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Assembly Line Balancing with Collaborative Robots under consideration of Ergonomics: a cost-oriented approach

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Abstract: The role of automation in modern manufacture experienced increasing relevance throughout past decades. However, manufacturers cannot efficiently automate many tasks to date and consequently utilize human workers, which are subject to limited physical capacity. In recent years, collaborative robots can support manual task execution at low costs. This novel technology may thus represent a cost-efficient opportunity of (partial) automation of assembly tasks. We consider an assembly line balancing problem to determine cost-efficient system configurations, in which collaborative robots and human workers may be assigned to the stations of the line. We develop a mathematical model and illustrate its functionality using a real-world oriented case study. Subsequently, we identify the determining factors of the use of collaborative robots. The results demonstrate that collaborative robots are an economic option for automation in manual manufacture.

Keywords: assembly line balancing, cost orientation, ergonomics, collaborative robots, industry 4.0.

1. INTRODUCTION AND BACKGROUND

Over the past decades, the role of automation in industrial production has increased significantly. In the current state, however, manufacturers cannot efficiently automate many tasks. Therefore, a large part of the value added is generated by manual work utilizing human workers characterized by flexibility and adaptability (Antonelli *et al.*, 2016; Krüger *et al.*, 2009). In recent years, novel trends arise to support manual manufacture. In this field, human-robot collaboration is an emerging technology. Since collaborative robots (cobots) are characterized by inherent security mechanisms, the installation of external devices (for instance, safety fences) is not necessary. By establishing stations comprising human worker and cobot, advantages of both manual and automated manufacture can be realized in a combined production system at low costs. As reported by Statistisches Bundesamt (2018), cobots face significantly increasing market demand.

Due to its efficiency, industrial manufacture is yet predominantly organized in Assembly Lines utilizing the flow principle. Assembly Line Balancing (ALB) is concerned with the allocation of tasks to stations, for instance in the initial design of the production system. Recognized summaries on the state of research in this field have been provided by Boysen *et al.* (2007), Boysen *et al.* (2008), and Battaïa and Dolgui (2013).

When humans are engaged in the assembly process, the consideration of ergonomics is required in the design of modern workplaces to optimize both human well-being and overall system performance (IEA, 2018). The neglect of physical ergonomics (as one domain of ergonomics, henceforth synonymously) in the design phase of an assembly system may consequently cause unforeseen costs in its operation (BMWi, 2017). Though most articles in ALB literature contribute to the design of manual assembly lines, approaches considering ergonomics are scarce. The first to explicitly incorporate ergonomic risk estimation methods into ALB models were Otto and Scholl (2011), who proposed the application of several risk estimation methods. A survey of subsequently published literature in this field is given by Otto and Battaïa (2017). Recent literature extends the problem towards more detailed description of ergonomic risk (Xu *et al.*, 2012; Bortolini *et al.*, 2017), integration of related planning tasks (Battini *et al.*, 2017, 2016a), or design of composite capacity-oriented (e.g. minimizing cycle time or number of stations) and ergonomic objectives (Battini *et al.*, 2016b; Bautista *et al.*, 2016).

The capacity-oriented objectives pursued in previous literature, however, are mere substitutes for the monetary value associated with them and become less applicable, the more generalized the problem becomes (Boysen and Fliedner, 2008). We therefore propose an approach for cost-oriented assembly line balancing with human workers and cobots under consideration of ergonomics.

To the best of authors' knowledge, only two articles in academic literature contribute to cost-oriented ALB under consideration of ergonomics. Kara *et al.* (2014) consider the assignment of workers to stations, where workers maintain an individual maximum of acceptable energy expenditure. Besides resource and station costs, they consider additional cost types. Tiacci and Mimmi (2018) suggest an ALB approach for multiple variants. They utilize the Occupational Repetitive Actions (OCRA) index for ergonomic risk assessment and pursue minimizing overall costs considering multiple cost types. Both approaches have in common, however, that only one resource can be assigned to each station. Consequently, they neglect parallel execution by

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multiple resources and the resulting necessity of scheduling tasks within stations. Furthermore, resources are assumed to have the identic performance, i.e., resource-dependent processing times are not considered. The approaches therefore neglect the time-cost tradeoff between different resources we exhibit in our study.

The remainder of this contribution is structured as follows: in Section 2, we give a detailed description of the decision-making situation we consider. Our mathematical model is presented in Section 3. Results of an illustrative example and a multivariate analysis are provided in Section 4. Finally, we conclude our study in Section 5.

2. PROBLEM SETTING

We face the problem of designing an assembly line for a particular product allocated from Network Planning. A maximum cycle time ct is assigned in order to meet sales targets. The expected revenue per product unit is determined by sales planning. Since production volume and product revenue are externally given, we assume the revenues of our mutually exclusive investment alternatives (i.e. assembly line configurations) to be identical. Therefore, we utilize the Cost Comparison Method (CCM) for static investment appraisal of one average period. In the contribution at hand, we suggest one cycle time as a representative time span. We pursue minimizing costs per cycle and consider salaries, depreciation, and interest costs, which we aggregate to costs of stations C_k^S and costs of utilized resources C_r^R (in EUR) (Götze *et al.*, 2015).

A set of n tasks $i, j \in I$ have to be allocated among the stations of the system with respect to their precedence relations $(i, j) \in E$. A set $r \in R$ containing $\overline{R}$ resource types are available. Resources are assumed to be either a human worker ($r \in R^W \subseteq R$) or a cobot ($r \in R^C \subseteq R$). Processing times t_{ir} (in min) are deterministic and constant for each task i and resource r. Whether resource r is able to perform task i is indicated in the capability matrix CM_{ir} ($n \cdot \overline{R}$ binaries). Binary variables x_{ikr} and y_{kr} indicate whether task i is assigned to station k and resource r, and resource r is assigned to station k, respectively. The maximum dimension of the line is constrained to $\overline{K}$ stations due to spatial restrictions.

Since human workers can be assigned to the stations of the system, ergonomic risks have to be considered. We therefore adapt the basic concept proposed by Price (1990). He determines the mean work rate (MWR) of workers based on energy expenditure (a physical, non-financial measurand) of the conducted tasks. Under consideration of an acceptable work level (AWL) to be maintained throughout a work day and a relaxation rate (RR), he determines relaxation allowances (RA) required for the worker to recover from load exceeding AWL, thus adding a time increment to the respective task. Since it simplifies ergonomics assessment and reduces computational complexity of the resulting problems, his approach is particularly attractive for consideration in ALB and has recently received increasing attention (Battini *et al.*, 2015; Battini *et al.*, 2016a, 2017; Battini *et al.*, 2016b; Finco *et al.*, 2018; Sgarbossa *et al.*, 2016). Additionally, energy expenditure can be predicted particularly well (Garg *et al.*, 1978). Following Price (1990) and Battini *et al.* (2017), workers may maintain $AWL = 4.3\,kcal/min$ throughout their work day, while $RR = 1.86\,kcal/min$ are required while relaxing in standing position. Since $MWR = \frac{e_{ir}}{t_{ir}}$, where e_{ir} (in kcal) is the energy expenditure of human worker r conducting task i, RA calculates to

$$RA = \frac{MWR-AWL}{AWL-RR} = 0.41\frac{1}{kcal/min} \cdot \frac{e_{ir}}{t_{ir}} - 1.76. \tag{1}$$

To allow for relaxation of workers, the corrected processing times η_{ir} are calculated according

$$\eta_{ir} = t_{ir}(1+RA) = \begin{cases} 0.41\frac{1}{kcal/min} \cdot e_{ir} - 0.76 \cdot t_{ir}, & \frac{e_{ir}}{t_{ir}} > 4.3\,kcal/min \\ t_{ir}, & else. \end{cases} \tag{2}$$

Since energy expenditure is utilized as a measure of human ergonomic load, (1) and (2) are limited to $\forall i \in I, r \in R^W$ and thus do not apply for cobots. Please note that $\eta_{ir} > t_{ir}$ for any task with $MWR > AWL$. Henceforth, we utilize the corrected processing times η_{ir} to limit the ergonomic load of workers, which (independent of actual processing times t_{ir}) must not exceed ct.

Additional complexity is induced by the presence of cobots. Since multiple resources can be assigned to each station, parallel execution of tasks within stations is allowed. Therefore, the necessity of task scheduling within stations arises. We introduce variables s_i to denote the start time of task i in the station it is assigned to. Regarding precedence relations of tasks $(i, j) \in E$, we not only have to ensure their compliance between stations (as is common in ALB) but also within stations, i.e. j can start earliest, after i is finished in their common station. This is not only true for tasks subject to precedence relations, but also for any tasks $i, j \in I$ which are assigned to both same station and resource. For these tasks, one task consequently has to precede the other on their common resource.

3. MODEL FORMULATION

Based on the description of the problem setting and the notation as summarized in Table 1, we set up the following model.

Minimize

$$Z(x,y) = ct \cdot \sum_{k\in K}\sum_{r\in R} C_k^S \cdot x_{nkr} \cdot k + ct \cdot \sum_{k\in K}\sum_{r\in R} C_r^R \cdot y_{kr} \tag{3}$$

$$\sum_{k\in K}\sum_{r\in R} x_{ikr} = 1 \qquad \forall i \in I \tag{4}$$

$$s_i + \sum_{k\in K}\sum_{r\in R} t_{ir} \cdot x_{ikr} \le ct \qquad \forall i \in I \tag{5}$$

$$\sum_{i\in I} x_{ikr} \cdot \eta_{ir} \le ct \qquad \forall k \in K, r \in R^W \tag{6}$$

$$\sum_{r\in R} x_{jkr} \le \sum_{h=1}^{k}\sum_{r\in R} x_{ihr} \qquad \forall (i,j) \in E, k \in K \tag{7}$$

$$s_i + \sum_{r\in R} t_{ir} \cdot x_{ikr} \le s_j + M(1 - z_{kij}) \; \forall i,j \in I, k \in K \tag{8}$$

$$z_{kij} \ge 1 - M(1 - \sum_{r\in R} x_{ikr}) - M(1 - \sum_{r\in R} x_{jkr}) \qquad \forall (i,j) \in E, k \in K \tag{9}$$

$$z_{kij} + z_{kji} \ge 1 - M(1 - x_{ikr}) - M(1 - x_{jkr}) \qquad \forall i,j \in I, i \ne j, k \in K, r \in R \tag{10}$$

$$z_{kij} \leq \frac{1}{2} \cdot \left(\sum_{r \in R} x_{ikr} + \sum_{r \in R} x_{jkr}\right) \quad \forall i,j \in I, k \in K \quad (11)$$

$$x_{ikr} \leq y_{kr} \cdot CM_{ir} \quad \forall i \in I, k \in K, r \in R \quad (12)$$

$$x_{ikr} \in \{0,1\} \quad \forall i \in I, k \in K, r \in R \quad (13)$$

$$y_{kr} \in \{0,1\} \quad \forall k \in K, r \in R \quad (14)$$

$$z_{kij} \in \{0,1\} \quad \forall i,j \in I, k \in K \quad (15)$$

$$s_i \geq 0 \quad \forall\, i \in I \quad (16)$$

Table 1. Introduced sets, parameters, and variables.

Sets and parameters	
$i,j \in I \equiv \{1,\dots,n\}$	Set of assembly tasks.
$k,h \in K \equiv \{1,\dots,\bar{K}\}$	Set of stations.
$r \in R \equiv \{1,\dots,\bar{R}\}$	Set of resource types, where $R = R^W \cup R^C$, with R^W set of worker resource types, and R^C set of cobot resource types.
E	Set of direct precedence relations (i,j).
ct	Cycle time (in min).
C_k^S	Costs per station and minute (in EUR), if k stations are utilized.
C_r^R	Costs of resource r per entity and minute (in EUR).
CM_{ir}	Capability matrix (1, if r is capable of performing i).
t_{ir}	Processing time of task i on resource r (in min).
e_{ir}	Energy expenditure of task i on resource r (in kcal).
η_{ir}	Corrected processing time of task i on resource r (in min).
M	Big M parameter, e.g. $M = ct$.
Decision and auxiliary variables	
x_{ikr}	1, if task i is assigned to station k and resource r.
y_{kr}	1, if resource r is assigned to station k.
z_{kij}	1, if task i precedes task j in station k.
s_i	Start time of task i in its respective station.

Objective (3) is to minimize costs per cycle, taking into consideration costs of stations and resources per minute, and the cycle time. Constraints (4) ensure that each task is assigned to one station and resource. Compliance with cycle time is ensured in constraints (5). Constraints (6) limit the ergonomic load of workers in each station. Precedence relations between stations are enforced by constraints (7). Constraints (8) are the general scheduling constraints indicating that task i has to precede task j in their common station. This holds true, if $z_{kij} = 1$. These cases are further specified by constraints (9)–(11): i has to precede j, if i is a direct predecessor of j and both are assigned to the same station. If two tasks i and j are assigned to the same station and resource, one has to precede the other independent of precedence relations. If these tasks are allocated to different stations, however, neither has to precede the other. By bounding auxiliary variables z_{kij} in constraints (9)–(11), we are able to limit the activation of computationally complex scheduling constraints (8) to the relevant cases. Constraints (12) ensure that task i is only assigned to resource r in station k, if resource r is allocated to station k and it is capable of performing task i. Finally, constraints (13)–(16) enforce the domains of the decision variables. The resulting model can be classified as mixed-integer linear program.

4. NUMERICAL EXAMPLES

To illustrate the effectiveness of our approach and derive quantitative evidence on the described problem, we present computational experiments in the following section. Therefore, we implemented the model in Java 8 and solved it using the Java CPLEX API (version 12.7.1). The computations were run on a standard computer with Intel Core i7-8550U CPU @ 1.80 GHz and 16 GB RAM. All instances discussed in the following could be solved to proven optimality in average computational time of 5.4 seconds with a maximum of 15.0 seconds.

4.1 Instance generation

For our experiments, the real-life case study provided by Battini *et al.* (2016b) serves as a basis scenario we extend to suit our problem. In their study, the authors describe the assembly process of a high-pressure cleaner for home and garden applications which yet is conducted utilizing manual stations. We adopt the product-related data and the maximum cycle time of three minutes as provided in their article (Fig. 1). Also, we limit the maximum dimension of the line to four stations.

Using constraints (2) and the information provided in the case study, we calculate the corrected processing times. For the given example problem, only Task 9 requires additional relaxation time when conducted by human workers (H):

$$\begin{aligned}\eta_{9H} &= \max\left(t_{9H}, 0.41 \frac{1}{kcal/min} \cdot e_{9H} - 0.76 \cdot t_{9H}\right) \\ &= \max\left(0.183\, min, 0.41 \frac{1}{kcal/min} \cdot 0.96\, kcal - 0.76 \cdot 0.183\, min\right) \\ &= \max(0.183\, min, 0.255\, min) = 0.255\, min\end{aligned} \quad (17)$$

In order to simplify the reproducibility of our investigations, we restrict the number of resource types to two (human worker and cobot) and consequently do not differentiate their individual entities. Additionally, we assume both resource types to be capable of performing each task. Also, we assume costs of stations to scale proportionately to their number. However, our generic model can accommodate more resource types, their potentially limited capabilities, and economies of scale in material flow and station installation without additional customization.

Since the study of Battini *et al.* (2016b) does not provide all the required parameters, we have to justify additional assumptions regarding costs of workers and stations, and costs and processing speed of cobots. To determine depreciation of stations and cobots, we have to take assumptions on operation in the model company. In this study, we assume a total of 552,000 minutes to be considered in machine hour rate depreciation, which corresponds to a five-year depreciation period with 230 work days per year and one daily eight-hour shift.

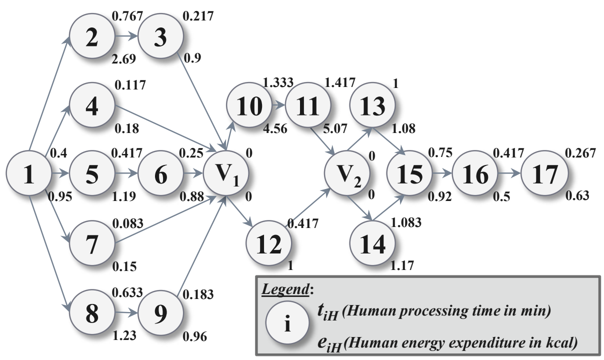

Fig. 1. Precedence graph of the example problem.

Eurostat (2018) estimates hourly labor costs in Germany at 35 EUR. Therefore, we assume worker costs of 0.6 EUR/min. Data to estimate the investment in stations are generally difficult to obtain and highly depend on the actual assembly processes. We suppose costs of 35,000 EUR per station, which comprise for equipment and installation of the station itself, the related material flow technology, and interest costs. The resulting depreciation consequently amounts to 0.06 EUR/min per station.

Cobots usually have a basic price between 25,000 EUR and 35,000 EUR (Robotiq, 2016). Taking into account additional accessories, installation, and interests, we assume overall costs of 45,000 EUR per cobot entity, which results in depreciation of 0.08 EUR/min. Consequently, cobots are rather low-priced, but they also lack of efficiency in the human environment. The Bosch APAS cobots, as an example, reduce working speed to 0.5 m/s in presence of persons (Bosch, 2018). We therefore conservatively assume that the robot requires three times the human processing time and thus introduce a time-cost tradeoff between cobots' low costs and high processing times and workers' high costs and low processing times.

4.2 *Illustrative example*

Based on the assumptions outlined in Section 4.1, we present a numerical example with consideration of cobots and without (both calculated utilizing our model). The resulting system configurations are illustrated in Fig. 2 for both cases.

In the manual case, one worker is allocated to each of the four stations. Since only one resource is available in each station, tasks are executed serially with respect to their precedence relations. Task 9 requiring relaxation time of 0.072 min is assigned to Station 2 (relaxation time emphasized in orange), increasing human ergonomic load in this station (and thus its finish time) to 2.77 min. The resulting costs per cycle are calculated using objective function (3) and amount to

$$Z_{manual} = 3\,min \cdot 0.06 \frac{EUR}{min{\cdot}station} \cdot 4\,stations + 3\,min \cdot 0.6 \frac{EUR}{min{\cdot}worker} \cdot 4\,workers = 7.92\,EUR. \tag{18}$$

If cobots are available, three workers and two cobots are allocated among four stations. Tasks conducted by cobot require three times the human processing time (for instance, observe length of Task 1 in both configurations). In Station 2, both worker and cobot are assigned and consequently execute tasks in parallel. Please note that precedence relations within stations are respected. This can be observed particularly well for Tasks 3 and 10. Since Task 3 has to be finished by the cobot prior Task 10 starts, the human experiences idle time between Tasks 3 and 10 resulting in a delayed start of Task 10. In case cobots are available, costs per cycle result to

$$Z_{collaborative} = 3\,min \cdot 0.06 \frac{EUR}{min{\cdot}station} \cdot 4\,stations + 3\,min \cdot 0.6 \frac{EUR}{min{\cdot}worker} \cdot 3\,workers + 3\,min \cdot 0.08 \frac{EUR}{min{\cdot}cobot} \cdot 2\,cobots = 6.6\,EUR, \tag{19}$$

indicating a 16.7% cost reduction compared to the manual case. In this example, deployment of cobots consequently represents an economic option for (partial) automation.

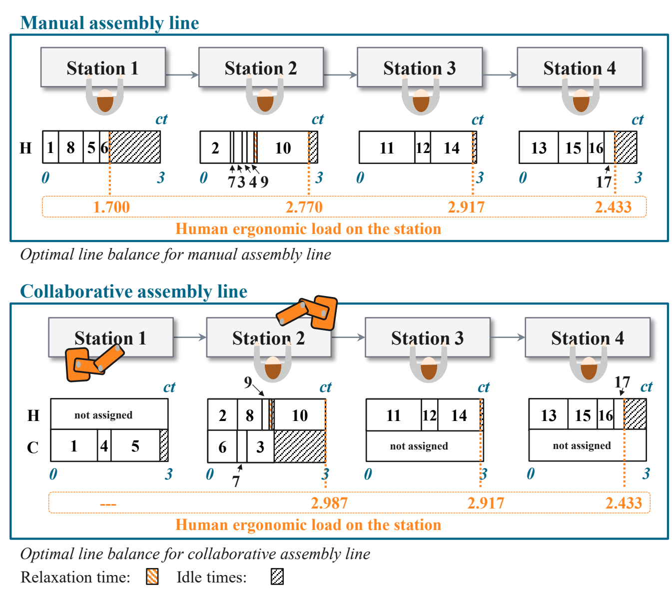

Fig. 2. Configuration of example systems.

The presence of cobots could also lead to a reduction of ergonomic load of human workers. Please note that this relation does not apply for the example illustrated. While workers experience an average ergonomic load of 2.46 min in the manual scenario, the (remaining) workers in the automated scenario witness an average ergonomic load of 2.78 min.

4.3 *Determining factors of cobot deployment*

Since the illustrative example suggests high potential, we further investigate the determining factors of cobot deployment in manual lines. We therefore conduct a multivariate analysis in a full factorial design. The parameter variations considered are given in Table 2. Characteristics of the basis scenario described in the preceding sections are indicated by asterisks. Parameters not listed here remain as introduced.

Table 2. Parameters of multivariate analysis.

Parameter	Characteristics		
Station costs in EUR/min	0.06*	0.12	0.18
Workers costs in EUR/min	0.06	0.18	0.6*
Energy expenditure (factor)	1.00*	1.25	1.50
Speed of cobot (factor)	1.00	2.00	3.00*

In our analysis, we consider variation of four parameters. An increase in station costs serves to investigate scenarios with more sophisticated station and material flow equipment. The reduction of worker costs to 0.18 EUR/min relates to labor costs experienced in Eastern European countries, for instance, Czech Republic, Estonia, and Poland (Eurostat, 2018). Worker costs of 0.06 EUR/min are below labor costs of any European country. Since cobots are assumed to induce costs of 0.08 EUR/min, however, this scenario serves to investigate environments with comparatively expensive cobots compared to human labor. An increase in energy expenditure serves to research ergonomically more demanding environments (value serves as an increase factor applied on the original scenario). Finally, we investigate scenarios with faster cobots. The increase factors of the latter two parameters are applied on the energy expenditure characteristics and human processing times of the original case provided by Battini *et al.* (2016b). Additionally, we subsequently allow the line to comprise a maximum of six stations to provide for higher freedom of system design.

Table 3. Incidence on cost-efficient configurations subdivided by the resulting number of stations.

Number of stations	Occurrence (of 81)	$\emptyset(\sigma)$ Costs per cycle	$\emptyset(\sigma)$ Resources per station	$\emptyset(\sigma)$ Workers per station	$\emptyset(\sigma)$ Cobots per station
3	15	2.20 (0.53)	1.33 (0.00)	0.53 (0.28)	0.80 (0.28)
4	38	2.99 (1.54)	1.07 (0.11)	0.59 (0.42)	0.48 (0.41)
5	12	3.34 (1.05)	1.03 (0.08)	0.80 (0.26)	0.23 (0.32)
6	16	5.98 (1.82)	1.06 (0.08)	0.26 (0.14)	0.80 (0.07)

Information on the resulting system configurations are reported in Table 3, subdivided by the resulting number of stations. The most cost-efficient configurations are realized utilizing three stations. These solutions are characterized by high degree of parallelization (1.33 resources per station on average of all three-station systems), high degree of cobot use (0.80 cobots per station), and comparatively few workers (0.53 workers per station). These systems are realized for any level of station costs and energy expenditure, however, only if cobots are as fast as workers and workers induce low or medium costs. Please note that cobots are also utilized in three-station systems in cases, in which cobot costs are higher than worker costs. Making advantage of parallel work, assignment of a cobot to an (existing) manual station is beneficial compared to introducing an additional manual station.

Configurations with four stations are realized comprising a variety of characteristics, for instance, (i) human workers may exclusively be utilized throughout all levels of station costs, if worker costs are low and cobot speed and ergonomic requirements are low or medium, or (ii) cobots may exclusively be utilized throughout all levels of station costs and energy expenditures, if worker costs are medium or high and cobots are as fast as humans. Subject to high ergonomic requirements, five-station systems with similar characteristics result at higher costs.

Six-station systems are configured throughout all levels of station costs and energy expenditures, if cobot speed is medium or slow and worker costs are high. Though cobots are slow in these cases, it is beneficial to introduce an additional station with a cobot rather than using an expensive worker at an existing station in parallel.

Finally, we report results on system configurations subdivided by the level of induced ergonomic requirements in Table 4. If the ergonomic environment gets more challenging, i.e. higher energy expenditure is required for manual task execution, fewer workers and more cobots are used for assembly. Consequently, a trend towards higher degree of automation can be observed for ergonomically more demanding environments. Though cost-efficient configurations comprise increasing utilization of cobots, the overall costs per cycle increase with the ergonomic requirements. In order to achieve cost-efficient assembly system configurations, decisions should not only be taken about (partial) automation. Supplementary decisions lowering the energy expenditure experienced within manual task conduction may thus also contribute to cost-efficiency in manual production systems.

Table 4. Impact of ergonomic requirements on resulting system configurations.

Energy expend.	Occurrence (of 81)	$\emptyset(\sigma)$ Costs per cycle	$\emptyset(\sigma)$ Resources per station	$\emptyset(\sigma)$ Workers per station	$\emptyset(\sigma)$ Cobots per station
1.00	27	3.32 (1.77)	1.11 (0.14)	0.58 (0.39)	0.53 (0.39)
1.25	27	3.38 (1.84)	1.14 (0.15)	0.58 (0.36)	0.56 (0.36)
1.50	27	3.75 (2.12)	1.10 (0.14)	0.48 (0.36)	0.61 (0.41)

As illustrated in our analysis, cost-efficient assembly lines may yield a vast variety of characteristics ranging from fully automated to exclusively manual configurations (even for the very same product). Consequently, a thorough analysis of the considered production environment is necessary in order to generate economic assembly system designs. Utilizing our approach, we are able to support decision making processes and contribute to cost-efficiency in manual manufacture.

5. OUTLOOK

Our field requires further research. During the development of this contribution we initially additionally considered costs of the energy consumption of collaborative robots. Since this cost component did not have any explanatory effect, we decided to neglect it in the contribution at hand. However, in further research we strive to extend our planning approach towards recognized management accounting methodologies. In the current state, we model the processing times of collaborative robots as constant. The processing speed of collaborative robots, however, varies depending on the presence or absence of humans. Our assumption of fully capable cobots needs to be refined such that tasks may be incompatible with execution by cobot. Additionally, actual collaboration of human and robot may reduce the energy expenditure of the human worker. We therefore pursue more realistic modeling of the characteristics of collaborative robots.

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