universität wien

# MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master‘s Thesis

„Assembly line balancing during a pandemic crisis: A modelling and solution approach considering collaborative robots and physical distancing constraints. “

verfasst von / submitted by

Nina Monika Findeisen, B.Sc.

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2021 / Vienna 2021

| | |
|---|---|
| Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet: | UA 066 915 |
| Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet: | Masterstudium Betriebswirtschaft |
| Betreut von / Supervisor: | Univ.-Prof. Mag. Dr. Karl Franz Dörner |

# Assembly line balancing during a pandemic crisis: A modeling and solution approach considering collaborative robots and physical distancing constraints

Nina Monika Findeisen, B.Sc.

University of Vienna
Vienna, 2021

Degree Program: MSc Betriebswirtschaft
Supervisor: Univ.-Prof. Mag. Dr. Karl Franz Doerner
Chair: Business Decisions and Analytics

**Abstract**

This work investigates the assembly line balancing problem with collaborative robots against the background of the corona pandemic. An existing assembly line with manual workstations is reconfigured taking into account physical distancing constraints as well as short-time work and assembly line extension. Physical distancing constraints between workers are considered by finding the cost minimizing combination of short-time workers and additional stations that reduces the number of workers per station to one. A mixed-integer quadratic programming formulation for balancing and scheduling of assembly lines with collaborative robots and physical distancing constraints is developed. The model decides on the number of stations in the line, the number of workers in short-time work, the assignment of workers and robots to stations, and the distribution of workload to resources. The objective is to minimize the total costs of the production line including wages for regular workers, reduced wages for short-time workers, and costs for adding new stations to the line. Additionally, a computational study using a simplex optimizer is conducted. The results indicate that the model can provide useful support for decision makers during a pandemic crisis. Moreover, they show that the deployment of cobots can generate significant gains in terms of productivity, safety and cost efficiency.

# Contents

## List of Abbreviations

| | |
|---|---|
| ALB | Assembly line balancing |
| ALBP | Assembly line balancing problem |
| ALWABP | Assembly line worker assignment and balancing problem |
| CF | Collaboration flexibility |
| cHRCALBSP | Cost-oriented human-robot collaborative assembly line balancing and scheduling problem |
| Cobot | Collaborative robot |
| COVID-19 | Coronavirus disease 2019 |
| F-ratio | Task flexibility ratio |
| GALBP | Generalized assembly line balancing problem |
| HRC | Human-robot-collaboration |
| HRCALBSP | Humon-robot collaborative assembly line balancing and scheduling problem |
| MAL | Multi-manned assembly line |
| MALBP | Multi-manned assembly line balancing problem |
| MILP | Mixed-integer linear programming |
| MIQP | Mixed-integer quadratic programming |
| NP | Non-deterministic polynomial time |
| RALBP | Robotic assembly line balancing problem |
| RD | Robot density |
| RF | Robot flexibility |
| SALBP | Simple assembly line balancing problem |
| SES | Structure of Earnings Survey |
| SMEs | Small- and medium-sized enterprises |
| WD | Worker density |
| WR | West ratio |

# List of Figures

# List of Tables

# 1 Introduction

Over the past years digital transformation has become inevitable for almost every company. Industry 4.0 technologies, smart robotics and automation are on the rise and shape the future of the manufacturing sector. This modern form of automated manufacturing is based on the standardization of processes and an increasing application of robots in production [1, 2]. Within the past five years, the worldwide stock of industrial robots has increased by about 85% resulting in a new record of 2.7 million operating units in 2020 [3].

The implementation of robots in production brings many benefits such as enhanced product quality, line efficiency, and safety [4]. Automated flow lines allow for reduced labor costs and a higher degree of flexibility while at the same time they reduce risks and physical strains for workers by taking on dangerous, exhausting, and repetitive tasks [5, 2]. However, reaching an efficient level of automation using traditional robots can be challenging and, in some cases, even impossible. Difficulties in automation arise especially for small-batch production in small- and medium-sized enterprises (SMEs) and for the manufacturing of very complex or fragile products [6]. Industrial robots frequently lack the required accuracy and judgment for the tasks related to this kind of products wherefore these are commonly manufactured in manual assemblies [7, 2]. A complementary deployment of traditional robots in such manual assembly lines is due to safety requirements hard to achieve and therefore only offers limited potential for combined production systems.

Recent advances in automation technologies, however, might have brought a solution to this problem: collaborative robots. These so-called cobots are a special sort of lightweight robots that can collaborate with human workers without physical separation or safety barriers [8]. The result are flexible human-robot work teams that share a joint working space in which they can process tasks collaboratively at the same workpiece but also work in parallel on different tasks if required [9]. These teams combine the flexibility, adaptability, and decision-making skills of humans with the strength, speed, and endurance of robots and allow for increased efficiency and improved cycle times [10, 11].

The benefits of human-robot-collaboration (HRC) in production are manifold and interesting not only for SMEs. Over the past years, the market for collaborative robots has grown exponentially with 18,000 newly installed cobots in 2019 [12]. The increasing range of application, the improved working conditions, and the competitive advantages have made the adoption of HRC more and more attractive for mass production companies as well since they can beneficially integrate them in their smaller and usually manual feeder lines [13]. Especially, automotive manufacturers such as BMW and Daimler have recognized the potential of HRC in their production systems in terms of increased quality and efficiency and the ergonomic support cobots can offer for their employees [14, 15].

In 2020, the urgency of digital transformation and the shift towards automated manufacturing has been intensified even more. The novel human coronavirus SARS-CoV-2 has been discovered and led the world into a global crisis with unforeseeable consequences. The virus is extremely contagious and transmitted from person to person via direct contact, respiratory secretions, and contaminated surfaces [16]. Infection with the virus causes a respiratory disease called the Coronavirus Disease 2019 (COVID-19) that has proven to be seriously dangerous, not only for elderly people and those with previous illnesses. A hardly traceable infection chain combined with long incubation times of up to two weeks led to a rapid spread of the virus resulting in a worldwide pandemic that affected many countries socially and economically [17, 18]. To prevent further spread of the virus safety measures such as distance regulations and mask requirements were taken, and social contacts had to be reduced drastically. Eventually, governments were forced to impose nationwide lockdowns with the aim of containing and slowing down the pandemic while at the same time avoiding an overload of critical supply structures.

Apart from the huge impact on people's social lives, these restrictions also entailed strong economic consequences. Most of the workforce had to stay home, some production came to partial or even complete standstill, supply chains were interrupted, and economies impended to collapse. According to the Austrian Association of Metaltechnology Industries, utilization of production temporarily went down to around 60% accompanied by a decline in sales of almost 85%. In April 2020, the first of the pandemic's peaks, up to 80% of Austrian companies had to make use of short-time working or at least planned on doing so. This way they could reduce labor costs and limit at least some of their losses [19, 20]. One major reason for the standstill of production was the lack of physical distance between workers in many facilities. Especially, in manual assemblies the required distance could not be kept wherefore production had to be restricted or in some instances stopped entirely.

Companies must be prepared for events such as the current pandemic and be able to react quickly and adequately. As a consequence, almost every second company already seeks to increase its level of automation and even more plan on reconfiguring their work sites to promote physical distancing [21]. Considering the mentioned problems, the potential that can be achieved through human-robot collaboration becomes apparent once again. The deployment of cobots in the manufacturing process allows for a high level of productivity with reduced workforce and without having to compromise the health and safety of the workers [22].

Against the presented background, a new planning problem arises that requires the consideration of short-time work and safety distances in the manufacturing process. Therefore, in this work, a model is developed that facilitates the redesign of an existing manual assembly line so that a high level of production can be maintained even in times of crises. It considers physical distancing constraints between workers by finding the cost minimizing combination of short-time workers and additional stations that reduces the number of workers per station to one. Additionally, it provides decision support over the deployment of collaborative robots and gives insights into the productivity potential that can be achieved through a higher level of automation.

The remainder of this work is structured as follows. The next section gives a brief review of the relevant literature on the subject. In section 3, the problem setting is presented in more detail and an illustrative example is given for a better understanding of the problem. Section 4 introduces the developed model and provides a description of the mathematical formulation. The results of the conducted computational study are then discussed in section 5. Finally, the work completes with a conclusion and recommendations for future research in section 6.

# 2 Literature Review

The contribution of this work falls into the fields of assembly line balancing (ALB) with the underlying planning problem being known as the assembly line balancing problem (ALBP). Within that context three other problems are relevant: the equipment selection problem, the worker assignment problem and the scheduling problem. Combined they form the basis for the balancing of assembly lines with collaborative robots. This section aims at providing a brief review of the relevant research on the mentioned problems. Moreover, it discusses additional characteristics considered in this work and depicts how it contributes to the existing literature.

### Assembly line balancing

ALB can be described as the process of assigning several assembly tasks to an ordered sequence of workstations where the tasks are then to be executed by workers and/or machines. For the assignment a predefined objective as well as different constraints such as precedence, resource, or cycle time constraints have to be respected [23, 24]. The objective commonly focuses on the minimization of cycle time, the minimization of the number of stations, the minimization of costs, or alternatively on the maximization of profits [2].

In the literature, this planning problem was initially addressed by Salveson [25] who provided a first mathematical formulation for the so called simple assembly line balancing problem (SALBP). In this basic model, the problem is reduced to its very core, i.e. one homogenous product is produced on a serial line with one-sided single-manned workstations and only precedence constraints between tasks have to be considered for their assignment to the stations. The SALBP can be categorized into different types according to their objective function which is to either minimize the cycle time, the number of stations, or both, or - in the case that both parameters are given - to determine the feasibility of the problem [24].

Since the first formulation of the SALBP, the problem has been of great interest to researchers and several solution approaches have been developed. However, due to very simplifying assumptions it lacks realistic features and therefore only has limited applicability to real world problems. As a result, a large variety of extensions has been introduced by researchers with the focus on formulating and solving more realistic problems. They are referred to as generalized assembly line balancing problems (GALBP) and may also incorporate more complex objectives in the form of cost-oriented or multi-objective functions as well as additional characteristics and constraints [27]. Some contributions, for instance, investigate different assembly designs such as mixed-model production, U-shaped or two-sided assembly lines or multi-manned workstations. Other problem extensions include equipment selection, processing alternatives, varying processing times or other assignment restrictions. Detailed reviews on existing literature regarding the SALBP and different kinds of extensions are, amongst others, given by Becker and Scholl, Boysen et al., and Battaïa and Dolgui [24, 2, 28].

### Human-robot-collaboration

Amongst the many aspects that need to be considered for the balancing problem addressed in this work, the concept of human-robot-collaboration is of major importance. However, in the fields of ALB, it has not been discussed extensively yet. So far, most of the research on collaborative robots has investigated technical requirements for HRC in assembly lines, efficient behavior learning, ergonomic aspects, or the interaction within human-robot work teams.

El Zaatari et al. [29], for instance, give an overview of collaborative industrial scenarios and the cobot-related programming requirements. Schou et al. [30] introduce a method for the manual parameterization of robot skills and provide a task-level programming software tool for the programming of assembly tasks on cobots. An approach for the configuration and integration of cobots in the architecture of assembly stations is proposed by Realyvásquez-Vargas et al. [31]. Müller et al. [32] analyze the skills of humans and robots and use their insights to develop a descriptive approach for the process-dependent assignment of tasks in assembly processes with human-robot interaction. Other frameworks for the allocation of tasks in human-robot collaborative assemblies focus on the interaction of human and robot within the assembly cell and the risk and safety aspects associated with it [33, 34, 35]. However, even though most of the mentioned contributions address the collaborative processing of assembly tasks and their assignment to resources, they do not concentrate on the balancing of an entire assembly line.

Integrating stations with collaborative task execution in the assembly line balancing problem forms a novel problem type that requires the focus on several other problems. First, collaborative robots are considered as additional resources and consequently have to be allocated to stations. In the literature, this problem is referred to as equipment selection problem. Furthermore, tasks have to be assigned to stations and within collaborative stations to cobots, workers, or both. Therefore, temporal dependencies between tasks and resources exist wherefore a collection of scheduling problems needs to be solved as well. Within both contexts allocation-dependent task times are relevant. For the integration of overtime and the optional use of short-time work, varying wage rates need to be taken into account. This topic is frequently discussed within the worker allocation problem. Literature streams on these problem types with focus on cost-oriented approaches are examined in the following.

**Equipment selection**

The equipment selection problem commonly arises within robotic assembly line balancing problems (RALBP) in which tasks are assigned to workstations and different types of industrial robots are selected to process the allocated tasks in the most efficient manner. Rubinovitz et al. [36] were the first to explicitly investigate the design and balancing of a robotic assembly line. In their heuristic approach they consider different equipment alternatives with varying processing times depending on the type of robot and minimize the number of stations. Bukchin and Tzur [37] introduce the idea of additionally associating each equipment type with different costs. They develop an optimal and a heuristic algorithm that aim at minimizing the total equipment costs for a predetermined cycle time. An extended version is presented by Yoosefelahi et al. [38]. They formulate a mixed-integer linear programming (MILP) model with a multi-objective function that minimizes cycle time, robot setup costs and robot purchasing costs. The problem is solved using three versions of multi-objective evolution strategies and the results are compared among each other.

Nilakantan et al. [39] provide two models for the RALBP with dual focus on time and cost for a given number of stations. The time-based model primarily minimizes the cycle time and simultaneously evaluates the incurring total production cost of the robotic assembly line. Conversely, the cost-oriented model puts the focus on the optimization of the overall assembly line cost while evaluating the corresponding cycle time. The developed differential evolution algorithm is used to solve straight and U-shaped robotic assembly line problems. A similar problem is formulated by Pereira et al. [40], whereby they explicitly consider fixed and variable costs and add a cycle time constraint to account for throughput requirements. For the solution of the problem a hybrid meta-heuristic is proposed. An attempt to integrate varying purchasing costs and to minimize them simultaneously with the cycle time was recently presented by Li et al. [41]. Their contribution investigates the cost-oriented RALBP with setup times and provides a formulation for the developed MILP model as well as two population-based multi-objective algorithms. The results of their computational study suggest a trade-off between line efficiency and purchasing cost.

The examined literature demonstrates that research on the equipment selection problem in RALBP considers allocation-dependent task times. Cost-oriented approaches additionally focus on the purchasing and/or operating costs of equipment. Common objectives are the minimization of costs or stations for a given cycle time or the optimization of line efficiency. However, station costs are usually not considered and the establishment of new stations in the assembly line is of little concern.

Moreover, in robotic assembly lines workers are typically not directly involved in the execution of tasks and therefore labor costs and potentially accruing overtime hours are neglected for line balancing.

### Worker allocation

Wage rates and other aspects associated with labor are frequently integrated in the assembly line worker assignment and balancing problem (ALWABP) which is closely related to the equipment selection problem. Instead of deciding on the allocation of different types of equipment, however, in this problem type a set of workers with different skills is assigned to stations and paid according to their specific qualification.

Bock [42], for instance, analyzes the trade-off between wages and different worker skills in mixed-model assemblies. A study carried out by Moon et al. [43], concentrates on the assignment of tasks and multi-functional workers with different skills and salaries to stations in an integrated assembly. Their proposed MILP and the developed genetic algorithm minimize the total annual work station cost as well as the annual salary for a given cycle time. Most recently, Salehi et al. [44] published an extended version of this problem. In their work they formulate a mathematical programming model with an objective function that minimizes the sum of equipment costs, labor wage, and station establishment costs. Wage rates are assumed to vary depending on the qualification level of the worker as well as on the specific task that is being processed. Several meta-heuristic solution approaches are proposed and the performance of all algorithms are compared among each other.

Kim et al. [45] propose a balancing approach for the simultaneous assignment of skilled permanent and unskilled temporary workers in an integrated mixed-model assembly line. The employment of unskilled temporary workers can enhance productivity since they can support skilled permanent workers in stations where the total operation time for tasks exceeds the cycle time. However, even thought they can cooperate with skilled workers on certain tasks and reduce the required processing time, they cannot perform entire tasks themselves due to lack of experience.

Therefore, collaboration is not optional. Kim et al.'s contribution includes three different models to minimize the costs for stations and workforce, cycle time and work overload. Additionally, a hybrid genetic algorithm for the minimization of the overall costs is developed. In their findings they emphasize the trade-off between labor costs and operation costs of stations.

Potentially accruing overtime shifts and the corresponding labor costs are considered by Doerr [46]. They develop two solution algorithms for the allocation of workers and tasks to stations that allow for overtime if otherwise daily production quotas cannot be achieved. The results from their computational study suggest that for such cases a planned amount of overtime is beneficial and reduces costs. Similar indications are derived by Li and Gao [47]. Their attempt integrates the planned use of overtime work in the balancing problem to meet possible variations in demand. They present different solution methods including a branch, bound and remember algorithm to minimize the costs occurring for regular work and overtime shifts.

Even though there are many contributions that account for different wage rates, overtime costs or the use of temporary workers, the option to make use of short-time work has not been introduced to that context yet. Neither has the concept of optional collaboration between allocated workers or machines been taken into account in either of the two presented streams of literature.

### Scheduling in assembly line balancing

With regard to the collaboration of resources, contributions with focus on scheduling problems in the context of assembly line balancing seem more promising. The consideration of scheduling problems is required if tasks are assigned to stations with multiple resources so that these can process them simultaneously on the same workpiece. This is particularly the case in multi-manned assembly lines (MAL) which allow for more than one worker per station. In the corresponding multi-manned assembly line balancing problem (MALBP) it is essential to not only decide over the allocation of tasks to stations but to explicitly assign each task to a specific worker.

A first attempt to provide a mixed-integer programming formulation for this problem was made by Fattahi et al. [48]. In their model, the primary objective is to minimize the number of workers while the second objective aims at minimizing the number of opened multi-manned workstations. Kazemi and Sedighi [49] present a cost-oriented approach for the same problem that takes into account station costs and wage rates and minimizes the total cost per production unit. They develop a mathematical model and a heuristic method based on the genetic algorithm to solve real-sized problem instances.

The minimization of the number of workers for an assembly line with multi-manned stations is pursued by Kellegöz and Toklu [50]. Later, Kellegöz [51] provides an improved formulation that requires less variables and constraints and minimizes both the number of workers and the number of opened stations in the line. Additionally, a simulated annealing based heuristic method is developed. Roshani and Giglio [27] minimize the cycle time as a primary objective and the total number of workers as a secondary objective. Two meta-heuristic solution methods based on the simulated annealing algorithm are provided to solve the problem. A solution approach for the minimization of the number of workstations and workers as well as the cycle time was recently proposed by Yadaf et al. [52]. They develop a mixed-integer programming formulation for the MALBP and apply it to a real life case study of an automobile plant.

Zamzam et al. [53] introduce a new indicator to determine the maximum number of workers permitted in each station. The objective of their model is to reduce the number of workers and the length of the assembly line for better space utilization. They solve it using a hybrid genetic algorithm. Although, their approach sets a limit to the number of workers per station it lacks the consideration of an initially given number of workers that may exceed the allowed number of workers in the line. A team-oriented approach for the MALBP is provided by Yilmaz and Yilmaz [54]. Hereby, workers have to be assigned to teams according to the required skills and equipment. Afterwards, tasks are assigned to those teams which are then distributed to the stations. However, even though the workers are organized in teams they do not perform tasks collaboratively.

Yazgan et al. [55] concentrate on multi-manned assembly lines where some common tasks must to be processed by more than one worker simultaneously. The objective of their proposed solution method is to minimize both the number of stations and workers. Their work is one of the first attempts to integrate collaborative task execution in the MALBP. More insights on collaborative aspects can be found in Sikora et al. [56]. They integrate a traveling salesman problem formulation in the MALBP and investigate different scenarios including human and robotic workers and common tasks. The most recent contribution in that context was given by Yilmaz and Yilmaz [57]. They propose a mathematical model to minimize the number of workers and open multi-manned workstations in an assembly line and add a variety of assignment restrictions. Most mentionable among them are station and synchronous task restrictions. Synchronous tasks are defined by their need to be performed simultaneously by different workers on the same station. Collaborative execution is therefore obligatory.

Overall, the presented literature indicates that most approaches either lack any consideration of collaboration between multiple resources or they take collaboration into account, but solely as an externally given assignment restriction. None of the mentioned contributions considers collaboration as an optional processing alternative. Furthermore, the workforce is usually assumed to be homogeneous and consequently resource-dependent task times are neglected. For the balancing of assembly lines with human workers and cobots, however, they are indispensable.

**Human-robot collaborative assembly line balancing and scheduling**

Weckenborg et al. [58] are the first to explicitly consider the deployment of collaborative robots in the assembly line balancing problem. In contrast to existing contributions, their approach integrates optional collaboration of resources, i.e. cobots can either support manual task execution by working collaboratively with the human worker on the same workpiece or they can process tasks themselves in parallel. To account for that, they consider aspects associated with equipment selection and scheduling and introduce the human-robot collaborative assembly line balancing and scheduling problem (HRCALBSP). For this novel problem type, they propose a mixed-integer programming formulation to minimize cycle time. Additionally, a hybrid genetic algorithm is developed as a solution procedure for larger instances. The results from their computational study indicate that with the deployment of collaborative robots a significant increase in productivity can be achieved.

The contribution of Weckenborg et al. provides the basis for the model presented in this thesis. However, it lacks certain aspects that are relevant for the balancing of collaborative assembly lines with distancing constraints as it is investigated in this work. First of all, Weckenborg et al. minimize cycle time as only objective. This seems beneficial when the number of stations and workers is given and constant and when labor costs are of little concern. If the number of stations and workers in the line, however, is variable and it has to be decided over the most efficient combination of both, a cost-oriented objective seems more convenient as multiple factors can be taken into account. Secondly, they do not distinguish between different shifts within the overall cycle time and therefore do not define and penalize accruing overtime. Yet, to properly model the trade-off between establishing new stations and accepting overtime work, this differentiation is particularly important. Finally, the concept of short-time work and the consequential variation of wage rates is not represented in their problem at all.

### Conclusion

The literature review indicates that amongst the large variety of extensions of the assembly line balancing problem, there is no published study yet that considers all three the collaboration between human and cobot, costs for labor and stations and restrictions regarding the number of workers in the line. Therefore, in this thesis a mathematical formulation for the novel cost-oriented human-robot collaborative assembly line balancing and scheduling problem (cHRCALBSP) is developed. The contribution is manifold. First, it extends the proposed approach of Weckenborg et al. by adding a cost-oriented perspective. Second, it contributes to literature by introducing the concept of short-time work to assembly line balancing. Third, managerial insights regarding the trade-off between overtime work and the establishment of additional stations in the line are derived from the conducted computational study. In the following section, a detailed description of the underlying problem setting is provided.

# 3 Problem Description

## 3.1 Problem Setting

The outbreak of SARS-CoV-2 in 2020 and the resultant worldwide pandemic has left the world in a state of emergency that confronts governments, companies and individuals alike with great challenges. Containing the virus and minimizing the social and economic damages has become a superior goal for governmental actions. Thus, a variety of regulations was imposed that should prevent a further and uncontrolled spread of the virus. The measurements range from temporary lockdowns, travel restrictions and prohibition of public gatherings to the request to wear face masks and maintain sufficient distance from others. Moreover, the public is strongly encouraged to reduce social contacts to a minimum and to work from home as much as possible.

While the concept of home office may be easily implemented in sectors that do not rely on the physical presence of employees, in many professions it is simply not possible to attend the daily business digitally. This applies for construction, retail, personal care or food services, but also for production as the workforce is usually tied to machines and depends on upstream or downstream processes on site [59]. Especially during the first lockdown in April 2020, many companies were forced to shutdown their business temporarily so that their employees could stay home safely [19, 20]. During that period most of the affected enterprises made extensive use of “Corona short-time work”. This new form of short-time work is easier obtainable and relieves the employer from labor costs. The state agrees to pay a short-time work allowance as partial compensation for the employees’ wages that were lost due to the temporary absence from work. This way the government aims at securing jobs while at the same time maintaining the liquidity of companies during the pandemic [60].

Nevertheless, the entire workforce cannot go on short-time work if the business is to be kept going. In the manufacturing sector, manual assembly lines are particularly affected and especially multi-manned workstations are hard to put in line with distance requirements. It is precisely in these areas therefore that the hygiene requirements must be strictly adhered to so that the risk of workers becoming infected with COVID-19 is minimized. An initially unnoticed infection of one worker not only endangers the health of all workers assigned to the same station, but ultimately requires measures such as self-quarantine for the entire shift in order to prevent a further spread of the virus. The sudden shortage of labor can affect a facility's productivity heavily and at worst even result in a temporary shutdown.

The risk of such unpredictable and harmful events can most likely be reduced with the deployment of collaborative robots. As mentioned before, collaborative robots are a novel sort of lightweight robots that unlike traditional robots are able to safely collaborate with human workers without physical separation or safety barriers. This characteristic becomes particularly important with regard to the above mentioned problems as cobots can closely work alongside humans without having to keep the required physical distance. By taking over some of the workload, they allow for an ongoing production with a reduced workforce who can more easily keep their distance from one another [22]. Cobots are quickly programmed and installed, safe and easy to use and can support the human with the execution of a variety of industrial tasks. The range of applications is wide and includes pick-and-place, screwing, handling, inspection, assembly, and many more [13, 29].

There are numerous definitions and categorizations regarding the interaction between human worker and machine throughout the execution of tasks. So far, in production facilities, coexistence is the most common form of operation where human and cage-free robot only occasionally share a common workspace and therefore barely interact with each other. In the case that both permanently share the same workspace but alternately perform different tasks one after the other, a synchronized operation form is applied. As soon as human worker and machine not only share a common workspace but also simultaneously execute different tasks, a cooperative form of interaction is achieved. Collaboration, finally, is defined as the closest form of cooperation where human and cobot explicitly perform a common task on the same product simultaneously [9, 32].

The adoption of human-robot-collaboration is growing steadily and the post-corona recovery will further accelerate this development [3]. Especially, cooperative and collaborative forms of interaction offer great potential and facilitate a corona compliant configuration of manual assembly lines. However, many companies still struggle with the integration of HRC in their assembly systems and need additional support for their planning processes [9]. The focus of this work therefore lies on manual assembly lines and in particular on stations that have more than one worker assigned to as these involve a high risk of infection with the virus. Due to distance requirements, these multi-manned workstations have to be dispersed and it must be decided whether to establish new stations for surplus workers or whether to put them in short-time work. Moreover, collaborative robots may be deployed in order to enable an ongoing production even with reduced workforce and to further increase the line's efficiency.

On one hand, using short-time work means having less regular workers in the line. Hence, as short-time wages are a lot lower than regular wages, labor costs can be reduced. However, the absent workers are not available for the processing of tasks. This may lead to higher cycle times and possibly even overtime which is penalized with higher wage rates, eventually increasing labor costs. Adding new stations to the line, on the other hand, allows for the integration of more resources and therefore may result in lower cycle times. Nevertheless, extending the line involves setup costs and implies higher costs for regular wages. The resultant trade-off between the use of short-time work with potentially occurring overtime and the establishment of new stations in the line is best measured in a cost-oriented objective. This way all factors can directly be taken into account that are labor costs for regular work, overtime work and short-time work as well as costs for newly added stations.

The main goal of implementing HRC is usually to improve operational efficiency. In the pandemic, however, many companies struggle with meeting distance requirements and therefore for some of them the primary goal has become being able to continue production at all. Compared to an optimally balanced assembly line where no distance requirements need to be considered, a temporary reconfiguration of the assembly system may imply less efficiency and higher costs. However, at least a standstill of production is avoided and thus, losses are reduced. The presented model gives insights about the relevant cost drivers and whether the use of short-time work or line extension generates better solutions. Consequently, finding the cost-minimizing combination of both options that allows for an ongoing production is paramount to this work.

Purchasing costs of cobots are neglected in this problem setting. Since they are fast setup and easily programmable, they are not limited to a permanent deployment in one assembly line but can be used flexibly for multiple systems. Especially during the pandemic which is characterized by recurring lockdowns and changing regulations, it may be beneficial to frequently relocate existing cobots to assembly systems that otherwise would have to face downtime. Acquisition costs might then not arise or at least be spread over multiple products which makes them of no primary concern. This work aims at demonstrating the potential of HRC under pandemic circumstances and how the deployment of cobots can support in finding a feasible assembly configuration, enhance efficiency and reduce additional costs associated with a temporary reconfiguration. A resultant cost reduction then represents a premium on the basis of which further decisions regarding the relocation or acquisition of cobots can be made.

## 3.2 Assumptions

The model presented in this work is based on the following assumptions. A homogeneous product is produced in an existing manual assembly line with a serial order of stations. The initial line configuration comprises a given number of stations and workers while at each station there may be one or two workers all of which are equally skilled. The ratio of number of workers and number of stations is defined as worker density (WD) where WD = 1 indicates that one worker is assigned to each station while WD = 2 describes a scenario with two workers at every station.

Distance requirements are fulfilled by reducing the number of workers per station to one. Therefore, in the optimized configuration the number of open stations must equal the number of regular workers in the line. The maximum number of stations that may be added to the existing line depends on the number of surplus workers and cannot exceed the initial number of stations. The production facility is a greenfield facility, i.e. there is enough space to establish the maximum number of stations in the line and no restrictions regarding the work flow path have to be considered. These new stations are manual assembly stations that are mobile and fast setup. They are equipped with all portable powered tools that are necessary to process any of the given tasks.

A predefined number of cobots is available and must be allocated to the stations. As defined by Weckenborg et al. [58], robot density (RD) reflects the ratio of robots to stations, similar to worker density. RD = 1 indicates that one cobot is deployed at each station. On the contrary, with RD = 0, no cobot is available and all tasks have to be processed by humans. A given number of tasks needs to be processed while each task may be assigned to exactly one station and processing alternative. To measure the task density in each station of the assembly system, the west ratio (WR) is defined as the average number of tasks per station [61]. Precedence relations of tasks are known and summarized in a precedence graph. They must be respected for the assignment of tasks to stations. The flexibility within the assignment is measured by the task flexibility ratio ($F$-ratio) [61, 62]. With $F$-ratio = 1, no precedence relations between tasks have to be taken into account while $F$-ratio = 0 implies no flexibility so that all tasks have to be processed in a predetermined order.

For the processing of tasks, several processing alternatives are available that are human, robotic, and collaborative execution. Robotic and collaborative task execution are not available for all of the tasks since cobots are assumed to have limited capabilities compared to human workers. The portion of tasks that may be processed by robots or in collaboration is captured in robot flexibility (RF) and collaboration flexibility (CF), respectively [58]. Maximum robot flexibility (i.e. all tasks are executable by robots) is described by RF = 1, whereas RF = 0 refers to a case in which robotic execution is not applicable for any of the tasks. The same applies for collaborative task execution and collaboration flexibility, accordingly. According to Teiwes et al. [63] who present a procedure to assess the collaboration potential of workplaces, manual assembly systems usually have low to medium automation potential. The authors investigate an automotive assembly line and find that on average a medium potential of 34% for the implementation of HRC is reached.

The processing times for all processing alternatives are based on the determination of Weckenborg et al. [58] who compare the motion speed of human worker and cobot to derive consistent times. They find that the velocity of robots is strongly reduced in the presence of humans. In such safety mode the cobot requires almost twice as much time as the human worker for the processing of tasks. Consequently, processing times for robotic execution are assumed to be significantly higher than manual execution in this problem setting. Collaborative execution of tasks, on the other hand, can reduce processing times as both resources are able to support each other on the common task. All processing times are deterministic, known, and constant for any processing alternative.

One cycle time unit represents one working hour. Occurring overtime hours are subdivided into two sequential shifts that are compensated differently. Due to legal constraints, workers are not allowed to work more than 12 hours per day. This limit is therefore not to be exceeded. The wage rates for regular working time, overtime 1 and 2 and short-time are each fixed, known, and equal for all workers. Short-time wages are assumed to be significantly lower and overtime costs to be higher than regular wages. Overtime wages 2 are defined to be higher than overtime wages 1. Costs are only relevant from the business perspective, i.e. any short-time allowances that are borne by the state are not taken into account as negative side-effect. Workers that are assigned to short-time work are assumed to not work at all and they are paid the regular working time but no overtime. The cost for establishing an additional station is fixed, known, and equal for all stations. It is based on the assumption that the optimized assembly configuration is applied for 60 days in order to reflect a lockdown of two months. The constellation of costs strongly affects the weighting of the trade-off and consequently the model outcome. All costs are therefore considered as external decision variables that are to be set by the system designer.

## 3.3 Illustrative Example

In the following, a simple example is given to illustrate the problem setting presented above. Figure 1 shows the initial situation.

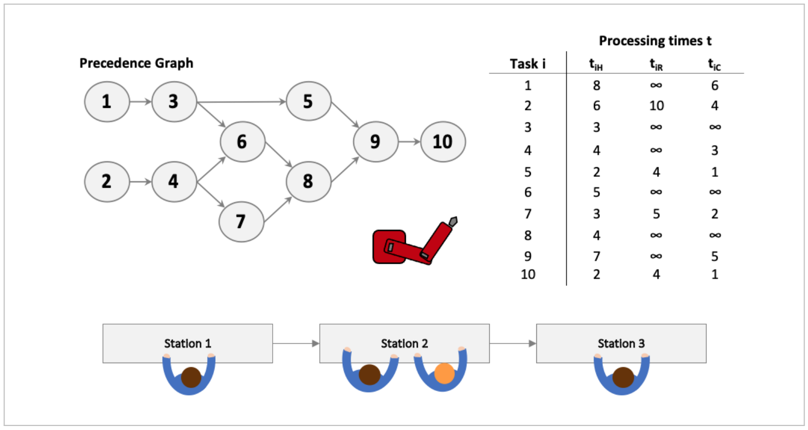
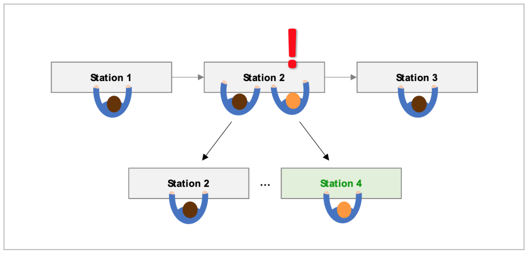


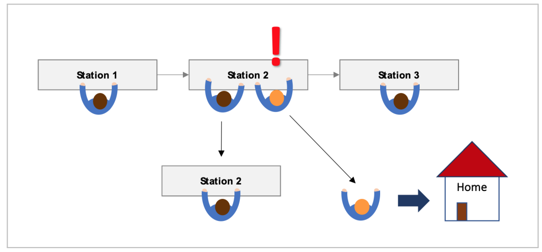

**Figure 1:** Initial manual assembly line

A manual assembly line is given that comprises three stations and a total of four workers. Worker density is consequently 1.33. While station 1 and 3 both have one worker assigned to, at station 2 there are currently two workers. Physical distance requirements are therefore not fulfilled. On these stations one homogeneous product with ten tasks is to be processed resulting in a west ratio of 3.33. All precedence relations are captured in the presented precedence graph and lead to a $F$-Ratio of 0.76 which represents a rather high level of flexibility for the assignment of tasks. Additionally, one cobot is available and needs to be allocated to any of the three stations. Robot density is consequently calculated as 0.33. Since the cobot is capable of processing 4 out of the 10 tasks by himself, robot flexibility is 0.4. Human and robot can collaborate on 7 tasks which results in a collaboration flexibility of 0.7.

Due to distance requirements, only one human worker is allowed at each station. Hence, station 2 must be split and it has to be decided how to proceed with the exceeding worker. The two possible options are illustrated in Figure 2. Option a) shows the scenario in which a new station is added to the line so that one worker remains assigned to station 2 while the other one is relocated to the new station 4. Option 2, on the other hand, refers to the case that one of the workers is sent on short-time work so that the assembly is continued on three stations with reduced workforce.




(a) Add new station




(b) Use short-time work

**Figure 2:** Options for the allocation of surplus labor

For the given example problem, the following costs are applied. Regular wages are € 15 while overtime wages 1 and 2 are set to € 22.5 and € 30, respectively. Wages for short-time workers are significantly lower with € 5. The upper bound for the cycle time is 12 while the thresholds for the overtime shifts are set to 8 (overtime period 1) and 10 (overtime period 2). The costs for establishing new stations amount to € 50 each. This represents a rather simplified cost parameter setting. A more specific determination of all relevant costs for the conducted computational study is given in section 5.

The optimal solution of this example problem is calculated using the model introduced in section 4. It decides for option a) and consequently a new station is added to the line. The resulting optimized collaborative assembly line with the required physical distance between all human workers is shown in Figure 3.

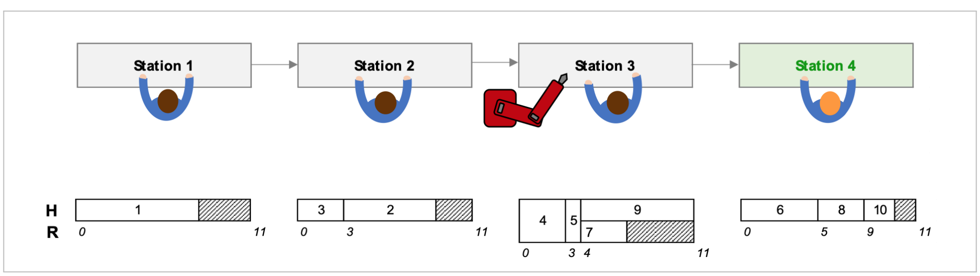



**Figure 3:** Optimized collaborative assembly line with the required physical distance

It now comprises four stations with one worker each and no worker is sent to short-time work. Additionally, the model decides to assign the available cobot to station 3 where tasks 4 and 5 are processed in collaboration while tasks 7 and 9 are executed by human and cobot in parallel. The assembly process results in a cycle time of 11 and generates costs of € 830. For the given constellation of costs this represents the cost-minimizing line configuration. However, adaptations in the cost parameter setting such as higher station costs or lower overtime wages might generate different solutions.

# 4 Model Description

## 4.1 Notation

To concisely describe the problem setting presented above, in this section a mathematical model formulation is given. It extends the formulation introduced by Weckenborg et al. [58] by adding physical distancing constraints and a cost-oriented objective. A detailed description of the used notation is provided in the following.

Initially, the assembly line consists of $m$ installed stations that are connected with a material handling system and up to $m$ new stations may be established. Whether a station $k \in K_2$ is added to the line is captured by the binary decision variable $u_k$. The set of stations $K_1$ contains both initial and potential stations. The number of workers at each station is encoded in the binary decision variable $w_k$ and there is a total of $p$ workers.

A set of tasks $I$ has to be assigned to the stations while each task can be executed by a set $P$ of different processing alternatives. $P$ contains the alternatives of execution by human ($p_H$), by robot ($p_R$), and in collaboration ($p_C$). The binary decision variable $x_{ikp}$ captures whether a task $i \in I$ is processed at station $k \in K_1$ with processing alternative $p \in P$. Each task $i \in I$ requires a deterministic processing time $t_{ip}$ depending on its processing alternative $p \in P$. Note that in practice, not every task can be executed with every processing alternative. For these tasks, processing times for execution by robot or in collaboration are set to a sufficiently high number which ensures that the respective processing alternative is not chosen for this task [5].

In case a task is being processed by robot or in collaboration, one of $q$ equal collaborative robots has to be assigned to the respective station which is indicated by the binary decision variable $r_k$. The decision variable $z_i$ holds the station number a task $i \in I$ is assigned to while $s_i$ indicates the task's starting time within the station. For the scheduling of tasks direct precedence relations between two tasks $(i, j) \in I$ have to be considered. They are defined in the corresponding set $E$. Whether task $i \in I$ must start before task $j \in I$ is indicated by the auxiliary variable $y_{ij}$.

$CT$ equals the overall cycle time of the assembly configuration. It includes the regular working time $CT_1$ and the overtime shifts $CT_2$ and $CT_3$. $CT_2$ takes values if the cycle time exceeds the first threshold $TH_1$. The same applies for $CT_3$ and the second threshold $TH_2$, respectively. Whether no, the first or the second threshold is surpassed is indicated by the auxiliary variables $b_1$, $b_2$, and $b_3$. The parameter M represents a very large number and serves as Big-M parameter for the relaxation of constraints.

In this model formulation labor and station costs are considered. Labor costs include wages for regular working time, overtime, and short-time while station costs apply for any new station that is established. Wage rates per worker are set in the parameters $C_W$, $C_{STW}$, $C_{TH_1}$ and $C_{TH_2}$. The regular wage $C_W$ is incurred for every regular working time unit $CT_1$. Overtime wage $C_{TH_1}$ applies for each time unit between $TH_1$ and $TH_2$ and $C_{TH_2}$ for each time unit that exceeds $TH_2$. Each short-time worker is paid $C_{STW}$ per regular working time unit $CT_1$. Finally, the parameter $C_S$ equals the cost for adding a new station to the line. All symbols used to define the sets, parameters, and variables are summarized in table 1.

**Table 1:** General notation of sets, parameters, and decision variables

| | |
|---|---|
| | Sets and parameters |
| $I$ | Set of tasks $I = \{i, j = 1, \ldots, n\}$ |
| $K_1$ | Set of stations $K_1 = \{k = 1, \ldots, 2m\}$ |
| $K_2$ | Set of potential stations $K_2 = \{k = 1, \ldots, m\}$ |
| $P$ | Set of processing alternatives $P = \{p = p_H, p_R, p_C\}$, in which tasks are processed by human ($p_H$), robot ($p_R$) or in collaboration ($p_C$), respectively |
| $E$ | Set of direct precedence relations $(i, j)$ |
| $t_{ip}$ | Execution time of task $i \in I$ with processing alternative $p \in P$ |
| $M$ | A very large number |
| $m$ | Number of initial stations |
| $p$ | Number of initial workers |
| $q$ | Number of robots to be allocated |
| $C_S$ | Costs for adding a new station to the line |
| $C_W$ | Costs per time unit and worker |
| $C_{STW}$ | Costs per time unit and short-time worker |
| $C_{TH_1}$ | Costs per overtime unit and worker in case $CT$ exceeds Threshold 1 |
| $C_{TH_2}$ | Costs per overtime unit and worker in case $CT$ exceeds Threshold 2 |
| $TH_1$ | Threshold 1 |
| $TH_2$ | Threshold 2 |
| | Decision and auxiliary variables |
| $x_{ikp}$ | Binary variable with value 1, if task $i \in I$ is assigned to station $k \in K_1$with processing alternative $p \in P$ |
| $z_i$ | Variable for encoding the station number a task $i \in I$ is assigned to |
| $s_i$ | Variable for encoding the start time of task $i \in I$ in the station it is assigned to |
| $r_k$ | Binary variable with value 1, if a robot is assigned to station $k \in K_1$ |
| $u_k$ | Binary variable with value 1, if a new station $k \in K_2$ is added to the line |
| $w_k$ | Binary variable for encoding the number of workers assigned to station $k \in K_1$ |
| $y_{ij}$ | Binary variable with value 1, if task $i \in I$ starts before task $j \in I$ $(s_i \leq s_j)$ |
| $CT$ | Variable for encoding the overall cycle time |
| $CT_1$ | Variable for encoding the regular working time all workers are paid for |
| $CT_2$ | Variable for encoding the working time regular workers are paid overtime costs $C_{TH_1}$ |
| $CT_3$ | Variable for encoding the working time regular workers are paid overtime costs $C_{TH_2}$ |
| $b_1$ | Binary variable with value 1, if $CT \leq TH_1$ |
| $b_2$ | Binary variable with value 1, if $TH_1 < CT \leq TH_2$ |
| $b_3$ | Binary variable with value 1, if $TH_2 < CT$ |

## 4.2 Model Formulation

Based on the notation and the assumptions presented in the previous sections, a mathematical model formulation is derived in the following. The formulation considers human-robot collaboration as introduced by Weckenborg et al. [58] and additionally takes into account physical distancing constraints as well as cycle time restrictions and costs.

$$\min \rightarrow \sum_{k \in K_1} w_k \Big( C_W \cdot CT_1 + C_{TH_1} \cdot CT_2 + C_{TH_2} \cdot CT_3 \Big) + \Big( p - \sum_{k \in K_1} w_k \Big) C_{STW} \cdot CT_1 + \sum_{k \in K_2} u_k \cdot C_S \tag{1}$$

Subject to:

$$\sum_{k \in K_1} \sum_{p \in P} x_{ikp} = 1 \qquad \forall i \in I \tag{2}$$

$$x_{ikp} \leq u_{k-m} \qquad \forall i \in I, k \in \{m+1, \ldots, 2m\}, p \in P \tag{3}$$

$$\sum_{k \in K_1} \sum_{p \in P} k \cdot x_{ikp} = z_i \qquad \forall i \in I \tag{4}$$

$$s_i + \sum_{k \in K_1} \sum_{p \in P} t_{ip} \cdot x_{ikp} \leq s_j + M \left( z_j - z_i \right) \qquad \forall i, j \in E \tag{5}$$

$$s_i + t_{ip_C} \cdot x_{ikp_C} \leq s_j + M \Big( 1 - \sum_{p \in P} x_{jkp} \Big) + M \left( 1 - x_{ikp_C} \right) + M \left( 1 - y_{ij} \right) \qquad \forall i, j \in I, k \in K_1 \tag{6}$$

$$s_i + \sum_{p \in P} t_{ip} \cdot x_{ikp} \leq s_j + M \left( 1 - x_{jkp_C} \right) + M \left( 1 - y_{ij} \right) \qquad \forall i, j \in I, k \in K_1 \tag{7}$$

$$s_i + t_{ip} \cdot x_{ikp} \leq s_j + M \left( 1 - x_{ikp} \right) + M \left( 1 - x_{jkp} \right) + M \left( 1 - y_{ij} \right) \qquad \forall i, j \in I, k \in K_1, p \in \{p_H, p_R\} \tag{8}$$

$$x_{ikp} \leq r_k \qquad \forall i \in I, k \in K_1, p \in \{p_R, p_C\} \tag{9}$$

$$\sum_{k \in K_1} r_k \leq q \tag{10}$$

$$y_{ij} = 1 - y_{ji} \qquad \forall i, j \in I, i < j \tag{11}$$

$$\sum_{k \in K_1} w_k \leq p \tag{12}$$

$$\sum_{k \in K_1} w_k = m + \sum_{k \in K_2} u_k \tag{13}$$

$$s_i + \sum_{k \in K_1} \sum_{p \in P} t_{ip} \cdot x_{ikp} \leq CT \leq 12 \qquad \forall i \in I \tag{14}$$

$$CT = CT_1 + CT_2 + CT_3 \tag{15}$$

$$CT_1 \leq b_1 \cdot TH_1 \tag{16}$$

$$CT_2 \leq b_2 \cdot (TH_2 - TH_1) \tag{17}$$

$$CT_3 \leq b_3 \cdot M \tag{18}$$

$$TH_1 \cdot b_2 \leq CT_1 \tag{19}$$

$$(TH_2 - TH_1) \cdot b_3 \leq CT_2 \tag{20}$$

$$b_3 \leq b_2 \tag{21}$$

$$b_2 \leq b_1 \tag{22}$$

$$x_{ikp} \in \{0; 1\} \qquad \forall i \in I, k \in K_1, p \in P \tag{23}$$

$$z_{i,} s_i \geq 0 \qquad \forall i \in I \tag{24}$$

$$w_k \in \{0; 1\} \qquad \forall k \in K_1 \tag{25}$$

$$r_k \in \{0; 1\} \qquad \forall k \in K_1 \tag{26}$$

$$u_k \in \{0; 1\} \qquad \forall k \in K_2 \tag{27}$$

$$y_{ij} \in \{0; 1\} \qquad \forall i, j \in I, i \neq j \tag{28}$$

$$b_{TH_0}, b_{TH_1}, b_{TH_2} \in \{0; 1\} \tag{29}$$

The objective (1) is to minimize the total costs of the production line. This includes wages for regular workers, reduced wages for short-time workers, and costs for adding new stations to the line. All regular workers $\sum_{k\in K_1} w_k$ are paid $C_W$ over all regular working time units $CT_1$. Overtime costs $C_{TH_1}$ are added to the wage for each overtime unit $CT_2$ while overtime cost $C_{TH_2}$ apply for any overtime unit $CT_3$ . Short-time wages are calculated by multiplying the number of short-time workers with the corresponding costs $C_{STW}$ and the regular working time $CT_1$. The number of short-time workers is defined as the difference between the initial number of workers $p$ and the final number of regular workers. Finally, the costs for new stations result from the product of the sum over all entries of the decision variables $u_k$ with the station cost $C_S$.

Each task $i \in I$ can only be processed at exactly one station $k \in K_1$ which is assured by constraints (2). Moreover, constraints (3) determine that tasks cannot be assigned to stations that are not included in the line. Constraint set (4) serves to define the station number each task is assigned to. Constraints (5) assure that precedence relations between tasks $(i, j) \in E$ are not violated with $i$ being a direct predecessor of $j$. If task $i \in I$ is processed in collaboration, both worker and cobot are occupied. Therefore, task $j \in I$ can only start at the same station $k \in K_1$ if the processing of task $i$ has finished. On the other hand, if task $j \in I$ is executed collaboratively, both human and cobot have to be available to perform the task. Thus, it can only start after any preceding task $i \in I$ is finished regardless the processing alternative of $i$. These availability requirements are ensured by constraints (6) and (7). Accordingly, the same principle applies for a task $j \in I$ that is processed with the same processing alternative as any task $i < j$ at the same station. Tasks that are manually processed require any preceding manually processed tasks to be completed first, while tasks executed by cobots can only start after previous robotically processed tasks at that same station are finished. Constrain set (8) defines this relationship.

Constraints (9) secure that execution by robot or in collaboration is only available at stations that have a robot assigned to while the total number of robots is limited to $q$ as specified in constraint (10). In the cases where no robots can be allocated to stations ($q = 0$) tasks can only be processed by humans and therefore only with one processing alternative ($p_H$). As a consequence, in these cases the index $p$ as well as the number of robots $q$ and the decision variables $r_k$ can be neglected. Within each station the processing order of tasks is determined by constraint set (11). Constraints (12) and (13) serve to fulfill physical distancing requirements and reduce the number of workers per station to one. They assure that the total number of workers at all stations $k \in K_1$ does not exceed the initial number of workers while at the same time it equals the total number of stations included in the line. Upper and lower bound for overall cycle time $CT$ are set in constraints (14). Further cycle time specifications, particularly for regular working time $CT_1$ as well as overtime periods $CT_2$ and $CT_3$ are indicated in constraints (15)-(22). Finally, all remaining variables are defined by constraints (23)-(29).

The presented model can be classified as a mixed-integer quadratic programming (MIQP) model. It adapts and extends the formulations from Weckenborg et al. [58] and includes additional aspects from Salehi et al. [44] and Kim et al. [45]. From Weckenborg the approach is taken to consider the collaboration of resources for the processing of tasks as a variable, and thus, not as obligatory. Worker and cobot may work together on common tasks, however, this collaboration is not given as an external assignment restriction so that both resources can also process tasks at the same workstation in parallel. Their constraints are extended to include the total number of workers in the assembly system and to allow for additional stations in the line. Moreover, the concept of short-time work is added and the cycle time is modeled differently so that overtime can be taken into account.

Instead of minimizing the cycle time as proposed by Weckenborg et al. a cost-oriented objective is chosen that allows for the integration of the newly added aspects. The general approach of minimizing all costs associated with labor wage, and station establishment is adapted from Salehi et al. [44] and Kim et al. [45]. Equipment costs are neglected for the reasons mentioned in section 3.1. From Salehi et al., the idea is derived to encode the number of workers at each station in decision variables $w_k$ and to take its values as a premise for the final number of stations in the line. Inspiration for the differentiation between regular and short-time workers is taken from Kim et al. who distinguish between skilled permanent and unskilled temporary workforce in their objective function.

# 5 Computational Study

This section describes the computational study that was carried out for the presented problem and discusses its effectivity. First, the set of test instances is described in subsection 5.1. Subsection 5.2 then determines all necessary cost parameters used to solve the proposed model formulation. Afterwards, the complexity of the problem and the performance of the solution method are evaluated in subsection 5.3. Finally, managerial insights are derived from the obtained results in subsection 5.4.

## 5.1 Generation of Test Instances

In the following, the set of test instances is described in detail. As there is no benchmark set available that accounts for all constraints relevant for the studied problem, self generated test instances are used. As already mentioned, the focus lies on manual assembly lines such as they are commonly used in SMEs or in feeder lines in component manufacturing of mass production companies [64, 65, 66]. These types of assembly lines are usually of small size wherefore data sets with low instance sizes regarding the number of tasks are constructed. Small instances contain 15 tasks, medium instances 20 tasks, and large instances 30 tasks. They are small enough to be solved in reasonable computational time using an optimization solver. As the problem belongs to the non-deterministic polynomial time (NP)-hard class of optimization problems, larger instances are assumed to take significantly longer to be solved [39].

Regarding the flexibility within the task assignment, instances with high ($F$-ratio $= 0.8$) and low ($F$-ratio $= 0.4$) task flexibility ratio are generated. The specific precedence relations between tasks are chosen randomly. For each flexibility category and for each instance size, three data sets are generated resulting in 18 different precedence graphs. Since Teiwes et al. [63] conclude from their study that in manual assembly systems on average a medium potential of 34% for the implementation of HRC is reached, robot and collaboration flexibility are set to 0.3 for all test instances. Tasks are randomly chosen to be executable by robot or in collaboration such that the desired level for RF and CF is reached.

The processing times of tasks are defined as follows. Times for human execution are generated randomly and form the basis for the processing times of robots and in collaboration. The maximum time for human execution is set to 8 so that generally all tasks are processable by a human worker within the regular working time. As outlined in subsection 3.2 the motion speed of a robot is strongly reduced in the presence of humans and hence, the cobot requires almost twice as much time as the human worker for the processing of the same task. For each task $i$, robotic execution takes therefore a processing time of $t_{ip_R} = 2 \cdot t_{ip_H}$. Collaborative execution, on the other hand, improves working speed and therefore reduces the processing time. In line with Weckenborg et al. [58], a reduction of 30% is applied so that $t_{ip_C} = 0.7 \cdot t_{ip_H}$.

Regarding west ratio and robot density the same settings as investigated by Weckenborg et al. are considered. West ratio $\in \{2, 4\}$ leads to $m \in \{4, 8\}$ stations for small instances, $m \in \{5, 10\}$ stations for medium instances and $m \in \{8, 15\}$ stations for large instances, respectively. The number of robots depends on the respective number of stations according to robot density $\in \{0, 0.2, 0.4\}$. This setting corresponds with the presented findings of Teiwes et al. [63] regarding the automation potential of manual assembly systems. The dependency on the number of stations also applies for the number of workers in the line. Worker density $\in \{1, 1.5, 2\}$ defines scenarios with one worker at each station, one worker at each and an additional one at half of the stations, and two workers at each station, respectively. The setting of all parameters and the resultant 18 different scenarios are presented below in table 2. The 18 generated data sets applied to these 18 different scenarios finally gives a total of 324 test instances used for the computational study in this work.

**Table 2:** Parameter settings of scenarios

| Scen. | WR | RD | WD | Small instances ($n = 15$ tasks) | | | Medium instances ($n = 20$ tasks) | | | Large instances ($n = 30$ tasks) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Stations | Robots | Workers | Stations | Robots | Workers | Stations | Robots | Workers |
| 1 | 4 | - | 1 | 4 | 0 | 4 | 5 | 0 | 5 | 8 | 0 | 8 |
| 2 | 4 | - | 1.5 | 4 | 0 | 6 | 5 | 0 | 8 | 8 | 0 | 12 |
| 3 | 4 | - | 2 | 4 | 0 | 8 | 5 | 0 | 10 | 8 | 0 | 16 |
| 4 | 4 | 0.2 | 1 | 4 | 1 | 4 | 5 | 1 | 5 | 8 | 2 | 8 |
| 5 | 4 | 0.2 | 1.5 | 4 | 1 | 6 | 5 | 1 | 8 | 8 | 2 | 12 |
| 6 | 4 | 0.2 | 2 | 4 | 1 | 8 | 5 | 1 | 10 | 8 | 2 | 16 |
| 7 | 4 | 0.4 | 1 | 4 | 2 | 4 | 5 | 2 | 5 | 8 | 4 | 8 |
| 8 | 4 | 0.4 | 1.5 | 4 | 2 | 6 | 5 | 2 | 8 | 8 | 4 | 12 |
| 9 | 4 | 0.4 | 2 | 4 | 2 | 8 | 5 | 2 | 10 | 8 | 4 | 16 |
| 10 | 2 | - | 1 | 8 | 0 | 8 | 10 | 0 | 10 | 15 | 0 | 15 |
| 11 | 2 | - | 1.5 | 8 | 0 | 12 | 10 | 0 | 15 | 15 | 0 | 23 |
| 12 | 2 | - | 2 | 8 | 0 | 16 | 10 | 0 | 20 | 15 | 0 | 30 |
| 13 | 2 | 0.2 | 1 | 8 | 2 | 8 | 10 | 2 | 10 | 15 | 3 | 15 |
| 14 | 2 | 0.2 | 1.5 | 8 | 2 | 12 | 10 | 2 | 15 | 15 | 3 | 23 |
| 15 | 2 | 0.2 | 2 | 8 | 2 | 16 | 10 | 2 | 20 | 15 | 3 | 30 |
| 16 | 2 | 0.4 | 1 | 8 | 4 | 8 | 10 | 4 | 10 | 15 | 6 | 15 |
| 17 | 2 | 0.4 | 1.5 | 8 | 4 | 12 | 10 | 4 | 15 | 15 | 6 | 23 |
| 18 | 2 | 0.4 | 2 | 8 | 4 | 16 | 10 | 4 | 20 | 15 | 6 | 30 |

## 5.2 Cost Parameter Setting

The model formulation presented in this work is based on a cost-oriented approach according to which costs for workforce as well as for the establishment of new stations are to be minimized. Therefore, a set of cost parameters must be defined that can be used for solving the problem. It must be mentioned that the costs vary from company to company and that the respective constellation of the parameters strongly influences the results. For the conducted study, realistic average values for all relevant cost parameters are determined and presented in the following.

### 5.2.1 Wages

In this subsection, all costs related to employee remuneration are defined. This includes wages paid for regular working hours and overtime shifts as well as short-time work compensation.

Regular working hours are set at 8 hours per day by law. Therefore, threshold $TH_1 = 8$ so that regular wages are incurred for the first eight hours. Regular wages are derived from the Structure of Earnings Survey (SES) 2018 in Austria [67]. The collected data is subdivided according to economic sectors and personal information about the employees such as gender, length of service with the company, occupation and training qualification. The structure of earnings survey thus enables statements to be made about the distribution of employee earnings. For the determination of an appropriate average regular wage, this data has been narrowed down to the manufacturing area (B-F) and within that category to the manufacturing of goods (C). The median wage for full time employed men and women is chosen and thus, a regular wage $C_W =$ € 17.17 per regular cycle time unit and worker is defined.

Accruing overtime shifts are compensated according to the employee collective agreement for the metalworking industry for regular workers [68]. It states that a 50% surcharge on the regular wage is payable for the first two hours of overtime. This consequently applies for all time units between $TH_1$ and the second threshold $TH_2 = 10$. The third and subsequent overtime hours on a day are remunerated with a bonus of 100%. As a result, wages for overtime units $CT_2$ that are between $TH_1$ and $TH_2$ are set to $C_{TH_1} =$ € 25.76 while wages for overtime units $CT_{3,}$, i.e. cycle time that exceeds threshold $TH_2$, are determined as $C_{TH_2} =$ € 34.34. The employee collective agreement for the automotive industry provides the same overtime compensation structure and thus validates this parameter setting [69].

The extent to which companies make use of short-time work is industry-specific and for the determination of an appropriate short-time work wage rate the metal-technology industry is taken as a benchmark. According to the Austrian Association of Metaltechnology Industries, during lockdown phases, short-time work was commonly applied to most of the workforce with a 90% hourly reduction [19]. For the company, this means reduced wage costs to the same extent since the state covers the employees' lost compensation through the short-time work allowance. Applying a 90% reduction on the regular wage rate results in a short-time wage $C_{STW} = € \ 1.72$ per regular time unit and short-time worker.

### 5.2.2 New Stations

Apart from labor costs the model also takes into account costs for establishing additional stations in the line. For this purpose, manual work stations are considered. Manual workstations are mobile stations that can be flexibly integrated into existing assembly systems or production lines. Particularly in times of uncertain order books and changing regulations, such small assembly cells enable a flexible adaptation of production. They usually consist of standardized components that can be tailored to the needs of the customer by adding or leaving out certain components or by making the structure more or less complex. For more information on manual workstations see [70, 71, 72, 73]. Acquisition costs vary depending on the equipment and size of the respective manual workstation. Figure 4 gives a simple example for costs of several components in such a workplace.

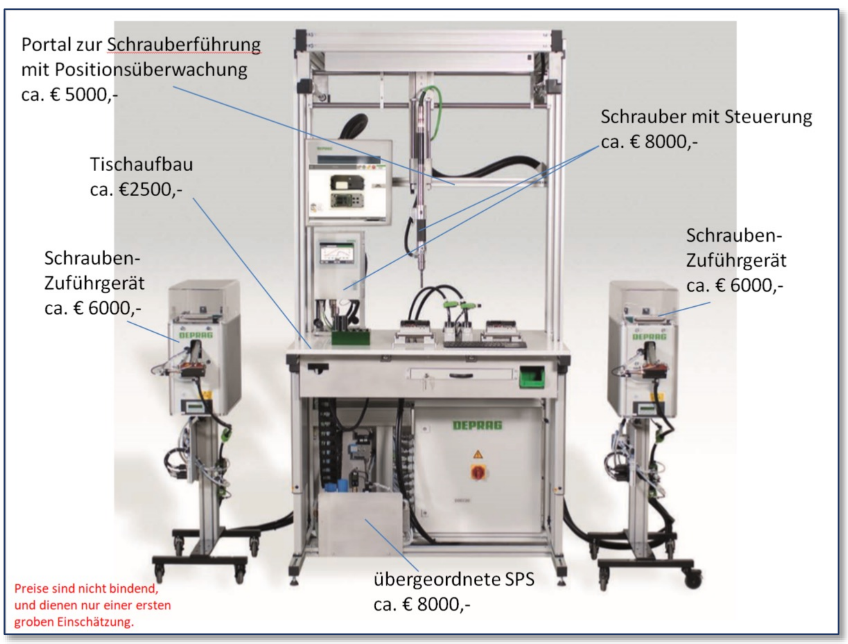



**Figure 4:** Exemplary manual workstation and acquisition costs
Source: Customer Support of DEPRAG Schulz GmbH u. Co.

These costs add up to € 35,500 and serve as reference point for the determination of the station costs used in the computational study. However, one screw feeder is assumed to be sufficient wherefore only one is included in the calculation. Hence, acquisition costs are assumed to be € 29,500. Apart from costs for the acquisition of such stations certain other factors have to be taken into account. In the main, this includes depreciation, operational and planned time of use, cost of capital, maintenance work, and running costs such as for energy [74]. For the calculation of depreciation a lifespan of 10 years and a residual value of zero are used. Furthermore, since the mobile stations are supposed to serve only as temporary solution during lockdowns a running period of 60 days per year is assumed. Considering depreciation and a cost of capital of 8%, acquisition costs can be narrowed down to € 68.83 per day. Finally, maintenance costs of 5% on the daily depreciation and a small amount of energy costs are added which results in a daily new station cost of $C_S =$ € 71.85. Note that this represents a simplified exemplary calculation that needs to be extended and specified in real world applications. Extensions might amongst others include the consideration of setup or reconfiguration costs while specifications depend on the considered company. For the computational study conducted in this work, however, the presented setting is sufficient.

## 5.3 Performance Evaluation

In this section, the performance of the introduced MIQP model formulation is studied. The model formulation has been implemented using the IBM ILOG® Optimization Programming Language and solved using CPLEX® 12.10. All tests were then run on the Vienna Scientific Cluster VSC-3 using the parameter settings presented in the previews sections. Furthermore, a time limit of 28,800 s was set which corresponds to eight hours. This appears to be an appropriate timespan within which the model should be able to generate a feasible solution when used in the reconfiguration process of a real world assembly system.

For the evaluation of the computational complexity of the problem and the impact of the parameters on it, the following three performance indicators are analyzed:

1. The number of instances with feasible/optimal solutions obtained within the runtime: *Feasible (optimal) (# of ##).*

2. The average relative gap to the optimal solution remaining after termination of the solution procedure and its standard deviation: *Gap Ø* $(\sigma)$.

3. The average computational time in seconds needed until the solution procedure is terminated: *CPU Ø* $(\sigma)$ *(s).*

First, an analysis of the 18 scenarios on the complexity indicators over all instance sizes is provided. The different scenarios are defined by the varying parameter settings of west ratio WR, robot density RD, and worker density WD as determined in subsections 3.2 and 5.1. The results are shown in table 3.

**Table 3:** Analysis of the scenarios on complexity indicators

| Scenario | WR | RD | WD | All instances<br>Feasible (optimal) (# of 18) | <br>Gap Ø($\sigma$) | <br>CPU Ø($\sigma$) (s) |
|---|---|---|---|---|---|---|
| 1 | 4 | - | 1 | 1 (1) | 0 (0) | 0 (0) |
| 2 | 4 | - | 1.5 | 12 (7) | 0.09 (0.13) | 11,812 (14,365) |
| 3 | 4 | - | 2 | 18 (12) | 0.14 (0.15) | 8,082 (13,222) |
| 4 | 4 | 0.2 | 1 | 5 (3) | 0.18 (0.26) | 10,682 (14,655) |
| 5 | 4 | 0.2 | 1.5 | 14 (6) | 0.17 (0.15) | 10,979 (13,868) |
| 6 | 4 | 0.2 | 2 | 18 (10) | 0.17 (0.16) | 8,418 (13,030) |
| 7 | 4 | 0.4 | 1 | 7 (5) | 0.12 (0.17) | 6,117 (11,269) |
| 8 | 4 | 0.4 | 1.5 | 15 (7) | 0.17 (0.15) | 10,042 (13,780) |
| 9 | 4 | 0.4 | 2 | 18 (10) | 0.14 (0.14) | 8,738 (12,917) |
| 10 | 2 | - | 1 | 18 (16) | 0.08 (0.11) | 3,022 (8,697) |
| 11 | 2 | - | 1.5 | 18 (16) | 0.06 (0.08) | 3,626 (8,757) |
| 12 | 2 | - | 2 | 18 (15) | 0.09 (0.01) | 6,206 (11,883) |
| 13 | 2 | 0.2 | 1 | 18 (14) | 0.08 (0.08) | 6,275 (10,940) |
| 14 | 2 | 0.2 | 1.5 | 18 (14) | 0.06 (0.06) | 6,275 (10,940) |
| 15 | 2 | 0.2 | 2 | 18 (11) | 0.06 (0.06) | 8,495 (11,898) |
| 16 | 2 | 0.4 | 1 | 18 (15) | 0.04 (0.07) | 4,130 (9,612) |
| 17 | 2 | 0.4 | 1.5 | 18 (13) | 0.03 (0.05) | 5,027 (9,356) |
| 18 | 2 | 0.4 | 2 | 18 (14) | 0.07 (0.06) | 5,607 (10,982) |

It becomes apparent that the complexity is strongly influenced by the west ratio and therefore the number of stations in the assembly system. While Weckenborg et al. [58] report increasing complexity with decreasing WR (i.e. an increasing number of stations) caused by the resultant higher number of decision variables, with this model formulation, a lower WR leads to decreased computational complexity and a higher number of feasible solutions. This is due to the fact that a higher WR offers more available stations for the processing of tasks so that consequently physical distancing constraints and cycle time constraints can be fulfilled more easily. For WR = 2, all instances are feasible and most of them are solved to optimality. Furthermore, compared to the scenarios with high west ratio, lower average gaps and lower running times can be obtained. Nevertheless, with increasing worker density, the number of decision variables eventually becomes too large and less optimal solutions can be obtained within larger running times. Table 4 illustrates this effect more clearly.

**Table 4:** Analysis of worker density and west ratio on complexity indicators

| | West ratio = 2 | | | West ratio = 4 | | |
|---|---|---|---|---|---|---|
| WD | Feasible (optimal) (# of 54) | Gap Ø(σ) | CPU Ø(σ) (s) | Feasible (optimal) (# of 54) | Gap Ø(σ) | CPU Ø(σ) (s) |
| 1 | 54 (45) | 0.07 (0.07) | 4,017 (9,660) | 13 (9) | 0.15 (0.18) | 7,402 (12,045) |
| 1.5 | 54 (43) | 0.05 (0.06) | 4,976 (9,605) | 41 (20) | 0.15 (0.14) | 10,880 (13,647) |
| 2 | 54 (40) | 0.07 (0.05) | 6,769 (11,444) | 54 (32) | 0.15 (0.14) | 8,413 (12,811) |

In contrast, in scenarios with high west ratio (i.e. a small number of stations), feasibility is significantly lower, especially in the cases of low worker density. Feasibility and optimality improve with both, increasing worker density and increasing robot density. While in scenario 1 (WD = 1 and RD = 0) only one solution can be obtained within the runtime, in scenario 9 (WD = 2 and RD = 0.4) all instances are at least feasible (table 3). The latter applies to all scenarios with WD = 2 since the high number of available workers allows for the establishment of more new stations so that eventually a low west ratio can be reached in the optimized assembly design. This facilitates the assignment of tasks to stations. However, for these scenarios, optimality decreases with increasing robot density as the problem becomes too complex due to the high number of decision variables. With both parameters set to the maximum, too many resources are available than actually needed for the processing of the tasks and it becomes more difficult for the model to decide on the most beneficial combination of resources.

The poor performance of the MIQP for scenarios with WD = 1 is neither surprising nor is it an indicator for a poor formulation of the problem. The intention behind the presented model is to provide a solution procedure that solves problem settings in which currently more than one worker is assigned to a station and wherefore distance requirements are violated. In scenarios with WD = 1, this is not the case. Nevertheless, they are intentionally included in the study to show the potential of deploying cobots in the assembly system as they increase feasibility when only a limited number of workers is available. More insights into this are given in subsection 5.4.

Apart from parameters like west ratio, worker density and robot density, the computational complexity of ALB problems is known to be strongly influenced by the number of tasks and the considered $F$-ratio. The reason for this is the dependency of the number of feasible task sequences on both parameters. It can be estimated with $n!/2^{|E|}$ where $n$ contains the number of tasks to be processed and $|E|$ corresponds to the number of precedence relations between those tasks. Consequently, if the number of tasks or the $F$-ratio increases the number of feasible task sequences increases and therefore computational complexity [58, 76, 77]. In the following, the impact of both parameters on the efficiency of the model formulation is analyzed with regard to the above mentioned theoretical implications.

The results prove both implications to be right. Even though a higher $F$-ratio and the corresponding higher number of feasible task sequences allow for more feasible solutions for all instance sizes, the number of instances that can be solved to optimality decreases, as can be seen in table 5. This applies especially to medium and large instances where the number of optimal solutions for cases with high $F$-

**Table 5:** Analysis of $F$-ratio and instance size on complexity indicators

| $F$-ratio | Small instances (n = 15 tasks) | | | Medium instances (n = 20 tasks) | | | Large instances (n = 30 tasks) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Feasible (optimal) (# of 54) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) | Feasible (optimal) (# of 54) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) | Feasible (optimal) (# of 54) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) |
| 0.4 | 45 (43) | 0 (0) | 2 (2) | 38 (38) | 0 (0) | 40 (48) | 45 (32) | 0.1 (0.1) | 7,882 (11,694) |
| 0.8 | 49 (39) | 0.01 (0.03) | 1,237 (5,746) | 44 (19) | 0.08 (0.1) | 12,659 (12,928) | 49 (18) | 0.19 (0.13) | 17,832 (13,263) |

ratio is reduced by almost half compared to the ones with low $F$-ratio. Additionally, the average computational time needed for a feasible solution to be found is significantly higher and the average gap to the optimal solution larger than in the cases of low task flexibility. Regarding the impact of the number of tasks, the results implicate that complexity increases with larger instance sizes as all performance indicators show decreasing efficiency. The more tasks need to be processed the less optimal solutions are found and the higher the average gap and the average CPU. These findings are in line with the theoretical aspects presented before. When evaluating the impact of the $F$-ratio in combination with the different scenarios over all instances, it can be derived that in general, a higher $F$-ratio indeed results in worse performance. However, there is an exception for scenarios with high west ratio. An increasing robot density combined with high task flexibility leads to reduced complexity in terms of decreasing computational time (table 6). More insights on the analysis of the scenarios and the $F$-ratio on complexity indicators are shown in table 12 in appendix A.

**Table 6:** Analysis of robot density and $F$-ratio on complexity indicators for WR = 4

| | | $F$-ratio = 0.4 | | | $F$-ratio = 0.8 | | |
|---|---|---|---|---|---|---|---|
| WR | RD | Feasible (optimal) (# of 17) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) | Feasible (optimal) (# of 17) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) |
| | 0 | 14 (14) | 0 (0) | 116 (337) | 17 (6) | 0.12 (0.13) | 16,800 (14,344) |
| 4 | 0.2 | 16 (11) | 0.09 (0.13) | 4,216 (9,720) | 21 (8) | 0.2 (0.16) | 13,866 (14,212) |
| | 0.4 | 17 (15) | 0.2 (0.14) | 4,041 (9,480) | 23 (7) | 0.15 (0.14) | 12,263 (13,868) |

Overall, the results show that using this model formulation a reasonable number of solutions can be found. However, due to the NP-hardness of the problem, the solver experiences difficulties determining feasible solutions in reasonable time with increasing problem complexity, especially when limited resources are available (high WR, low WD, low RD). Since the investigated planning problem is yet unconsidered in the literature, a comparison with other approaches is not possible yet. Heuristic solution procedures seem promising for future research so that larger instances can be solved with less computational effort.

## 5.4 Managerial Insights

While in the previous section the results are evaluated with regard to the computational complexity of the model formulation, in this section the focus lies on the managerial insights that can be derived from the study. First, decisions regarding the use of short-time work and the establishment of new stations in the line are analyzed. Afterwards, the effect of the deployment of collaborative robots on the cost development is investigated and the potential for improvement is shown. Finally, the results are examined with regard to the assignment of tasks to processing modes depending on the different parameter settings.

### 5.4.1 Short-time Work vs. New Stations

Due to physical distancing regulations, in the presented problem setting only one worker is allowed at each station. In the case that the number of workers in any station exceeds this limit, it has to be decided whether to put surplus workers into short-time work or whether to establish additional stations in the line. The results of what decisions the model makes for large problem instances in dependence on the respective parameter settings are illustrated in figure 5. Note that surplus workers are only present in scenarios with worker density WD $\in \{1.5, 2\}$ and that therefore scenarios with WD $= 1$ are excluded from this part of the analysis.

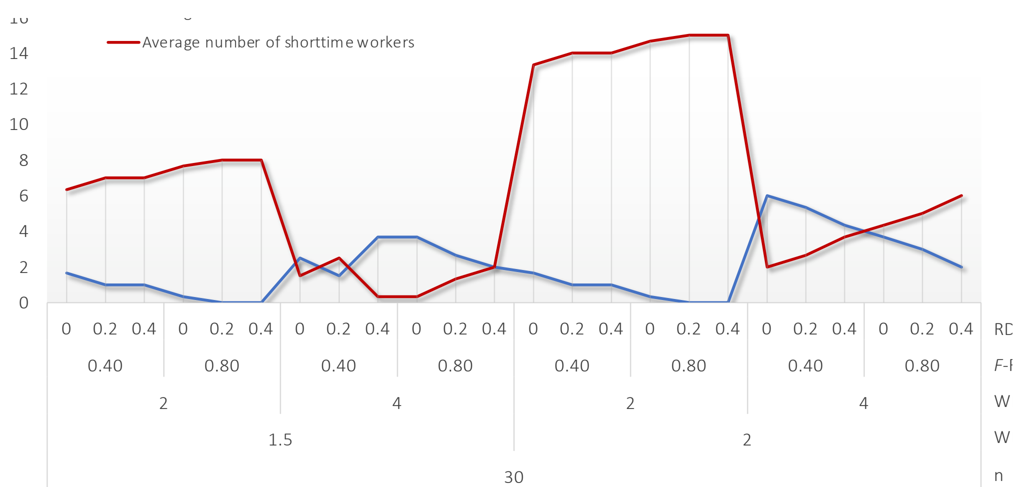



**Figure 5:** Short-time work vs. extended assembly line

The results are broken down to different levels of robot density, $F$-ratio, west ratio, and worker density and clearly show opposing trends for the number of new stations and the number of workers on short-time work. For any increase in the number of short-time workers, the number of stations that are added to the line decreases. This effect is rational as any exceeding worker can either be assigned to short-time work or a new station but never to both. It confirms that the model makes logical decisions and that the results can be trusted in this regard.

Furthermore, a definite trend for an increasing use of short-time work with increasing RD, $F$-ratio, and WD can be identified. In contrast to that, an increasing WR leads to a higher number of new stations instead. These relations seem reasonable and are partly caused by the number of resources available. As already mentioned, cobots are considered as additional resources and can therefore take over tasks from human workers or collaborate with them on certain tasks. Due to the high extent of parallel work and the reduced cycle times resulting from joint task execution, a higher RD demands for less workers and thus stations in the production facility. Distance requirements can be fulfilled easier and more workers are assigned to short-time work. A similar effect is caused by a low west ratio. Compared to scenarios with high WR, there is already a high number of stations in the initial line configuration so that less new stations are required.

The dependency on the $F$-ratio can be explained by the number of feasible task sequences. The higher flexibility within the task assignment allows for an efficient line balancing even with less stations and thus more workers can be put in short-time work. The impact of worker density on the number of short-time workers is based on the fact that a high number of workers in scenarios with WD $= 2$ naturally leads to a greater number of short-time workers compared to scenarios with WD $= 1.5$ as there are more workers in the system. Similar trends with regard to the other parameters can be observed for both settings of worker density, however, for a high density the magnitude of the impact is simply greater.

Nevertheless, a discrepancy can be found in the results for west ratio $= 4$ as they show dissimilar developments for both worker densities. While for WD $= 2$ and WR $= 4$ the mentioned trend regarding RD and $F$-ratio can be seen, this is not the case for WD = 1.5. However, this deviation can be explained with the results from the performance evaluation in subsection 5.3. Table 3 demonstrates that in contrast to all scenarios with WD = 2 which are characterized by complete feasibility, in scenarios 2, 5, and 8 (WD = 1.5, WR = 4) not all instances could be solved. This is particularly true for cases with low $F$-ratio (see appendix A). This partial infeasibility has to be kept in mind when evaluating the results presented in figure 5 as it most likely distorts the obtained results. In the respective cases of high $F$-ratio the trend seems peculiar at first, however, this is deceptive. The number of new stations in fact shows the same development for low WD as for high WD while the number of short-time workers shows the same trend as well, just at a different level. These varying levels for different worker densities are in line with the explanations previously made as there are less workers in the system which consequently lowers the upper bound for the number of short-time workers.

The corresponding results for all instance sizes in total show a similar development and can be found in appendix B. In conclusion, it can be stated that the deployment of cobots increases the availability of resources wherefore more workers can be put in short-time work in order to safe costs and to fulfill distance requirements. However, if the goal was to enable as many workers as possible to come to work (e.g. for mental health reasons) and therefore to establish a preferably high number of stations then this would be most beneficial for assembly systems with high west ratio in combination with low cobot density and $F$-ratio. Nevertheless, it must be mentioned once again that the results strongly depend on the previously defined cost parameters and that they may show different characteristics for other settings.

### 5.4.2 Effect of Robot Density on Cost Improvement

This subsection aims at investigating the effect of the various parameters and particularly of the robot density on the development of the costs. For this reason, the average relative improvement of the total costs for large instances and the possible drivers are examined. Table 7 shows for each worker density the total cost improvement for different levels of robot density in relation to the base scenario with RD = 0 which represent a fully manual assembly line.

**Table 7:** Analysis of robot density on relative improvement of total costs for large instances (Ø)

| | | West ratio = 2 | | West ratio = 4 | |
|---|---|---|---|---|---|
| WD | RD | $F$-ratio = 0.4 | $F$-ratio = 0.8 | $F$-ratio = 0.4 | $F$-ratio = 0.8 |
| 1 | 0 | - | - | - | - |
| 1 | 0.2 | 0.05 | 0.06 | 0.00 | 0.00 |
| 1 | 0.4 | 0.05 | 0.06 | 0.00 | 0.00 |
| 1.5 | 0 | - | - | - | - |
| 1.5 | 0.2 | 0.05 | 0.03 | 0.11 | 0.06 |
| 1.5 | 0.4 | 0.05 | 0.03 | 0.04 | 0.13 |
| 2 | 0 | - | - | - | - |
| 2 | 0.2 | 0.05 | 0.03 | 0.06 | 0.06 |
| 2 | 0.4 | 0.05 | 0.03 | 0.10 | 0.12 |

It becomes clear, that almost all robotic scenarios generate significant cost improvements compared to the corresponding manual assembly settings and that therefore the deployment of collaborative robots should be favored. This applies especially to scenarios with increasing worker density and west ratio. Nevertheless, some of the results attract attention such as the lack of cost improvement for scenarios with WD = 1 and WR = 4 or the decreasing cost improvement for increasing RD in scenarios with medium worker density, high west ratio and low task flexibility. In order to evaluate these irregularities, a more detailed analysis with focus on the underlying drivers for improvement is provided in the following.

Firstly, scenarios with WD = 1 are examined. They represent cases where no distance measures need to be taken as there is only one worker at each station. As a consequence, no short-time work is applied and no additional stations can be established in the line. Cost improvements therefore cannot result from a reduction in short-time work wages or station costs as both take values of zero for all robot densities. Instead, any reduction of costs must be attributed entirely to a reduction of cycle time and thus overtime wages. The relative improvement in cycle time depending on different levels of worker density and robot density in relation to each base scenario with RD = 0 is presented in table 8.

**Table 8:** Analysis of robot density on relative improvement of cycle time for large instances (Ø)

| | | West ratio = 2 | | West ratio = 4 | |
|---|---|---|---|---|---|
| WD | RD | $F$-ratio = 0.4 | $F$-ratio = 0.8 | $F$-ratio = 0.4 | $F$-ratio = 0.8 |
| 1 | 0 | - | - | - | - |
| 1 | 0.2 | 0.03 | 0.04 | 0.00 | 0.00 |
| 1 | 0.4 | 0.03 | 0.04 | 0.00 | 0.00 |
| 1.5 | 0 | - | - | - | - |
| 1.5 | 0.2 | 0.00 | 0.00 | 0.00 | -0.04 |
| 1.5 | 0.4 | 0.00 | 0.00 | 0.11 | -0.04 |
| 2 | 0 | - | - | - | - |
| 2 | 0.2 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.4 | 0.00 | 0.00 | -0.03 | -0.04 |

As expected, the deployment of cobots indeed leads to cycle time improvements for WD = 1 and WR = 2 which is in line with the cost reduction observed in table 7. The effect is slightly stronger for a high $F$-Ratio as the higher task flexibility allows for a more beneficial use of the additional resources. Hence, for these cases, the deployment of cobots effectively reduces cycle time and therefore wages.

For WD = 1 and WR = 4, however, neither cost nor cycle time improvements can be observed. At this point, the results from the performance evaluation in subsection 5.3 must be considered. Table 4 had shown that the model performed worse for test instances with WD = 1 and WR = 4 compared to the other scenarios. Out of 54 instances only 13 were feasible and just 9 could be solved to optimality. For large instances, without the deployment of cobots no instance could be solved at all and even with high RD not all instances were feasible (table 9). Consequently, no cost improvement could be obtained. Nevertheless, this observation implies that the cobots facilitate the generation of feasible solutions and therefore enable production even with limited workforce. This would be especially beneficial in the case of workers being infected with COVID-19 and thus being forced to stay absent from work. This is in line with real world cases in which cobots took over shifts from workers that had to go into self-quarantine while the company did not suffer any losses in productivity [22].

**Table 9:** Analysis of robot density on feasibility for large instances (# of 3)

| | | West ratio = 2 | | West ratio = 4 | |
|---|---|---|---|---|---|
| WD | RD | $F$-ratio = 0.4 | $F$-ratio = 0.8 | $F$-ratio = 0.4 | $F$-ratio = 0.8 |
| 1 | 0 | 3 | 3 | 0 | 0 |
| 1 | 0.2 | 3 | 3 | 1 | 2 |
| 1 | 0.4 | 3 | 3 | 1 | 2 |
| 1.5 | 0 | 3 | 3 | 2 | 3 |
| 1.5 | 0.2 | 3 | 3 | 2 | 3 |
| 1.5 | 0.4 | 3 | 3 | 3 | 3 |
| 2 | 0 | 3 | 3 | 3 | 3 |
| 2 | 0.2 | 3 | 3 | 3 | 3 |
| 2 | 0.4 | 3 | 3 | 3 | 3 |

With increasing worker density feasibility increases and for west ratio = 2 all instances could be solved. Similar cost savings as for scenarios with WD = 1 can be observed (table 7). However, as it can be seen in table 8, for these scenarios no cycle time improvement is generated wherefore the obtained cost reduction must be caused by varying decisions regarding the number of short-time workers and new stations. Figure 5 (previous subsection) illustrates these decisions in dependence on the respective parameter settings implying that for WR = 2 an increasing robot density and task flexibility increases the average number of short-time workers. Consequently, less costs for new stations and less regular wages must be paid.

Nevertheless, an increase of RD from 0.2 to 0.4 cannot generate further benefit in these cases. With WR = 2 there is already a high number of resources available so that a little number of cobots is already sufficient to improve the costs to the maximum. Table 10 underlines these findings. It can be seen that the costs for new stations decrease while the costs for short-time work increase. Additionally, the reduced number of regular workers results in lower wages for regular time and overtime. These generated cost savings are in total greater than the additional costs for short-time workers and the difference corresponds to a premium that can be used as a measure for whether the acquisition of new cobots or the reallocation of existing ones from other product lines may be justified.

**Table 10:** Analysis of robot density on costs for large instances with west ratio = 2 (Ø)

| | | West ratio = 2 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $F$-ratio = 0.4 | | | | | $F$-ratio = 0.8 | | | | |
| WD | RD | Total | $C_W$ | $C_{OT}$ | $C_{STW}$ | $C_{NS}$ | Total | $C_W$ | $C_{OT}$ | $C_{STW}$ | $C_{NS}$ |
| 1 | - | 2,747 | 2,060 | 687 | 0 | 0 | 2103 | 1,975 | 129 | 0 | 0 |
| 1 | 0.2 | 2,618 | 2,060 | 558 | 0 | 0 | 1,975 | 1,975 | 0 | 0 | 0 |
| 1 | 0.4 | 2,619 | 2,060 | 558 | 0 | 0 | 1,975 | 1,975 | 0 | 0 | 0 |
| 1.5 | - | 2,634 | 2,289 | 137 | 87 | 120 | 2,145 | 2,020 | 0 | 101 | 24 |
| 1.5 | 0.2 | 2,495 | 2,198 | 129 | 96 | 72 | 2,080 | 1,975 | 0 | 105 | 0 |
| 1.5 | 0.4 | 2,495 | 2,198 | 129 | 96 | 72 | 2,080 | 1,975 | 0 | 105 | 0 |
| 2 | - | 2,730 | 2,289 | 137 | 183 | 120 | 2,238 | 2,020 | 0 | 193 | 24 |
| 2 | 0.2 | 2,591 | 2,198 | 129 | 193 | 72 | 2,171 | 1,975 | 0 | 198 | 0 |
| 2 | 0.4 | 2,591 | 2,198 | 129 | 193 | 72 | 2,171 | 1,975 | 0 | 198 | 0 |

In scenarios with a high west ratio, the benefit of collaborative robots becomes even more apparent (table 7). These scenarios are characterized by a small amount of initial stations. With medium and high worker density feasibility is higher since many stations can be added to the line and hence enough resources are available for the processing of tasks. However, this is costly as many stations and thus workers are integrated in the line which leads to high costs for regular wages and additional station costs. An increasing robot density can reduce the number of additionally required stations and thus reduce those costs. Nevertheless, an analysis of the impact of robot density on the cycle time improvement shows that these savings in station costs and regular wages are commonly accompanied by an increase in cycle time. The model intentionally allows for overtime since the generated savings overcome the increase in overtime costs (table 11). Especially for high $F$-ratio, significant cost reductions can be obtained.

Furthermore, in table 7 another irregularity is notable. For scenarios with high west ratio, low $F$-ratio and medium worker density, the improvement for robot density = 0.2 is higher than the improvement for RD = 0.4 in relation to the manual scenario. In other words, applying a medium amount of cobots to the base

**Table 11:** Analysis of robot density on costs for large instances with west ratio = 4 (Ø)

| | | West ratio = 4 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $F$-ratio = 0.4 | | | | | $F$-ratio = 0.8 | | | | |
| WD | RD | Total | $C_W$ | $C_{OT}$ | $C_{STW}$ | $C_{NS}$ | Total | $C_W$ | $C_{OT}$ | $C_{STW}$ | $C_{NS}$ |
| 1 | - | - | - | - | - | - | - | - | - | - | - |
| 1 | 0.2 | 2,060 | 1,099 | 962 | 0 | 0 | 1,923 | 1,099 | 824 | 0 | 0 |
| 1 | 0.4 | 2,060 | 1,099 | 962 | 0 | 0 | 1,786 | 1,099 | 687 | 0 | 0 |
| 1.5 | - | 2,905 | 1,442 | 1262 | 21 | 180 | 2,274 | 1,603 | 404 | 5 | 263 |
| 1.5 | 0.2 | 2,589 | 1,305 | 1142 | 34 | 108 | 2,139 | 1,465 | 464 | 18 | 192 |
| 1.5 | 0.4 | 2,792 | 1,603 | 922 | 5 | 263 | 1,986 | 1,374 | 441 | 28 | 144 |
| 2 | - | 3,051 | 1,923 | 670 | 28 | 431 | 2,329 | 1,603 | 404 | 60 | 263 |
| 2 | 0.2 | 2,875 | 1,831 | 624 | 37 | 383 | 2,182 | 1,511 | 386 | 69 | 216 |
| 2 | 0.4 | 2,760 | 1,694 | 704 | 50 | 311 | 2,041 | 1,374 | 441 | 83 | 144 |

scenario decreases costs whereas then adding more cobots to the scenario with medium RD results in increased costs again. Even though, these costs are still below the costs of the manual assembly system and therefore still beneficial, the development seems unusual compared to the development in other scenario settings. Once again, the evaluation of the performance indicators gives an explanation. The application of high robot density results in one more feasible solution compared to scenarios with medium robot density. Consequently, the use of further cobots allows for an additional feasible solution and therefore ongoing production at the cost of higher total costs. Examining the distribution of the costs, this new feasible solution was obtained by adding new stations to the line so that more resources are available for the processing of tasks. The cost increase arises mostly from the high amount of regular wages and represents the minimal cost increase if production is to be continued. Consequently, compared to a standstill of production, these additional costs are still beneficial in the long run.

From the presented analysis it can be derived that the deployment of cobots can reduce cycle time significantly for assembly lines with low worker density and guarantee an ongoing production if workers must go into self-quarantine. Additionally, they enable a high extend of short-time work so that workers can stay home safely during the crises and only few additional stations have to be established in the line. This way distance requirements are fulfilled while at the same time costs can be saved.

### 5.4.3 Assignment of Tasks to Processing Modes

The further analysis concentrates on the assignment of tasks to the different processing modes and how the allocation is influenced by the various parameters. For this reason, the average number of tasks assigned to human, robotic, and collaborative processing alternative is investigated for large instances and illustrated in figure 6. The distribution is evaluated with regard to west ratio, $F$-ratio and robot density. Moreover, the proportion of tasks assigned to each processing mode in stations with cobots is presented (figure 7). The influence of worker density on the allocation of tasks is mainly driven by different levels of west ratio and shown in figure 8.

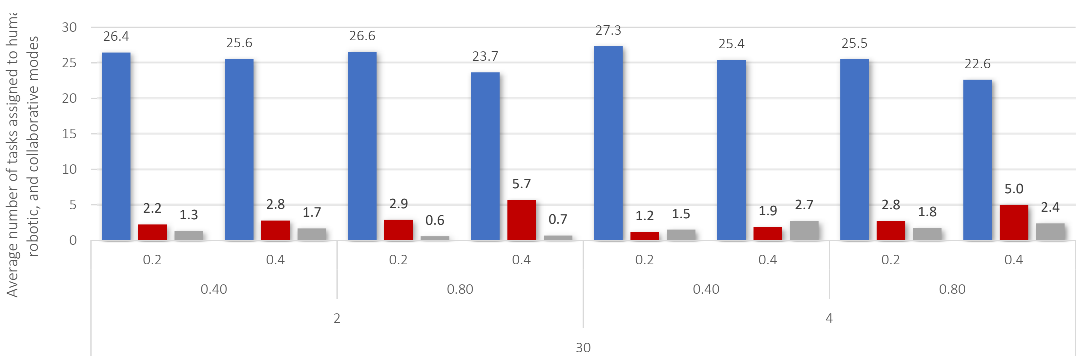



**Figure 6:** Assignment of tasks to modes (WR, $F$-ratio, RD)

All in all, it can be derived that no processing alternative dominates the others and that the distribution is therefore strongly affected by the different settings which is in line with the findings of Weckenborg et al. [58]. The results show that an increasing $F$-ratio, i.e. an increasing task flexibility, allows for a higher extent of parallel work and thus an increasing autonomous performance of the cobots (figure 6). This way less resources and additional stations are required which saves both labor and station costs. These deductions are consistent with the findings illustrated in figure 5 (subsection 5.4.1) which suggest that increasing task flexibility increases the number of short-time workers and decreases the number of additional stations. The level of robotic task execution is even higher for low west ratio. Since there are less tasks per station the higher processing times of cobots can be accepted without having to compromise on the overall cycle time. The initial high number of stations therefore does not necessarily require collaboration.

Collaborative processing, on the other hand, is favored for low $F$-ratio. The higher number of precedence relations between tasks demands for a rather serial than parallel assignment of tasks and for this the shorter processing times of the collaborative processing modes can be utilized beneficially. Figure 7 shows these effects even better. It also shows, that in stations with cobots the number of tasks being processed by cobots is not influenced by the degree of robot density as it could be observed in the analysis including all stations. This means that in the overall system the proportion of tasks being executed robotically increases with an increasing number of cobots as one would expect, but within robotic stations the allocation is mostly influenced by other parameters such as task flexibility and west ratio.

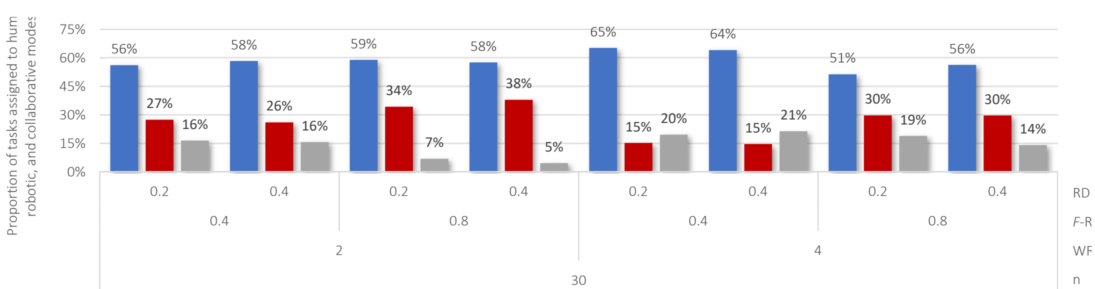



**Figure 7:** Assignment of tasks to modes in stations with cobots (%)

Finally, the effect of worker density on the assignment of tasks to modes is analyzed with regard to the underlying number of stations (figure 8). For cases of low west ratio, i.e. a high number of stations almost no effect can be observed. As there is a high number of resources available even for low worker density, an increasing number of workers does not result in varying allocation of tasks to processing modes. Exceeding workers are rather assigned to short-time work than to new stations in the assembly line. Consequently the distribution remains practically unchanged. This is different for high west ratio. The initially low number of stations in combination with a low worker density requires a higher proportion of tasks being processed automatically and in collaboration. As soon as there is additional workforce available it is included in the line by establishing new stations (table 11 in the previous subsection). Since there are now more human workers in the assembly system compared to a constant number of cobots the proportion of tasks executed by human workers increases while automated and collaborative work decreases. However, this effect only applies to a certain extent. For worker density = 2 the amount of available resources is high enough so that the additional number of exceeding workers is rather assigned to short-time work in order to save station and labor costs.

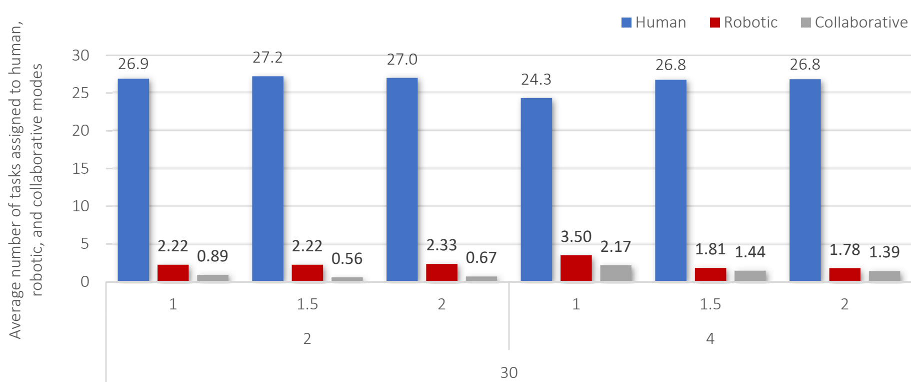



**Figure 8:** Assignment of tasks to modes (WD, WR)

Concluding, it can be derived that regarding the usage of the different processing modes, parallel work and therefore autonomous performance of cobots is especially beneficial for settings with a small amount of tasks per station and a high task flexibility. The preconditions for parallel processing in stations with cobots should therefore be provided in those cases. If the product structure, on the other hand, allows only for limited flexibility within the assignment of tasks and if more tasks have to be processed at each station then collaborative processing should be enabled preferably.

# 6 Conclusion

The global pandemic and its severe impact on societies and economies have revealed the urgency for companies to embrace digital transformation in order to be able to react quickly and adequately to changing environments. Manufacturing companies are challenged to set up automated and flexible production systems and to reconfigure their work sites to promote social and physical distancing which is especially difficult for manual production systems. Human-robot-collaboration is on the rise and plays a major role in this transition as it can generate significant benefits in terms of productivity, safety and cost efficiency. For companies to operate successfully in the future they must analyze their current production settings carefully and adapt them in a way so that they can respond best to these novel conditions.

In the context of this thesis, the novel planning problem of reconfiguring manual assembly lines with collaborative robots under consideration of short-time work and safety distances in the manufacturing process is investigated. In this problem setting, an existing manual assembly line is reconfigured so that initially multi-manned workstations are dispersed by assigning exceeding workforce either to short-time work or to newly added stations in the line. A mathematical model formulation is proposed to minimize the total costs of a production line including wages for regular workers, reduced wages for short-time workers, and costs for adding new stations to the line. An initial number of stations and workers and a limitation for cycle time are given. The model formulation is solved using a standard optimization solver and a reasonable number of solutions can be found. Due to the high complexity of the problem, however, the solver experiences difficulties determining feasible solutions in reasonable time with increasing number of tasks or if only limited resources are available for the processing of these tasks.

Overall, the results indicate that the deployment of cobots influences the decision making during a pandemic crisis. It increases the availability of resources wherefore more workers can be put in short-time work and stay home safely, especially in production systems with a low number of stations. This way distance requirements are fulfilled while at the same time additional costs are minimized.

Additionally, cobots can guarantee an ongoing production even if workers must go into self-quarantine so that consequently heavy profit losses can be prevented. The higher the flexibility within the task assignment the more workers should be assigned to short-time work, especially when cobots are available. The study also shows that the appropriate preconditions for parallel or collaborative processing in the stations depend on several factors and that they should be chosen carefully.

The presented model helps to identify potential cost savings which can be used as a measure for whether the acquisition of new cobots or the reallocation of existing ones from other product lines may be justified. Over a longer period, these savings may exceed the acquisition costs of new cobots or the productivity losses of other production lines from where the cobots would be reallocated. The potential is especially high for production systems that are characterized with a high number of tasks per station and a high number of workers. However, the decision situation is very complex and the specific setting differs for each company. Therefore the presented findings must be evaluated carefully as in another setting different conclusions may be drawn. Nevertheless, the model can provide useful support for the decision making in the context of a pandemic crises.

Although the presented approach can give interesting insights on the topic, further research is required in this field. For once, the development of heuristic solution procedures for the presented problem seems promising so that larger instances can be solved with less computational effort. Additionally, a data set that consists of a higher number of instances should be tested. Moreover, several model extensions should be investigated. A varying number of allowed workers per stations or the consideration of multiple production lines for the flexible use of cobots in more than one assembly line appear promising. Further research should also consider acquisition costs of cobots and alter the planning horizon so that long-term effects become visible. Finally, the presented approach only considers hard facts such as costs and time but neglects soft facts such as the state of mental health of the workers. As the pandemic has a strong impact on peoples mental health, this aspect should be taken into account as well.

# References


[1] Gao J. et al. (2009): An efficient approach for type II robotic assembly line balancing problems. *Computers & Industrial Engineering*, 56, 1065-1080. doi:10.1016/j.cie.2008.09.027.

[2] Boysen N., Fliedner M. & Scholl A. (2008): Assembly line balancing: Which model to use when?. International Journal of Production Economics, 111(2), 509-528. doi:10.1016/j.ijpe.2007.02.026.

[3] International Federation of Robotics (2020): IFR presents World Robotics Report 2020. *https://bit.ly/325hWAn*. Accessed 12.10.2020.

[4] Müller C., Grunewald M. & Spengler T. S. (2017): Redundant configuration of automated flow lines based on "Industry 4.0"-technologies. *Journal of Business Economics*, 87, 877-898. doi:10.1007/s11573-016-0831-7.

[5] Levitin G., Rubinovitz J. & Shnits B. (2006): A genetic algorithm for robotic assembly line balancing. *European Journal of Operational Research*, 168, 811-825. doi:10.1016/j.ejor.2004.07.030.

[6] Bi Z. M. & Zhang W. J. (2001): Flexible fixture design and automation: Review, issues and future directions. *International Journal of Production Research*, 39(13), 2867-2894. doi:10.1080/00207540110054579.

[7] Antonelli D., Astanin S. & Bruno G. (2016): Applicability of Human-Robot Collaboration to Small Batch Production. In: Afsarmanesh H., Camarinha-Matos L. & Lucas Soares A. (eds): *Collaboration in a Hyperconnected World*, PRO-VE 2016, AICT-480, 24-32. Cham: *Sprinter International Publishing.* doi:10.1007/978-3-319-45390-3_3.

[8] International Federation of Robotics (2018): SHAD opts for UR robot arms to optimize its manufacturing processes. *https://bit.ly/3jxojlO*. Accessed 12.10.2020.

[9] Bauer W. et al. (2016): Lightweight robots in manual assembly: best to start simply! Examining companies' initial experiences with lightweight robots. *Fraunhofer IAO. https://bit.ly/3aj76eA*. Accessed 17.09.2020.

[10] Bilberg A. & Malik A. A. (2019): Digital twin driven human–robot collaborative assembly. *CIRP Annals - Manufacturing Technology*, 68(1), 499-502. doi:10.1016/j.cirp.2019.04.011.

[11] Krüger J., Lien T. K. & Verl A. (2009): Cooperation of human and machines in assembly lines. *CIRP Annals - Manufacturing Technology*, 58, 628-646. doi:10.1016/j.cirp.2009.09.009.

[12] International Federation of Robotics (2020): IFR Press Conference - Presentation_WR_2020. *https://bit.ly/3oBsHEa*. Accessed 12.10.2020.

[13] Kuka AG (2018): LBR iiwa. *https://bit.ly/3otQqGh*. Accessed 13.10.2020.

[14] Daimler AG (2014): Employees and robots working directly together in production: Mercedes-Benz Cars receives international award for groundbreaking "Robot Farming" production concept. *https://bit.ly/3jDAltM.* Accessed 21.10.2020.

[15] Kuka AG (2017): HRC system in production at BMW Dingolfing. *https://bit.ly/34z82sk*. Accessed 12.10.2020.

[16] Liu Y. et al. (2020): Stability of SARS-CoV-2 on environmental surfaces and in human excreta. *medRxiv*. doi:10.1101/2020.05.07.20094805.

[17] Robert Koch Institut (2020): SARS-CoV-2 Steckbrief zur Coronavirus-Krankheit-2019 (COVID-19). *https://bit.ly/3e9cJvZ.* Accessed 18.09.2020.

[18] World Health Organization (2020): Q&As on COVID-19 and related health topics. *https://bit.ly/3jGcMkg*. Accessed 17.09.2020.

[19] Fachverband Metalltechnische Industrie (2020): Branchenausblick - Indikatoren und aktuelle Zahlen (COVID-19). *https://bit.ly/2TtnUpE.* Accessed 17.09.2020.

[20] Czypionka T. et al. (2020): Abschätzung der wirtschaftlichen Folgen des Ausbruchs des neuartigen Coronavirus (SARS-CoV-2). *Institut für Höhere Studien*, Policy Brief Nr. 15/2020. https://bit.ly/3bufoQX. Accessed 17.09.2020.

[21] PricewaterhouseCoopers GmbH (2020): PwC US CFO Pulse Survey. https://pwc.to/3e4GgXv. Accessed 21.10.2020.

[22] Reuters (2020): Coronavirus pandemic advances the march of 'cobots'. *https://reut.rs/37LGstL*. Accessed 21.10.2020.

[23] Amen M. (2006): Cost-oriented assembly line balancing: Model formulations, solution difficulty, upper and lower bounds. *European Journal of Operational Research*, 168, 747-770. doi:10.1016/j.ejor.2004.07.026.

[24] Becker C. & Scholl A. (2006): A survey on problems and methods in generalized assembly line balancing. *European Journal of Operational Research*, 168, 694-715. doi:10.1016/j.ejor.2004.07.023.

[25] Salveson M. E. (1955): The assembly line balancing problem. *Journal of Industrial Engineering,* 6, 18-25.

[26] Kriengkorakot N. & Pianthong N. (2007): The Assembly Line Balancing Problem : Review articles. *The KKU Engineering Journal*, 34(2), 133-140.

[27] Roshani A. & Giglio D. (2017): Simulated annealing algorithms for the multi-manned assembly line balancing problem: minimising cycle time. *International Journal of Production Research*, 55(10), 2731-2751. doi: 10.1080/00207543.2016.1181286.

[28] Battaïa O. & Dolgui A. (2013): A taxonomy of line balancing problems and their solution approaches. *International Journal of Production Economics*, 142, 259-277. doi:10.1016/j.ijpe.2012. 10.020.

[29] El Zaatari S. et al. (2019): Cobot programming for collaborative industrial tasks: An overview. *Robotics and Autonomous Systems*, 116, 162-180. doi:10.1016/j.robot.2019.03.003.

[30] Schou C. et al. (2018): Skill-based instruction of collaborative robots in industrial settings. *Robotics and Computer Integrated Manufacturing*, 53, 72-80. doi:10.1016/j.rcim.2018.03.008.

[31] Realyvásquez-Vargas A. et al. (2019): Introduction and configuration of a collaborative robot in an assembly task as a means to decrease occupational risks and increase efficiency in a manufacturing company. *Robotics and Computer Integrated Manufacturing*, 57, 315-328. doi:10.1016/j.rcim.2018.12.015.

[32] Müller R. et al. (2016): Process-oriented task assignment for assembly processes with human-robot interaction. *Procedia CIRP*, 44, 210-215. doi:10.1016/j.procir.2016.02.080.

[33] Pellegrinelli S. et al. (2016): A probabilistic approach to workspace sharing for human–robot cooperation in assembly tasks. *CIRP Annals - Manufacturing Technology*, 65, 57-60. doi:10.1016/j.cirp.2016.04.035.

[34] Michalos G. et al. (2018): Seamless human robot collaborative assembly - An automotive case study. *Mechatronics*, 55, 194-211. doi:10.1016/j.mechatronics.2018.08.006.

[35] Johannsmeier L. & Haddadin S. (2017): A Hierarchical Human-Robot Interaction-Planning Framework for Task Allocation in Collaborative Industrial Assembly Processes. *IEEE Robotics and Automation Letters*, 2(1), 41-48. doi:10.1109/LRA.2016.2535907.

[36] Rubinovitz J., Bukchin J. & Lenz E. (1993): RALB - A Heuristic Algorithm for Design and Balancing of Robotic Assembly Lines. *CIRP Annals - Manufacturing Technology,* 42(1), 497-500. doi:10. 1016/S0007-8506(07)62494-9.

[37] Bukchin J. & Tzur M. (2000): Design of flexible assembly line to minimize equipment cost. *IIE Transactions*, 32, 585-598. doi:10.1023/A:1007646714909.

[38] Yoosefelahi A. et al. (2012): Type II robotic assembly line balancing problem: An evolution strategies algorithm for a multi-objective model. *Journal of Manufacturing Systems*, 31, 139-151. doi:10.1016/j.jmsy.2011.10.002.

[39] Nilakantan J. M. et al. (2017): Differential evolution algorithm for solving RALB problem using cost- and time-based models. *The International Journal of Advanced Manufacturing Technology,* 89, 311-332. doi:10.1007/s00170-016-9086-2.

[40] Pereira J., Ritt M. & Vásquez Ó. C. (2018): A memetic algorithm for the cost-oriented robotic assembly line balancing problem. *Computers & Operations Research*, 99, 249-261. doi:10.1016/j.cor.2018.07.001.

[41] Li Z., Janardhanan M. N. & Ponnambalam S. G. (2020): Cost-oriented robotic assembly line balancing problem with setup times: multi-objective algorithms. *Journal of Intelligent Manufacturing*, 32, 989-1007. doi:10.1007/s10845-020-01598-7.

[42] Bock S. (2008): Supporting offshoring and nearshoring decisions for mass customization manufacturing processes. *European Journal of Operational Research*, 184, 490-508. doi:10.1016/j.ejor.2006.11.019.

[43] Moon I., Rasaratnam L. & Jeonghun Lee (2009): Integrated assembly line balancing with resource restrictions. *International Journal of Production Research*, 47(19), 5525-5541. doi:10.1080/00207540802089876.

[44] Salehi M., Maleki H. R. & Niroomand S. (2020): Solving a new cost-oriented assembly line balancing problem by classical and hybrid meta-heuristic algorithms. *Neural Computing and Applications*, 32, 8217-8243. doi:10.1007/s00521-019-04293-8.

[45] Kim D., Moon D. H. & Moon I. (2018): Balancing a mixed-model assembly line with unskilled temporary workers: algorithm and case study. *Assembly Automation*, 38(4), 511-523. doi:10.1108/AA-06-2017-070.

[46] Doerr K. H., Klastorin T. D. & Magazine M. J. (2000): Synchronous Unpaced Flow Lines with Worker Differences and Overtime Cost. *Management Science*, 46(3), 421-435. doi:10.1287/mnsc.46.3.421.12064.

[47] Li J. & Gao J. (2014): Balancing manual mixed-model assembly lines using overtime work in a demand variation environment. *International Journal of Production Research*, 52(12), 3552.3567. doi:10.1080/00207543.2013.874603.

[48] Fattahi P., Roshani A. & Roshani A. (2011): A mathematical model and ant colony algorithm for multi-manned assembly line balancing problem. *The International Journal of Advanced Manufacturing Technology*, 53, 363-378. doi:10.1007/s00170-010-2832-y.

[49] Kazemi A. & Sedighi A. (2013): A Cost-oriented Model for Multi-manned Assembly Line Balancing Problem. *International Journal of Services and Operations Management*, 16(3), 289-309. doi:10.1504/IJSOM.2013.056765.

[50] Kellegöz T., & Toklu B. (2015): A priority rule-based constructive heuristic and an improvement method for balancing assembly lines with parallel multi-manned workstations. *International Journal of Production Research*, 53, 736-756. doi:10.1080/00207543.2014.920548.

[51] Kellegöz T. (2017): Assembly line balancing problems with multi-manned stations: a new mathematical formulation and Gantt based heuristic method. *Annals of Operations Research*, 253, 377-404. doi:10.1007/s10479-016-2156-x.

[52] Yadaf A., Kumar S. & Agrawal S. (2020): Reconfiguration of assembly line balancing–an automobile case study solved by the exact solution procedure. *Benchmarking: An International Journal*, Vol. ahead-of-print, No. ahead-of-print. doi:10.1108/BIJ-08-2019-0386.

[53] Zamzam N. et al. (2015): Multi-Manned Assembly Line Balancing using Genetic Algorithm. *International Journal of Engineering Research & Technology*, 4(12), 56-61.

[54] Yilmaz H. & Yilmaz M. (2016): A multi-manned assembly line balancing problem with classified teams: a new approach. *Assembly Automation*, 36(1), 51-59. doi:10.1108/AA-04-2015-035.

[55] Yazgan H. R. et al. (2011): A new algorithm and multi-response Taguchi method to solve line balancing problem in an automotive industry. *The International Journal of Advanced Manufacturing Technology*, 57, 379-392. doi:10.1007/s00170-011-3291-9.

[56] Sikora C. G. S., Lopes T. C. & Magatão L. (2017): Traveling worker assembly line (re)balancing problem: Model, reduction techniques, and real case studies. *European Journal of Operational Research*, 259, 949-971. doi:10.1016/j.ejor.2016.11.027.

[57] Yilmaz H. & Yilmaz M. (2020): A mathematical model and tabu search algorithm for multi-manned assembly line balancing problems with assignment restrictions. *Engineering Optimization*, 52(5), 856-874. doi:10.1080/0305215X.2019.1618288.

[58] Weckenborg C. et al. (2019): Balancing of assembly lines with collaborative robots. *Business Research*, 13, 93-132. doi:10.1007/s40685-019-0101-y.

[59] Bücker T. (2021): Arbeit im Lockdown - Wo wird Homeoffice zum Problem? *Tagesschau*. *https://bit.ly/3n4XdFP*. Accessed 05.04.2021.

[60] Bundesministerium für Arbeit, Familie und Jugend (2020): COVID-19-Kurzarbeit - Häufig gestellte Fragen. *https://bit.ly/3naArwA*. Accessed 23.02.2021.

[61] Dar-El E. M. (1973): MALB - A Heuristic Technique for Balancing Large Single-Model Assembly Lines. *AIIE Transactions*, 5, 343-356. doi:10.1080/05695557308974922.

[62] Dar-El E. M. (1975): Solving Large Single-Model Assembly Line Balancing Problems - A Comparative Study. *AIIE Transactions*, 7(3), 302-310. doi:10.1080/05695557508975011.

[63] Teiwes J. et al. (2016): Identifying the Potential of Human-Robot Collaboration in Automotive Assembly Lines using a Standardised Work Description. *22nd International Conference on Automation and Computing*, 78-83. doi:10.1109/IConAC.2016.7604898.

[64] Kurth J. & Wagner M. (2020): Neue Planungsmethodik für Anlagen mit Mensch-Roboter-Kollaboration. *Zeitschrift für wirtschaftlichen Fabrikbetrieb*, 115(10), 689-702.

[65] Universal Robots A/S (2018a): Collaborative robot applications. https://bit.ly/2PYUNv4. Accessed 15.04.2021.

[66] Universal Robots A/S (2018b): Cobots offer game changing benefits. https://bit.ly/2vxAEQS. Accessed 15.04.2021.

[67] STATISTIK AUSTRIA (2020): Verdienststrukturerhebung 2018 - Bruttostunden-, Bruttomonats- und Bruttojahresverdienste nach Wirtschaftstätigkeit 2018. *Statistische Nachrichten 11/2020.* https://bit.ly/3fklIvr. Accessed 12.10.2020.

[68] Wirtschaftskammer Österreich (2020): Arbeiter-Kollektivvertrag in der für den Fachverband metalltechnische Industrie geltenden Fassung, Stand: 1.11.2020. https://bit.ly/2RdWuH7.

[69] Wirtschaftskammer Österreich (2020): Arbeiter-Kollektivvertrag in der für den Fachverband Fahrzeugindustrie geltenden Fassung, Stand: 1.11.2020. https://bit.ly/3fk7tqp.

[70] DEPRAG Schulz GmbH u. Co. (2021): Handarbeitsplätze. https://bit.ly/3wj36Tv. Accessed 12.10.2020.

[71] DEPRAG Schulz GmbH u. Co. (2009): Handarbeitsplätze in der Wirtschaftskrise - "Smart Work Benches" sorgen für Flexibilität und Prozesssicherheit. *Fachartikel April 2009.* https://bit.ly/3eU92wj. Accessed 12.10.2020.

[72] Bosch Rexroth AG (2020): Produktbeschreibung Arbeitsplatz. https://bit.ly/3we9YBi. Accessed 12.10.2020.

[73] Xpertgate (2021): Flexible teilautomatisierte Handarbeitsplätze THA® der Pfuderer Maschinenbau GmbH. https://bit.ly/33SyOuk. Accessed 12.10.2020.

[74] Hoberg Dr. P. (2020): Vorsicht bei der Anwendung von Maschinenstundensätzen. Fachbeitrag in *CONTROLLING-Portal.de*, https://bit.ly/3wepb5C. Accessed 12.10.2020.

[75] Fenebris - Expert Circle on Business Valuation (2021): Implied market risk premia. https://bit.ly/3wcCvXZ. Accessed 12.10.2020.

[76] Hoffmann T. R. (1959): Generation of permutations and combinations: Engineering Experiment Station, Report No. 13 (2013). Whitefish: *Literary Licensing, LLC.*

[77] Boysen N. & Fliedner M. (2008): A versatile algorithm for assembly line balancing. *European Journal of Operational Research*, 184, 39-56. doi:10.1016/j.ejor.2006.11.006.

# Appendices

## Appendix A

**Table 12:** Analysis of scenarios and $F$-ratio on complexity indicators

| | | | | $F$-ratio = 0.4 | | | $F$-ratio = 0.8 | | |
|---|---|---|---|---|---|---|---|---|---|
| Sc. | WR | RD | WD | Feasible (optimal) (# of 9) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) | Feasible (optimal) (# of 9) | Gap Ø($\sigma$) | CPU Ø($\sigma$) (s) |
| 1 | 4 | - | 1 | 1 (1) | 0 (0) | 0 (0) | 0 (0) | 0 (0) | 0 (0) |
| 2 | 4 | - | 1.5 | 4 (4) | 0 (0) | 333 (623) | 8 (3) | 0.09 (0.13) | 17,552 (14,531) |
| 3 | 4 | - | 2 | 9 (9) | 0 (0) | 32 (79) | 9 (3) | 0.14 (0.15) | 16,132 (15,023) |
| 4 | 4 | 0.2 | 1 | 2 (2) | 0 (0) | 29 (40) | 3 (1) | 0.18 (0.26) | 17,784 (15,505) |
| 5 | 4 | 0.2 | 1.5 | 5 (3) | 0.1 (0.14) | 6,911 (12,485) | 9 (3) | 0.19 (0.16) | 13,239 (14,782) |
| 6 | 4 | 0.2 | 2 | 9 (6) | 0.09 (0.15) | 3,649 (9,483) | 9 (4) | 0.22 (0.15) | 13,187 (14,821) |
| 7 | 4 | 0.4 | 1 | 2 (2) | 0 (0) | 18 (24) | 5 (3) | 0.12 (0.17) | 8,557 (12,823) |
| 8 | 4 | 0.4 | 1.5 | 6 (5) | 0.3 (0) | 5,631 (11,507) | 9 (2) | 0.15 (0.15) | 12,982 (15,008) |
| 9 | 4 | 0.4 | 2 | 9 (8) | 0.1 (0) | 3,874 (9,540) | 9 (2) | 0.15 (0.15) | 13,601 (14,501) |
| 10 | 2 | - | 1 | 9 (9) | 0 (0) | 7 (13) | 9 (7) | 0.08 (0.11) | 6,038 (11,844) |
| 11 | 2 | - | 1.5 | 9 (9) | 0 (0) | 474 (1,166) | 9 (7) | 0.06 (0.08) | 6,778 (11,801) |
| 12 | 2 | - | 2 | 9 (8) | 0.09 (0) | 3,243 (9,584) | 9 (7) | 0.09 (0.01) | 9,169 (13,729) |
| 13 | 2 | 0.2 | 1 | 9 (9) | 0 (0) | 44 (62) | 9 (5) | 0.08 (0.08) | 9,751 (14,290) |
| 14 | 2 | 0.2 | 1.5 | 9 (8) | 0.04 (0) | 5,335 (9,992) | 9 (6) | 0.07 (0.06) | 7,216 (12,348) |
| 15 | 2 | 0.2 | 2 | 9 (6) | 0.06 (0.05) | 7,842 (12,587) | 9 (5) | 0.06 (0.07) | 9,147 (11,892) |
| 16 | 2 | 0.4 | 1 | 9 (9) | 0 (0) | 71 (145) | 9 (6) | 0.04 (0.07) | 8,190 (12,618) |
| 17 | 2 | 0.4 | 1.5 | 9 (7) | 0.02 (0.03) | 3,789 (9,447) | 9 (6) | 0.04 (0.07) | 6,264 (9,661) |
| 18 | 2 | 0.4 | 2 | 9 (8) | 0.06 (0) | 3,483 (9,506) | 9 (6) | 0.08 (0.07) | 7,732 (12,480) |

# Appendix B

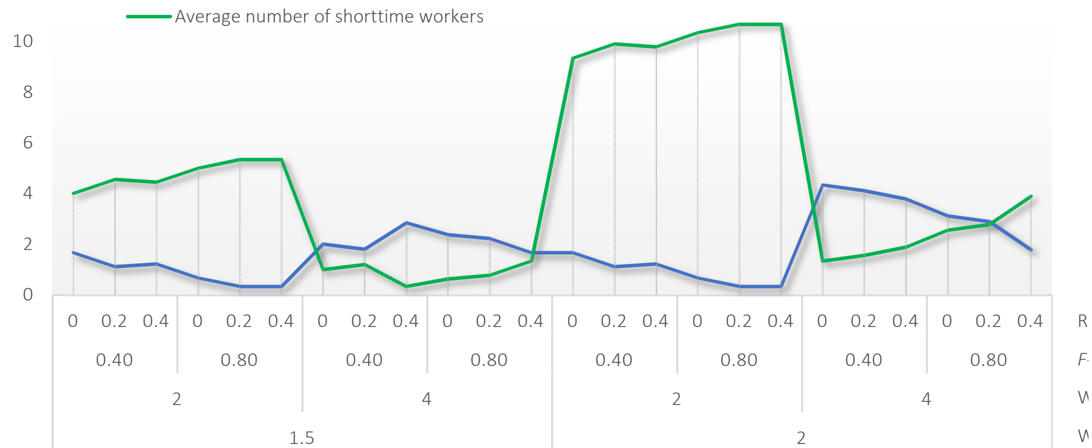



**Figure 9:** Short-time work vs. extended assembly line (all instances)

# Zusammenfassung

Diese Arbeit untersucht das Assembly Line Balancing Problem mit kollaborativen Robotern (Cobots) vor dem Hintergrund der Corona-Pandemie. Eine bestehende Montagelinie mit manuellen Stationen wird unter Berücksichtigung von Sicherheitsabständen sowie Kurzarbeit und Montagelinien-Erweiterung neu konfiguriert. Erforderliche Sicherheitsabstände zwischen Arbeitern werden berücksichtigt, indem die kostenminimierende Kombination von Kurzarbeitern und zusätzlichen Stationen gefunden wird, die die Anzahl der Arbeiter pro Station auf eins reduziert. Es wird eine gemischt-ganzzahlige quadratische Programmierformulierung (mixed-integer quadratic programming formulation) für die Planung von Montagelinien mit kollaborativen Robotern und Sicherheitsabständen entwickelt. Das Modell entscheidet über die Anzahl an Stationen im System, die Anzahl an Arbeitern in Kurzarbeit, die Zuordnung von Arbeitern und Robotern zu den einzelnen Stationen sowie die Verteilung der Arbeitsschritte auf die Ressourcen. Ziel ist es, die Gesamtkosten der Produktionslinie zu minimieren, welche aus Löhnen für reguläre Arbeiter, reduzierten Löhnen für Kurzarbeiter und Kosten für die Erweiterung der Montagelinie um neue Stationen bestehen. Zudem wird eine rechnerische Untersuchung mit Hilfe eines Simplex-Optimierers durchgeführt. Die Ergebnisse deuten darauf hin, dass das Modell Entscheidungsträgern in Pandemie-Zeiten sinnvolle Unterstützung bei der Planung von Montagelinien bieten kann. Darüber hinaus zeigen sie, dass durch den Einsatz von kollaborativen Robotern erhebliche Produktivitäts-, Sicherheits- und Kostenvorteile erzielt werden können.