99	442.00	24.75	0.00	0.00	451.00	37.81	0.00	0.00
16	248.00	13.35	267.00	21.94	246.00	24.40	272.00	20.90	280.00	14.51
17	299.00	15.00	321.00	26.00	0.00	0.00	327.00	18.58	336.00	26.10
18	143.00	11.68	153.00	10.79	141.00	11.96	156.00	9.49	0.00	0.00
19	194.00	10.44	209.00	14.11	192.00	13.66	213.00	19.35	0.00	0.00
20	1025.00	58.25	1100.00	80.85	1014.00	50.70	1122.00	88.08	1154.00	100.78
21	469.00	39.55	503.00	32.28	464.00	45.24	513.00	41.55	528.00	29.83
22	0.00	0.00	0.00	0.00	78.00	4.76	86.00	6.97	88.00	6.60
23	142.00	11.48	152.00	11.10	141.00	10.72	155.00	10.72	160.00	14.67
24	110.00	6.40	118.00	7.83	109.00	8.36	120.00	6.52	124.00	7.40
25	92.00	4.81	0.00	0.00	91.00	6.93	100.00	8.52	103.00	6.92
26	181.00	15.48	194.00	11.74	179.00	15.39	198.00	14.42	204.00	18.50
27	380.00	22.04	407.00	21.03	376.00	32.02	0.00	0.00	427.00	33.09
28	154.00	12.11	166.00	14.30	153.00	12.37	169.00	14.31	174.00	9.69
29	1293.00	95.04	1389.00	119.69	1280.00	88.11	1416.00	121.07	1457.00	125.30
30	152.00	8.31	163.00	9.10	150.00	8.85	166.00	11.12	171.00	14.22
31	516.00	39.82	554.00	39.61	511.00	37.47	565.00	30.89	582.00	53.16
32	177.00	13.04	190.00	13.62	175.00	9.71	194.00	12.58	200.00	14.70
33	45.00	3.50	48.00	2.98	45.00	3.07	0.00	0.00	51.00	4.45
34	203.00	14.24	218.00	15.99	201.00	17.09	222.00	18.61	228.00	12.96
35	96.00	8.35	104.00	9.52	95.00	5.24	106.00	7.17	109.00	8.88
36	66.00	5.05	71.00	5.96	65.00	4.98	72.00	4.68	74.00	5.30
37	194.00	15.71	209.00	10.83	192.00	16.22	213.00	15.66	219.00	11.32
38	448.00	23.74	481.00	43.05	0.00	0.00	490.00	44.59	504.00	31.92
39	549.00	45.57	589.00	33.38	0.00	0.00	601.00	46.68	618.00	50.78
40	220.00	16.17	236.00	15.73	0.00	0.00	241.00	16.51	248.00	18.23
41	129.00	10.62	138.00	8.49	127.00	11.51	141.00	12.57	145.00	11.70
42	182.00	13.56	195.00	10.92	180.00	15.60	199.00	17.61	205.00	16.02
43	157.00	12.98	169.00	9.94	156.00	13.65	172.00	15.16	177.00	16.20
44	0.00	0.00	395.00	25.68	364.00	33.37	403.00	20.28	0.00	0.00
45	394.00	22.46	423.00	32.50	390.00	33.80	431.00	36.99	0.00	0.00
46	112.00	10.14	120.00	8.32	110.00	7.70	122.00	10.45	0.00	0.00
47	61.00	4.72	66.00	3.96	61.00	4.60	67.00	5.33	0.00	0.00
48	0.00	0.00	44.00	2.65	41.00	3.02	45.00	2.85	47.00	3.91
49	198.00	10.10	213.00	12.21	196.00	17.84	217.00	13.09	223.00	13.01
50	50.00	3.97	54.00	3.60	49.00	4.67	55.00	3.22	56.00	5.11
51	120.00	10.30	129.00	8.75	119.00	7.40	132.00	10.14	135.00	7.49
52	0.00	0.00	178.00	11.24	164.00	14.49	181.00	12.82	187.00	13.18
53	0.00	0.00	377.00	28.90	347.00	21.63	384.00	29.25	395.00	28.37
54	93.00	5.80	99.00	6.86	92.00	4.80	101.00	5.86	104.00	7.05

55	230.00	11.54	247.00	13.59	0.00	0.00	252.00	23.06	259.00	18.82
56	122.00	6.79	131.00	10.65	0.00	0.00	134.00	9.67	137.00	12.44
57	158.00	9.93	170.00	13.88	157.00	9.52	173.00	13.64	178.00	11.36
58	133.00	9.42	143.00	13.11	0.00	0.00	146.00	10.80	150.00	8.68
59	96.00	7.82	104.00	8.30	95.00	6.90	106.00	6.52	109.00	6.63
60	250.00	14.00	269.00	19.64	248.00	18.81	274.00	20.82	282.00	14.38
61	0.00	0.00	91.00	5.51	84.00	5.73	93.00	7.52	96.00	7.79
62	393.00	30.72	422.00	26.02	389.00	24.25	430.00	36.98	442.00	33.08
63	173.00	11.65	0.00	0.00	172.00	15.80	190.00	11.50	195.00	12.68
64	45.00	2.70	0.00	0.00	45.00	3.83	49.00	3.59	51.00	4.14
65	196.00	12.38	0.00	0.00	194.00	15.16	215.00	18.99	221.00	18.05
66	227.00	20.73	243.00	13.93	224.00	12.88	248.00	15.21	255.00	14.49
67	174.00	15.40	187.00	12.37	173.00	15.11	191.00	11.11	196.00	9.80
68	227.00	17.25	243.00	22.07	224.00	15.46	248.00	19.84	0.00	0.00
69	430.00	23.65	462.00	33.73	425.00	33.79	471.00	27.24	484.00	29.20
70	75.00	6.30	80.00	4.44	74.00	4.56	82.00	5.41	84.00	4.80
71	72.00	4.13	77.00	6.80	71.00	6.20	78.00	6.57	0.00	0.00
72	95.00	8.28	101.00	8.21	94.00	7.97	103.00	8.10	0.00	0.00
73	129.00	9.55	138.00	11.96	127.00	9.21	141.00	11.23	145.00	9.11
74	32.00	2.31	34.00	2.70	32.00	2.30	35.00	3.19	36.00	2.94
75	126.00	6.91	135.00	9.16	125.00	8.13	138.00	8.00	142.00	10.58
76	292.00	25.06	314.00	17.37	289.00	21.68	320.00	23.41	329.00	21.55
77	90.00	7.17	0.00	0.00	89.00	4.70	98.00	7.79	101.00	9.09
78	291.00	24.10	0.00	0.00	288.00	27.65	319.00	28.60	328.00	23.23
79	140.00	11.92	150.00	9.80	139.00	8.29	0.00	0.00	158.00	8.14
80	228.00	18.01	245.00	16.86	226.00	14.88	0.00	0.00	257.00	21.42
81	118.00	7.00	123.00	6.46	113.00	6.76	125.00	7.06	129.00	10.81
82	43.00	2.29	54.00	3.56	49.00	4.36	55.00	3.43	56.00	3.21

Table A-1. Time and energy values related to each task of each model.

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