Annals of Operations Research
https://doi.org/10.1007/s10479-021-04265-z

ORIGINAL RESEARCH

An integrated approach for lean production using simulation and data envelopment analysis

Sinem Buyuksaatci Kiris[1] · Enes Eryarsoy[2] · Selim Zaim[3] · Dursun Delen[4,5]

Accepted: 30 August 2021

Abstract

According to the extant literature, improving the leanness of a production system boosts a company's productivity and competitiveness. However, such an endeavor usually involves managing multiple, potentially conflicting objectives. This study proposes a framework that analyzes lean production methods using simulation and data envelopment analysis (DEA) to accommodate the underlying multi-objective decision-making problem. The proposed framework can help identify the most efficient solution alternative by (i) considering the most common lean production methods for assembly line balancing, such as single minute exchange of dies (SMED) and multi-machine set-up reduction (MMSUR), (ii) creating and simulating various alternative assembly line configuration options via discrete-event simulation modeling, and (iii) formulating and applying DEA to identify the best alternative assembly system configuration for the multi-objective decision making. In this study, we demonstrate the viability and superiority of the proposed framework with an application case on an automotive spare parts production system. The results show that the suggested framework substantially improves the existing system by increasing efficiency while concurrently decreasing work-in-process (WIP).

✉ Dursun Delen
dursun.delen@okstate.edu; dursun.delen@ihu.edu.tr
http://spears.okstate.edu/~delen

Sinem Buyuksaatci Kiris
sinemb@istanbul.edu.tr

Enes Eryarsoy
enes@sabanciuniv.edu

Selim Zaim
selim.zaim@izu.edu.tr

1 Faculty of Engineering, Industrial Engineering Department, İstanbul University-Cerrahpasa, Avcilar Campus, Istanbul, Turkey

2 Sabanci Business School, Sabanci University, Sabanci University Tuzla Campus, Istanbul, Turkey

3 College of Engineering, Department of Industrial Engineering, Istanbul Sabahattin Zaim University, Istanbul Sabahattin Zaim University Campus Halkali, Istanbul, Turkey

4 Department of Management Science and Information Systems (MSIS), Spears School of Business, Oklahoma State University, Tulsa, OK 74106, USA

5 School of Business, Ibn Haldun University, Istanbul, Turkey

Keywords Lean production · Time study · Multi-machine set-up reduction (MMSUR) · Single minute exchange of dies (SMED) · Simulation · Data envelopment analysis (DEA)

1 Introduction

Companies shape their business strategies around competitive forces such as threats of substitutes and new entrants, bargaining power of buyers and suppliers, and the existing rivalries (Porter, 1989). Environment dynamics, including the increasingly competitive landscape, changing market conditions, recent developments in technology, variability in customer demands, and shorter product life cycles, are forcing manufacturing firms to adapt to these shifting trends rapidly. Firms are focusing more on flexibility and productivity to prevail under such unstable market dynamics. Within manufacturing, flexibility refers to (i) adaptation capability to accommodate different product mixes, (ii) varying production volumes, (iii) being capable of manufacturing a new product, (iv) being able to accommodate varying delivery-time requirements (Suarez et al., 1995). Productivity, on the other hand, is a measure of efficiency that draws attention to internal factors such as production rate, econometrics, and time aspect of manufacturing. Flexibility abilities are necessary but not sufficient for the firms to remain competitive. Productivity and flexibility are both sine qua non for all manufacturing firms (Gustavsson, 1984). Productivity is one of the critical determinants of competitiveness in the manufacturing landscape (Nicholas, 2015). Lean manufacturing or lean production (LP, in short, from here onwards) is defined as a management philosophy that simultaneously focuses on improving productivity and minimizing waste. Besides productivity, LP also requires flexibility in labor as well as machinery & equipment usages (Chauhan & Singh, 2011).

LP emerged at Toyota as a modus operandi aiming to eliminate all kinds of non-value-added activities (Ohno, 1988). Waste, "muda" in Japanese, refers to all sorts of redundancies such as overproduction, delay, excess inventory, unnecessary movements, process wastes, among others. For example, in their earlier and seminal work, Naylor et al. (1999) showed an application of LP principles on a personal computer (PC) supply chain, wherein by eliminating non-value-added activities, they significantly improved the value chain efficiency.

According to Womack and Jones (1997, p. 10), there are five key principles of LP: precisely specify values by specific products, identify the value stream for each product, make value flow without interruptions, let customers pull value from the producer, and pursue perfection. During the last few decades, researchers have developed a variety of techniques to achieve leanness. Expectedly, many LP techniques originated in Toyota as a part of the Toyota Production System (TPS). The Kanban and Just-in-Time (JIT) production introduced to the US by Monden (1984), Total Productive Maintenance (TPM), mistake proofing/Poka Yoke, shop floor organization/5S, changeover reduction Single-Minute Exchange of Dies (SMED), analyzing current state using Value Stream Mapping (VSM), Total Preventive Maintenance (TPM) to name a few. Although initial applications of LP were in the automotive industry, it has then been successfully applied to a variety of other sectors, including aerospace, ceramics, construction, electronics, information management, textile, finance, and services (Doğan & Unutulmaz, 2016).

LP can also be considered as a management paradigm, in which that it requires an organization such as a production system to undergo significant changes in terms of both culture and infrastructure (Kull et al., 2014). Applying LP tools and techniques in manufacturing environments requires a redesign, continuous adjustments, and reconfigurations (Greinacher et al., 2016). These continuous adjustments take place by migrating from the current state VSM of a production system to a leaner VSM corresponding to a leaner system (Rahani & Al-Ashraf, 2012). For example, the adjustments can bring about improvements in terms of work-in-process (WIP) levels (Rahani & Al-Ashraf, 2012), process cycle times (Biswas & Sarker, 2008; Rahani & Al-Ashraf, 2012), improved equipment replacements (Sullivan et al., 2002), optimizing batch quantities (Biswas & Sarker, 2008), minimized the number of defects (Dhafr et al., 2006), reduced waiting times (Gijo & Antony, 2014), reduced transport times (Villarreal et al., 2017), improved motion time study results (Meyers & Stewart, 2002), among others.

This paper presents SMED, multi-machine set-up reduction (MMSUR), and line balancing techniques in conjunction with simulation modeling and data envelopment analysis (DEA) to analyze and suggest productivity improvements in a manufacturing system. Accordingly, a simulation-enhanced LP case study for a Turkish automobile spare parts company is conducted. In this study, we use SMED and MMSUR methods to decrease setup times, assembly line balancing to balance workflow, Monte-Carlo simulation to assess the current system and generate alternative scenarios, and DEA to evaluate these scenarios and choose the best one for LP improvements. We believe that this study contributes to the literature by systematically combining several established techniques (e.g., SMED, MMSUR, Monte-Carlo simulation, and DEA) synergistically and by providing a generalized framework to solve similar LP improvement problems within manufacturing systems.

The organization of this paper is as follows. In the next section, we briefly introduce the background. In Sect. 3, the case and problem description are provided, and the proposed methodology is explained. Section 4 presents and discusses the findings of the study. Section 5 provides the summary and concluding remarks.

2 Background

Manufacturing systems are dynamic and complex systems that comprise interconnected sub-processes with both predictable and unpredictable variabilities. Improving such systems with LP may therefore lead to unforeseen issues and complexities. Hence, studies using quantitative techniques to achieve the LP objectives need to be designed to address such issues. These issues may arise because of (i) having to deal with multiple conflicting objectives pertaining to the LP problem, (ii) the need to assess the “leanness” of a system and/or its alternatives, (iii) dealing with overly complex objective functions to achieve LP goals.

(i) Conflicting objectives: multiple objectives may emerge when decision-makers face multiple lean measures or various alternatives that conflict with each other. These conflicting alternatives can be evaluated by creating a viable multi-objective optimization problem and solving it using multi-criteria optimization techniques (Gurumurthy & Kodali, 2008).
(ii) Leanness assessment: assessing different LP improvements or measuring/monitoring the “leanness” may not be trivial. Studies use statistics for monitoring/measuring (Markarian, 2004), or fuzzy logic to assess “leanness” (Li et al., 2020; Susilawati et al., 2015; Vinodh & Balaji, 2011). Studies also compare different LP design alternatives or VSMs applying techniques such as group decision making (GDM) with fuzzy approach (Vinodh & Chintha, 2011; Wu et al., 2016), or DEA (Azadeh et al.,

2017; Meza & Jeong, 2013) besides others. DEA is a linear programming-based, non-parametric deterministic method of measurement where the production function can assume any form (Zaim et al., 2008).

(iii) Complexities in optimization: using optimization techniques including linear or mixed-integer programming is among the viable approaches in LP (De Matta et al., 2001; Kilic & Durmusoglu, 2013; Mao et al., 2019). As the complexity of the systems increase, finding closed-form analytical solutions for such systems may become unworkable via formal mathematical models. Optimizing the objective functions within reasonable times by a computational system may become impossible. Therefore, in the cases of complex objective functions, heuristics (Monkman et al., 2008) or meta-heuristics (Agarwal et al., 2006; Ohlmann et al., 2008) may be used.

Another popular approach in dealing with overly complex systems is to use simulation modeling. Based on initial conditions and system control parameters, simulation modeling has proven to be instrumental for systems analysis tasks where no solution with a finite or manageable number of mathematical expressions (a.k.a., a closed-form solution) can be found. Because of the highly complex nature of the manufacturing systems, simulation modeling is one of the most widely used analytics tools to design, reconfigure and critically analyze complex dynamic manufacturing systems (Negahban & Smith, 2014; Robinson, 2004). Monte-Carlo simulation is among the most popular quantitative techniques used in the LP literature. Within LP, researchers have used simulation techniques in different domains such as healthcare (Baril et al., 2016; Barnabè & Giorgino, 2017; Doğan & Unutulmaz, 2016), management and services (Ahlstrom, 2004; Jordon et al., 2019; Zarrin & Azadeh, 2017), manufacturing (Diaz-Elsayed et al., 2013; Greinacher et al., 2016; Yang et al., 2015) successfully. For more applications of simulation in manufacturing system design and redesign, interested readers may refer to Esmaeilian et al. (2016).

Assembly or production lines are widely used in manufacturing systems for mass production. Unbalanced assembly lines often cause the formation of bottlenecks. These bottlenecks impede LP by causing excess levels of WIP, longer waiting times and delays, and overproduction of intermediate parts and components. LP aims at minimizing waste. Line balancing, therefore, has been an important research topic of LP in manufacturing (He et al., 2020; Scholl et al., 2009; Soroush et al., 2014).

3 Problem description and methodology

3.1 Problem description

Since its introduction in the 1940s, LP techniques such as VSM, SMED, MMSUR, TPM have been widely used to achieve leanness in manufacturing facilities. These techniques are used jointly or independently. Measuring the leanness of a production facility itself is a difficult problem. While there are widely used measures such as product cycle time, work-in-process levels, and lead time, measuring the leanness using such metrics that often correlate or conflict with each other has been proven to be difficult (Hopp & Spearman, 2000). While the reconfiguration of production systems to achieve LP is a smart practice, frequently doing so with the actual system is drawn-out and costly. Therefore, simulation under different production reconfigurations, using alternative production scenarios, may be used. In addition to simulation, herein, we propose using DEA to choose the most productive alternatives that are associated with a variety of inputs and outputs.

In this study, we offer a blueprint methodology to combine LP techniques with simulation and DEA. We demonstrate our approach via an application of process improvements within an automotive spare parts manufacturer. The manufacturer was founded in 1968 and is located in Turkey. The company, among other products, manufactures armrests for automobiles shown in Fig. 1.

In the existing system, the armrest production line includes six major stations (Fig. 2). In the first station, injection machines print all parts using Acrylonitrile–butadiene–styrene (ABS). Dimensional stability is important for the subsequent processes. Therefore, the parts coming out of the injection machine are measured prior to the next process, polyurethane (PU) coating. The third station is for the adhesive (gluing) application process for skin surface coating. The parts are then left to dry in the oven for ten minutes before moving to the fourth station, where bending and folding operations take place. The hinge is mounted, and the

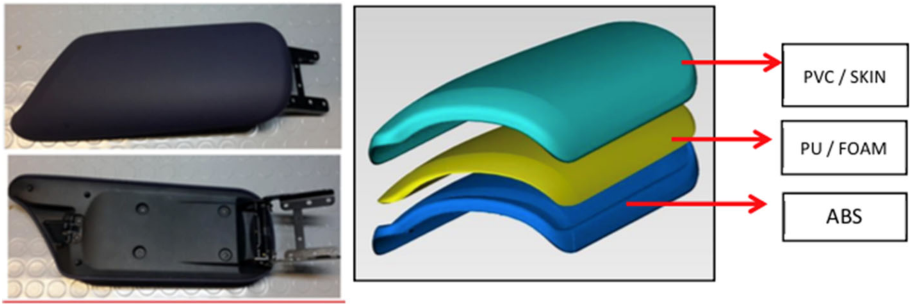


Fig. 1 The left armrest produced by the manufacturing system

Fig. 2 The production flow of the left armrest

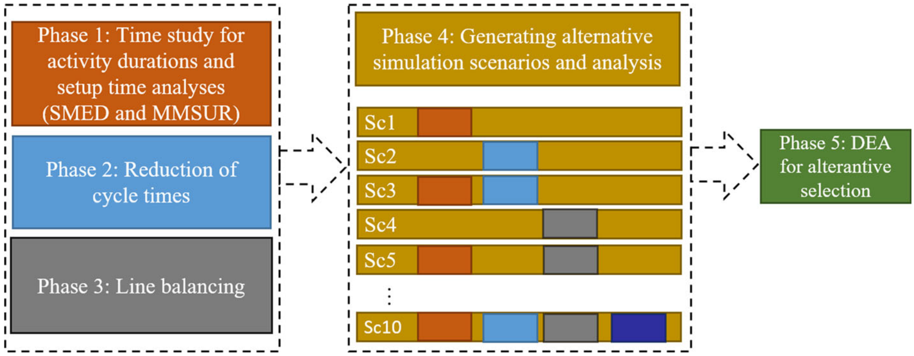


Fig. 3 The general framework of the applied approach

bottom part is screwed in the fifth station. Finally, the part is moved to the packaging station upon inspection.

Using the time study method on the armrest production line, we concluded that cooling times and unnecessary robot apparatus movements are over-extending the production times of parts in the injection machine. We also detected unbalanced operator workloads in the assembly line that were impeding productivity. We also found that the flexibility of the assembly line can be improved by reducing the in-between distances of the stations and enabling operators to perform more than one task at a time. Our study, therefore, suggested applying SMED, MMSUR, and line balancing techniques as lean tools and then, use different simulation scenarios coupled with DEA to analyze and evaluate the productivity improvement alternatives.

3.2 Methodology and analysis

For the current study, we propose a five-phased framework. These phases are (i) time study (SMED and MMSUR), (ii) cycle-time reduction, (iii) assembly line-balancing, (iv) simulating alternative scenarios, and (v) employing DEA for the alternative selection. We illustrate the proposed framework in Fig. 3.

3.2.1 Phase 1: time study, SMED, and MMSUR

Shorter setup (i.e., changeover) times are vital in LP. Shortening setup times can make smaller-lot production feasible, decrease setup scrap and setup labor cost, increase production flexibility, and reduce product lead times and manufacturing costs (Singh & Khanduja, 2010). SMED was initially applied by Shingo (Dillon & Shingo, 1985) at Mazda to reduce setup times. The primary purpose of the technique is to shorten equipment setup operations to under 10 min. SMED is a three-step procedure. In the first step, we label setup activities as internal or external. External activities are those that can be performed while the machine is still operational. Internal activities, however, can only take place when the machinery is not running. The second step identifies internal activities that can be converted to external activities via small, inexpensive changes (Trovinger & Bohn, 2005). The third and final step involves streamlining all setup activities, both internal and external, using techniques like method study, VSM, cause-and-effect analysis, or Pareto charts (Hines & Rich, 1997).

Table 1 Operator-time analysis

	OPERATOR 1		OPERATOR 2		OPERATOR 3	
	Time (s)	Perc. (%)	Time (s)	Perc. (%)	Time (s)	Perc. (%)
Internal setup time	68.38	3	37.0	1	510.1	19
Unnecessary time	680.01	25	168.7	6	173.4	6
External setup time	613.68	23	1188.3	44	202.5	8
Idle time	1337.97	50	1306.0	48	1814.1	67

The initially proposed version of SMED is effective with setups involving a single-machine. This was later generalized to MMSUR technique by Van Goubergen (2008). MMSUR relies on the creation of a multi-activity diagram both for operators and machines. The diagram depicts each successive machine or process in a column. All activities are then plotted along the time axis vertically, in their individual blocks, under their corresponding columns. A multi-person activity diagram shows who is doing what and when. If the diagram reveals setup time improvements, the activities are rearranged by repositioning the respective activity blocks. Because of the complexity of multi-machine systems, the rearrangements are carried out iteratively. At each iteration, the bottleneck machine is identified and targeted to reduce setup times.

In our manufacturing system, we replace the molds after one job order on each of the ten injection machines every 8 h. There are three separate setup operators for this mold-changing process. We give the internal and external activity times for each of the operators in Table 1. The table revealed operators were mostly idle.

Using root-cause analysis, we identified the causes as:

- High setup times in the injection machine
- Unscheduled and unbalanced operator workloads during the setup process
- Some external activities were carried out as if internal
- The operators initiated all mold-changing operations after stopping the machines.

Our root-cause analysis suggested:

- Assign existing workloads to the operator's idle times according to process priorities,
- Complete external activities such as raw material transportation, prior to stopping the injection machines,
- Standardize internal activities via the 5S method,
- Remove screw use during lock exchange.

In the light of the suggestions above, unnecessary waits and operations were eliminated, and a multi-activity diagram for the current system was produced. The changes achieved a 40.9% reduction in setup times (from 2700 s down to 1594 s). The current multi-activity diagram is provided in Appendix Table 8.

3.2.2 Phase 2: reduction of cycle times

Reducing the cycle time improves the productivity (i.e., throughput) of a process. Reduced cycle times may also improve quality by creating time buffers to help workers avoid unnecessary rushing to prevent making mistakes.

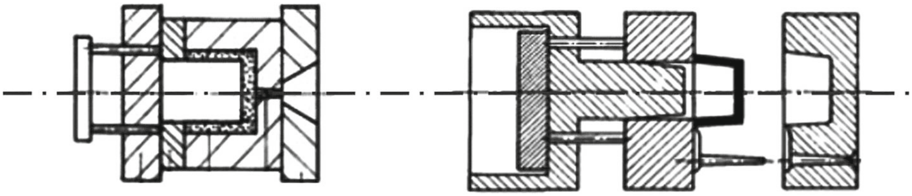


Fig. 4 Closed (left) and open (right) states of the injection mold

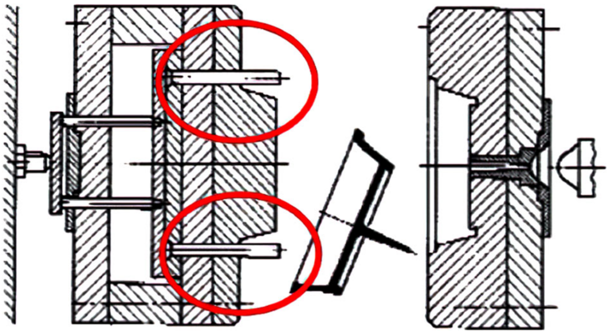


Fig. 5 Ejector pins and the mold

In our case, the removal of the part from the injection machine depends on the spacing of the molds (Fig. 4). That is, the gap must be just wide enough to insert the robot apparatus into the mold that separates the male part from the female part. By minimizing the gap, we reduced the cycle time by 5 s (from 48 down to 43).

After the use, molds required a significant time to cool down. We found the cooling time to be longer than necessary (43 s). Upon conducting quality tests, we reduced the cooling time by 4 s. Ejection pins are used to start the removal of parts from molds (Fig. 5). In the original setup, ejection pins stood by as the robot apparatus is inserted into the mold. The ejector pins were then pulled out. We improved the cycle time by an additional 4 s by pulling out ejector pins immediately.

3.2.3 Phase 3: assembly line balancing

When tasks are not evenly distributed over workstations in a production system, bottlenecks and idle capacities arise. Leveling the workload by reconfiguration is often achieved by reducing the number of workstations. Many studies in the literature suggested using a variety of techniques when leveling the workload, such as optimization, exact solution procedures, meta-heuristics, mixed integer programming depending on the objectives and the assembly line type. Boysen et al. (2008) offer an excellent review of the types of assembly line balancing problems and models to solve them.

In our manufacturing facility, the assembly line is comprised of polyurethane coating, outer coating, folding, screwing, and packing stations. The stations were positioned too far apart from each other, limiting operators' ability to perform multiple tasks simultaneously. We reconfigured the assembly layout and rebalanced the line using the ranked positional weight method suggested by Helgeson and Birnie (1961). The general idea behind their method is to prioritize the tasks that have long chains of succeeding tasks (Rekiek et al., 2002). The method assigns tasks to workstations according to their ranked positional weights by taking processing times and precedencies into account. Our assembly line comprised 110 tasks. Table 2 shows the predecessors and processing times for tasks. Following Becker and Scholl (2006), we calculated the minimum number of required workstations (n) and line efficiency $E(\%)$ as: $n = \frac{\sum_{i=1}^{j} t_i}{c} = \frac{449.5}{180.3} \cong 3$, and $E(\%) = \frac{\sum_{i=1}^{j} t_i}{n \times c} = \%83.1$ respectively (where t_i is the completion time for task $i,\ j$ is the number of tasks, and c stands for the cycle time). The results suggested balancing the 5-station assembly line by redesigning it with 3 stations.

Table 2 Assembly line task data

Task #	Time (s)	Predecessor task	Task #	Time (s)	Predecessor task	Task #	Time (s)	Predecessor task
1	1.6	–	52	1.8	51	82	2.0	80, 81
2	4.2	1	53	1.2	52	83	2.1	–
3	2.2	–	54	2.0	53	84	4.7	82, 83
4	7.9	2, 3	55	1.1	50	85	0.9	84
5	1.6	4	56	1.1	55	86	2.6	85
6	2.2	4	57	0.8	56	87	0.9	86
7	126.6	5, 6	58	1.8	57	88	1.7	87
18	1.1	7	59	1.4	54, 58	89	0.7	88
19	1.5	18	60	15.2	59	90	4.4	89
20	0.9	19	61	0.7	60	91	1.3	–
21	2.1	20	62	1.0	54,58	92	15.0	90
22	5.8	20	63	1.7	62	93	1.09	90
23	0.7	21, 22	64	1.1	61	94	7.4	93
24	17.7	23	65	3.0	64	95	4.3	92, 94
25	0.7	24	66	2.4	65	96	2.2	95
26	0.7	24	67	1.6	63	97	1.0	96
27	1.1	26	68	7.0	66, 67	98	4.3	97
28	2.2	25, 27	69	2.3	68	99	0.7	96
40	0.9	28	70	56.5	69	100	7.8	99
41	5.9	40	71	1.5	70	101	0.6	100
42	1.7	28	72	1.7	71	102	1.6	96
43	1.0	42	73	3.1	72	103	3.9	98, 101,102
44	4.2	43	74	1.4	73	104	1.3	103
45	1.3	44	75	1.3	–	105	0.8	104
46	1.2	28	76	3.4	75	106	0.7	103
47	4.4	41, 45, 46	77	0.6	76	107	1.8	106
48	0.9	47	78	0.5	76	108	1.1	107
49	0.8	48	79	3.7	77	109	0.7	105, 108
50	41.5	49	80	0.5	79	110	2.9	109
51	2.2	50	81	0.9	76			

3.2.4 Phase 4: simulating alternative scenarios

Physical reconfiguration of the production systems can be lengthy and costly. Using simulations for different production reconfigurations is typically used in LP literature.

In our manufacturing system, we performed simulations to determine improvements and to propose changes to the existing system. We made the following assumptions for simulation:

- The system operates 24 h a day.
- Work orders arrive every 8 h.
- No disruption of the apparatus and the injection machine.
- No repairs or daily maintenance.
- No accidents or interruptions involving the operators.

We also defined existing system components as follows:

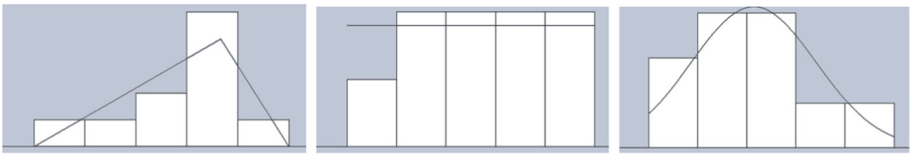
- Raw materials (Polyurethane, ABS, Polyvinyl chloride, Polypropylene)
- Injection machine
- Oven
- Gluing, folding, screwing, and control equipment
- Injection operator (1 person)
- Assembly Operators (5 people)
- Setup Operators (3 people)
- Raw material car
- Raw material controller
- Required lower parts (screw, hinge, etc.)
- Measuring and control instruments

Using the Input Analyzer in Rockwell Arena 13.5 Simulation software, we decided the statistical distributions of the processing times in polyurethane coating, outer coating, folding, screwing, and packaging stations. Some examples are given in Fig. 6.

We combined 110 tasks listed in Table 2 for further simplification. Figure 7 depicts the resulting combined tasks and the simulation model of the existing system on Rockwell Arena 13.5 simulation software. The existing system after balancing is illustrated in Fig. 8.

In order to assess the effects of each change made in the existing system, we created ten different scenarios. The scenarios included different combinations of SMED and MMSUR, cycle time reduction, assembly line balancing processes, and a varying number of operators (Table 3).

We tested the scenarios by running the simulations multiple times with cross-checks, and we validated the simulation process for both of the models. We simulated each scenario for 24-h with 100 replications in order to account for variations in process times. Tables 4 and 5 show our results.



Operation: 2
Distribution: Triangular
Expression: TRIA (2.21, 4.55, 5.4)

Operation 92:
Distribution: Uniform
Expression: UNIF (13.2, 16.5)

Operation 103
Distribution: Normal
Expression: NORM (4.14, 1.05)

Fig. 6 Examples of process distribution types using Arena Input Analyzer

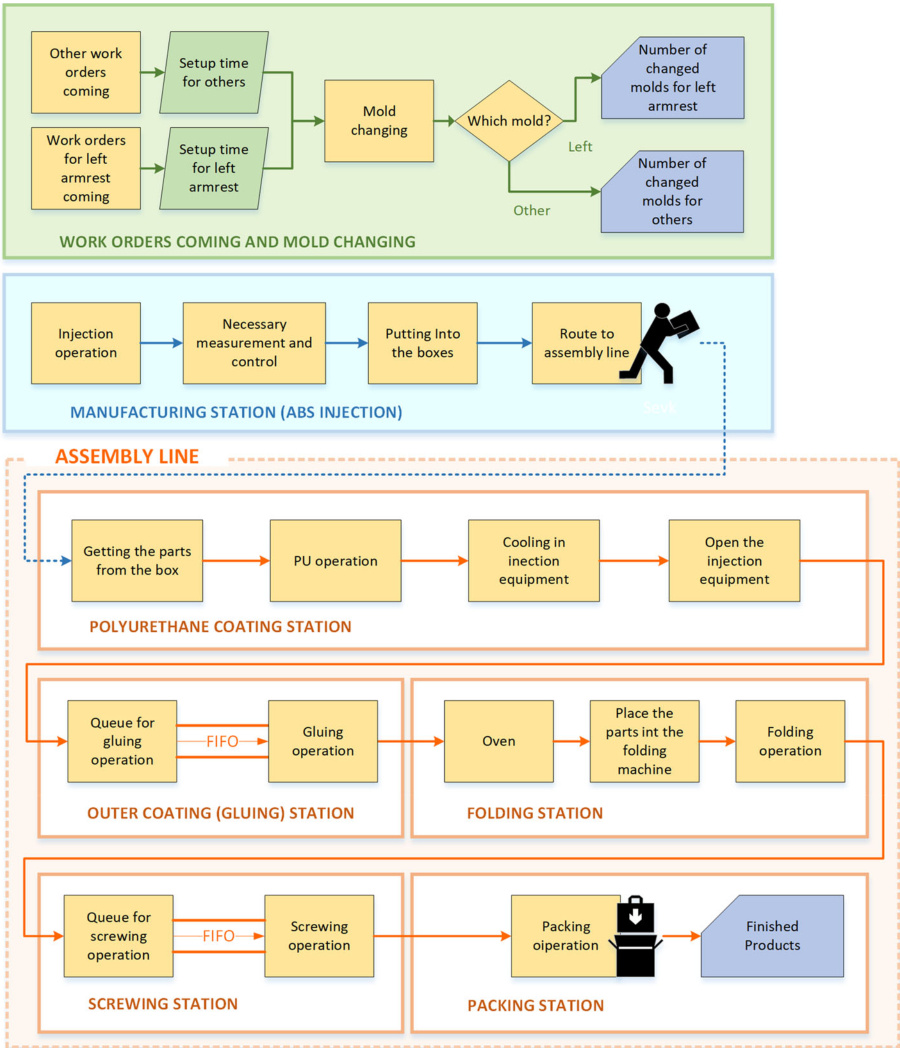


Fig. 7 Simulation model of the existing system

3.2.5 Phase 5: DEA for alternative selection

The first three phases in our proposed framework involve analysis and streamlining of the production processes. These precursor phases allow for creating streamlined, balanced, and more efficient alternatives. We then perform several shortened and streamlined alternative production scenarios using simulation. The last phase involves choosing the most efficient alternative using DEA.

DEA is a non-parametric method used to measure the productivity of different organizational units called decision-making units (DMU). These units are typically associated with incomparable inputs and outputs. DEA was proposed by Charnes et al. (1978) and is used

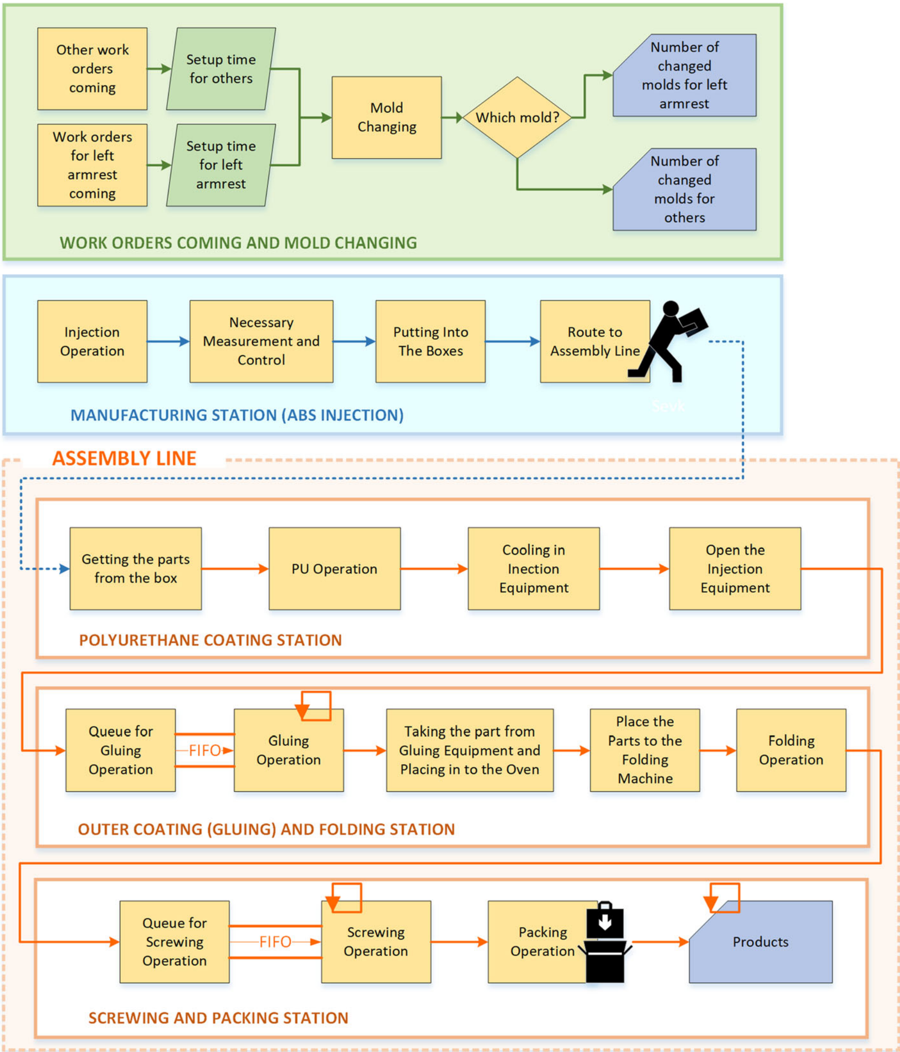


Fig. 8 Simulation model after assembly line corresponding to the combined tasks

to form a "best-practice frontier" of efficient DMUs, assuming no particular shape for the frontier. While DEA does not provide a particular function relating to inputs and outputs, it measures the relative efficiency of DMUs based on linear programming techniques. DEA establishes an efficient frontier by computing convex-combination of efficient DMUs and creates an efficiency index for each non-frontier DMUs based on their distances to the frontier. DEA, therefore, enables peer-group comparisons according to the "efficient frontier" rather than making comparisons according to, say, an average performer like in the case of OLS. DEA also can assess the relative strengths of relationships between multiple inputs and multiple outputs for DMUs, which presents considerable advantages over other traditional methods (Demirbag et al., 2009). Aldamak and Zolfaghari (2017) provide an excellent review

Table 3 Scenarios for analysis

	SCENARIOS									
	Sc1	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7	Sc8	Sc9	Sc10
SMED & MMSUR	✓		✓		✓	✓			✓	✓
Cycle time reduction in injection station		✓	✓				✓	✓	✓	✓
Assembly line balancing				✓	✓	✓	✓	✓	✓	✓
Change in number of operators						✓		✓		✓

and explanation of DEA techniques. A variety of DEA models exist in the literature. Due to its complex decision modeling capabilities, DEA is frequently used to analyze productivity changes in manufacturing systems and supply chains (Yang et al., 2015; Zhou et al., 2013; Nemati et al., 2020) related operations.

The CCR model While there are several types of DEAs that exist, the earliest due to Charnes et al. (1978), known as CCR. CCR assumes constant returns to scale and is suitable to use when inputs or outputs of DMUs do not vary significantly. DEA can be constructed using either an input orientation or an output orientation. While input-oriented DEA provides insights on how to improve input levels by keeping output levels the same, output-oriented DEA focuses on how much the outputs can be increased without changing current input levels. In this study, we used an output-oriented DEA model. The output-oriented DEA model proposed by Charnes et al. (1978) is as Eqs. (1)–(4):

$$Max\,Z_o = \theta_o + \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \tag{1}$$

$$s.t.$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \ldots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta_o y_{ro} \quad r = 1, \ldots, s \tag{3}$$

$$\lambda_j, s_r^+, s_i^- \geq 0 \quad for\ all \quad i, j, r \tag{4}$$

where θ is the corresponding efficiency score for scenario o under investigation, and λ_j are the dual variables. The scenario o generates output s by consuming input m, which are included as x_{io}, and y_{ro} respectively. Amounts of excess for input and the amount of deficit for output are represented by s_r^+ and s_i^- respectively. $\varepsilon > 0$ is a predefined non-Archimedean element. Equation (2) is the constraint that the level of input i for a scenario o is equal to a linear combination of inputs plus the excess s_i^-. Equation (3) maintains that the optimal output is also a linear combination of the outputs minus the slack s_r^+. When scenario o is efficient, the objective function yields ($\theta = 1$) and ($s_r^+ = s_i^- = 0$). Such scenarios are referred to as members of the "reference set", and form the efficiency frontier.

Table 4 Simulation results for the existing system and ten different scenarios

	EXISTING SYSTEM	Sc1	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7	Sc8	Sc9	Sc10
Setup time before injection machine (mold changing)	45 min	26 min	45 min	26 min	45 min	26 min	26 min	45 min	45 min	26 min	26 min
Cycle time of injection machine	48 s	48 s	35 s	35 s	48 s	48 s	48 s	35 s	35 s	35 s	35 s
Number of operators working in assembly line	5	5	5	5	4	4	3	4	3	4	3
Number of work orders for left armrest	4	4	4	4	4	4	4	4	4	4	4
Average number of armrests produced	412	506	474	563	413	507	506	474	474	5564	5563
Average number of parts waiting for injection	276.01	251.53	249.25	216.51	275.86	252.38	252.70	250.42	250.23	2214.29	2213.72
Average number of parts waiting for mold change	8.1525	5.4537	7.8080	4.4059	8.3205	5.3033	5.1502	7.6958	7.6683	4.5820	4.7402
Average number of parts waiting for gluing	10.8204	15.7967	13.8432	19.7803	0.0190	0.0233	17.2189	0.0213	15.1383	0.0260	21.3769

Table 5 Average utilization rates of machines and operators

	EXISTING SYSTEM	Sc1	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7	Sc8	Sc9	Sc10
Usage rate of injection machine	100	99.93	99.63	96.22	100	99.93	99.93	99.63	99.63	96.19	96.11
Usage rate of injection operator	26.55	38.69	31.18	46.39	26.52	38.30	38.72	31.14	30.56	45.82	45.99
Usage rate of injection equipment	48.52	115.35	53.09	64.90	48.52	115.15	57.66	53.09	53.09	64.90	64.85
Usage rate of gluing equipment	48.11	58.79	55.33	65.52	40.06	47.62	58.98	43.93	55.50	53.63	65.65
Usage rate of oven	18.83	23.00	21.64	25.63	6.35	7.55	6.91	6.96	6.50	8.51	7.69
Usage rate of folding equipment	48.23	58.98	55.45	65.68	48.23	58.94	58.95	55.45	55.42	65.71	65.60
Usage rate of screwing equipment	29.14	35.66	33.50	39.70	29.14	35.66	35.66	33.53	33.51	39.75	39.66
Utilization of Set-up Operators	20.03	41.78	21.82	15.13	20.05	42.37	13.91	21.83	22.05	15.33	15.25
Utilization of Line Operator 1	30.72	36.55	33.61	41.10	30.73	36.47	36.52	33.62	33.62	41.10	41.08
Utilization of Line Operator 2	48.11	58.79	55.33	65.52	18.24	21.68	46.94	20.01	44.17	24.42	52.26
Utilization of Line Operator 3	48.23	58.98	55.45	65.68	22.20	27.12	53.43	25.53	50.23	30.24	59.45
Utilization of Line Operator 4	29.14	35.66	33.50	39.70	43.68	53.44	–	50.23	–	59.57	–
Utilization of Line Operator 5	09.98	12.24	11.50	13.63	–	–	–	–	–	–	–

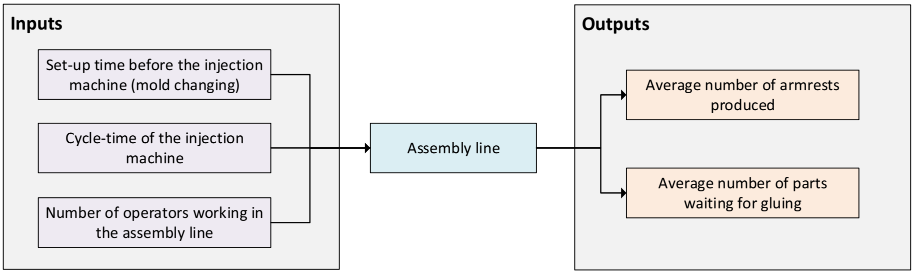


Fig. 9 The DEA model of Assembly Line

The super-efficiency model In the CCR model, all the DMUs in the reference set are indicated by an efficiency score of one, limiting the ability to compare DMUs in the reference set. We refer to methods that enable ranking and comparing different efficient DMUs in the reference sets to super-efficiency models. In this paper, we used the super-efficiency model introduced by Andersen and Petersen (1993). For each DMU, the super-efficiency model removes the investigated DMU from the reference set and monitors the rates of increases in the inputs of reference set DMUs. All DMUs are then sorted based on their efficiency scores. The super-efficiency model formulation is almost identical to the CCR model and is given in Eqs. (5)-(8).

$$\begin{aligned} &MinZ_0 = \theta \\ &s.t. \end{aligned} \tag{5}$$

$$\sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j x_{ij} \leq \theta x_{io} \quad i = 1, \ldots, m \tag{6}$$

$$\sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y_{rj} \geq y_{ro} \quad r = 1, \ldots, s \tag{7}$$

$$\theta, \lambda_j \geq 0 \quad j \neq o \tag{8}$$

In line with the company's expectations, expert opinions, and the reviewed literature, we select three indicators as our input variables. These indicators are "setup time before injection machine (mold changing)", "cycle-time of the injection machine," and "the number of operators working in the assembly line," respectively.

In general, selecting a single output variable as a performance indicator is difficult. In this study, we used "*Average number of armrests produced*" and "*Average number of parts waiting for gluing*" as our output variables. The proposed DEA model and the results obtained by solving the model in DEA Frontier Software are given in Fig. 9 and in Table 6, respectively.

4 Results and discussion

Efficiency is often described as "output divided by input". In complex systems, where there are multiple inputs and outputs, the measurement of efficiency (often referred to as "Pareto–Koopmans efficiency") is embedded in complex formulations within DEA analysis. The DEA analysis requires defining and carefully selecting the input and output variables.

Table 6 CCR-O and SE-O assembly line efficiencies according to given input and output values

Alternatives	INPUTS			OUTPUTS		CCR-O efficiency scores	Return-to-Scale	Super efficiency score
	INPUT1	INPUT2	INPUT3	OUTPUT1	OUTPUT2			
Existing	45	48	5	412	10.5596	0.53744	Constant	0.53744
Scenario 1	26	48	5	506	5.5833	0.89716	Increasing	0.89716
Scenario 2	45	35	5	474	7.5368	0.84043	Increasing	0.84043
Scenario 3	26	35	5	563	1.5997	0.99823	Increasing	0.99823
Scenario 4	45	48	4	413	21.361	1	Increasing	1
Scenario 5	26	48	4	507	21.3567	1	Increasing	1.00013
Scenario 6	26	48	3	506	4.1611	0.96333	Increasing	0.96333
Scenario 7	45	35	4	474	21.3587	1	Increasing	1.00022
Scenario 8	45	35	3	474	6.2417	0.9388	Increasing	0.9388
Scenario 9	26	35	4	564	21.354	1	Increasing	1.36365
Scenario 10	26	35	3	563	0.0031	1	Increasing	1.22556

We used Eqs. (1)–(4) to derive the efficiency score for each of the alternative scenarios and the existing system. 5 scenarios (Scenarios 4, 5, 7, 9, and 10) appeared as efficient units, as shown in Table 6. Although all the efficient units have the same conventional CCR efficiency score of ‘1’, their super-efficiency scores, which are ‘> 1’ may be different. This provides the motivation for discriminating between efficient units using the super efficiency procedure. The super-efficiency method shows that there are only two scenarios with an efficiency significantly greater than ‘1’. These are Scenarios 9 and 10 with the approximate values of 1.364 and 1.226, respectively.

In Table 6, ‘Return-to-Scale’ is a measure of the variation of inputs according to outputs. When constant, it translates to the marginal productivity of 1 (constant scale). The return to scale is increasing when the variation in inputs is smaller than the variation in outputs. Table 6 shows that, except for the existing assembly line, all other scenarios are in the stage of increasing returns to scale. Therefore, the overall operational efficiency can further be enhanced by expanding the production scales of the inputs.

Given the fact that there are six inefficient DMUs, there is an obvious need to further investigate the potential source of technical inefficiencies. To this end, the input excesses and the output deficits were individually derived for each of the inefficient scenarios. We summarize the results of the input excesses and the output deficits in Table 7.

Table 7 shows that the two inputs, “Setup time before injection machine (mold changing)/Input 1” and “Cycle time of injection machine/Input 2”, have the highest input excesses for the existing assembly line. The results indicate the presence of non-value-added activities in these processes. There is a significant difference between the projection value and production value (existing system) of the output 1 (average number of armrests produced), which are 1250.17 and 412, respectively.

Similarly, for Output 2, the projection value is computed as 40.66 compared to the existing value of 10.46. These findings suggest that the inputs have diminishing returns on the efficiencies of inefficient DMUs. In other words, to improve the efficiency of the existing assembly line, production planning should seek ways to reduce the inputs.

Our CCR and Super efficiency results suggest using Scenarios 9–10 as benchmarks to improve the existing system. To this end, λ values calculated with DEA were also taken into consideration. The positive values of the optimal λ scores for inefficient scenarios correspond to the reference set for that particular scenario. In our case, the reference set for Scenarios 9–10 of the existing system corresponds to $\lambda_9 = 0.92$ and $\lambda_{10} = 0.44$, respectively. This projects that the existing scenario resides on the line that connects Scenario 9 to Scenario 10.

For Scenarios 9 and 10, the actual and projected setup durations for mold value are both 26 min. However, the actual setup time for mold in the existing assembly line is measured as 45 min, and the projection value is estimated as 32.5 min. This suggests that the production planning department should prioritize reducing mold setup times. Similarly, while reducing cycle times positively contribute to productivity, increasing the number of operators has no effect on the existing system. Besides, on the output side, results point to significant inefficiencies. Projection value for the average number of armrests produced shows three times increased productivity given the same input values. But in this case, the projection value of the average number of parts waiting for gluing increases by four times, which is not desired.

Table 7 Results of input excesses and the output deficits

DMU	INPUT1		INPUT2		INPUT3		OUTPUT1		OUTPUT2	
	Data	Projection	Data	Projection	Data	Projection	Data	Projection	Data	Projection
Existing	45	32.5	48	43.75	5	5	412	1250.17	10.56	40.67
Sc1	26	26	48	35	5	4	506	674.04	5.58	22.57
Sc2	45	26	35	35	5	4	474	729.64	7.54	23.99
Sc3	26	26	35	35	5	4	563	565.99	1.60	21.36
Sc4	45	45	48	35	4	4	413	474	21.36	21.36
Sc5	26	26	48	48	4	4	507	507	21.36	21.36
Sc6	26	22.49	48	30.28	3	3	506	525.26	4.16	8.96
Sc7	45	45	35	35	4	4	474	474	21.36	21.36
Sc8	45	20.52	35	27.62	3	3	474	504.89	6.24	14.29
Sc9	26	26	35	35	4	4	564	564	21.35	21.35
Sc10	26	26	35	35	3	3	563	563	0.003	0.003

5 Conclusion

LP requires the manufacturing system to undergo significant alterations in terms of design changes, adjustments, and reconfigurations. This study presents a five-phase approach to combine and couple LP techniques with simulation and DEA. The method sequentially combines time-study, cycle-time reduction, line balancing, and simulation techniques. Managers and engineers may use simulation techniques to analyze various system configurations in LP applications before implementing the new system, saving time, money, and lowering risk. Often, there is more than one LP objective that may correlate or even conflict with each other. In order to eliminate sub-optimal alternatives that were generated in the simulation phase, this study suggests applying DEA to compare productivity levels of alternative scenarios with varying levels of inputs and outputs.

This research applies simulation and DEA, as well as LP techniques, to an automobile spare parts company in Turkey. In LP, a three-phase method, which comprises SMED and MMSUR techniques used for the setup time reduction of molds. Time study analysis is used for cycle time reduction, and assembly line balancing is used for balancing the workflow and the synchronization of the process. The case study results suggest significant improvements over the existing configuration.

Production systems are highly dynamic and complex systems that involve interconnected subprocesses with both predictable and unpredictable variations, all of which collectively further complicate studying their inner structures. Changing the system's input levels may have unexpected effects on the outputs. Companies must conduct comprehensive and reliable assessments to identify which inputs should be changed and in what direction. Although there are techniques using simulation or DEA in the literature, this study contributes to the literature in applying a variety of techniques (e.g., SMED, MMSUR, Monte-Carlo simulation, and DEA) systematically and synergistically to provide an analytical framework for a class of applications in the manufacturing. The proposed approach is open to new improvements by continuously applying lean tools and techniques. While we keep the method presented in this study general, more applications in manufacturing are needed to validate and further enhance the proposed methodology.

Appendix

See Table 8.

Table 8 Generated multi-activity diagram

Operator / Cum. Time (sec.)	OPERATOR 1	OPERATOR 2	OPERATOR 3
25,45	To disassemble the old robot apparatus and take it to the robot apparatus field	To adjust the mold hanger	To pick up the raw material sack To go to the machine raw material entry area
53,69	To get the new robot apparatus, make the necessary adjustments	To attach the mold hanger, to go down, to walk to the operator control area	To empty the raw material of the previous mold
75,97	WAIT	To remove old mold from machine	
87,99	To press the hydraulic lock and to return	WAIT	
103,88	To lock the mold		
206,49	WAIT	To remove old mold from the machine and to move it to the waiting area	To go to the raw material area To attach the appropriate raw material hose and to adjust the raw materials
254,3	Machine setup		To search for raw material controller
275,2	WAIT	To attach the crane's hook to a new mold	
293,7	To clean the inside of the mold		
437,83	WAIT	WAIT	To fasten the controller WAIT for raw material To adjust the paint of the raw material
470,41	Unnecessary Movement	WAIT	WAIT
739,46	WAIT	To place the new mold on the machine To remove the crane hanger from the new mold	To enter the raw material setting into the label machine
761,11	To adjust the mold with the controller	To wire	To walk to the car pickup area for carrying raw material and come back
778,88	To unscrew the mold screws		
815,97	To wait for the crane control and to take it to the machine area		
822,85	To make machine heat adjustment		
888,96	WAIT	Unnecessary To attach the water cables of the mold	To take the remained sack of raw materials
1098,59	To attach the right side of the mold and to walk to the side where the connecting cables are	To remove the piece from the mold WAIT	To put in the car To move the raw material of the old mold to the raw material field
1279,22	To correct the wrong connection cables in the mold	Machine setup	
1285,78	To get more raw material flowing from the machine	raw material setting	

Tasks can be external.

This task was removed by coloring the cables in the scope of 5S operation.

Table 8 (continued)

1874,11	WAIT		
1886,45	To control the quality of the first semi-product		
1914,26	To walk the area where the vans are located and close the vans		
1939,77	To control the mold		
1989,97	To adjust the robot apparatus		
2016	To control the semi-product		
2191,5	To enter the mold and set it again		
2265,06	WAIT		
2700	WAIT for the first semi-product		
1874,11	WAIT		
1886,45	To control the quality of the first semi-product		
1914,26	To walk the area where the vans are located and close the vans		
1939,77	To control the mold		
1989,97	To adjust the robot apparatus		
2016	To control the semi-product		
2191,5	To enter the mold and set it again		
2265,06	WAIT		
2700	WAIT for the first semi-product		

References

Agarwal, A., Colak, S., & Eryarsoy, E. (2006). Improvement heuristic for the flow-shop scheduling problem: An adaptive-learning approach. *European Journal of Operational Research, 169*(3), 801–815.

Ahlstrom, P. (2004). Lean service operations: Translating lean production principles to service operations. *International Journal of Services Technology and Management, 5*(5–6), 545–564.

Aldamak, A., & Zolfaghari, S. (2017). Review of efficiency ranking methods in data envelopment analysis. *Measurement, 106*, 161–172.

Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science, 39*(10), 1261–1264.

Azadeh, A., Yazdanparast, R., Zadeh, S. A., & Zadeh, A. E. (2017). Performance optimization of integrated resilience engineering and lean production principles. *Expert Systems with Applications, 84*, 155–170.

Baril, C., Gascon, V., Miller, J., & Côté, N. (2016). Use of a Discrete-event simulation in a Kaizen event: A case study in healthcare. *European Journal of Operational Research, 249*(1), 327–339.

Barnabè, F., & Giorgino, M. C. (2017). Practicing lean strategy: Hoshin Kanri and X-matrix in a healthcare-centered simulation. *The TQM Journal, 29*(4), 590–609. https://doi.org/10.1108/TQM-07-2016-0057

Becker, C., & Scholl, A. (2006). A survey on problems and methods in generalized assembly line balancing. *European Journal of Operational Research, 168*(3), 694–715.

Biswas, P., & Sarker, B. R. (2008). Optimal batch quantity models for a lean production system with in-cycle rework and scrap. *International Journal of Production Research, 46*(23), 6585–6610.

Boysen, N., Fliedner, M., & Scholl, A. (2008). Assembly line balancing: Which model to use when? *International Journal of Production Economics, 111*(2), 509–528.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chauhan, G., & Singh, T. P. (2011). Lean manufacturing through management of labor and machine flexibility: A comprehensive review. *Global Journal of Flexible Systems Management, 12*(1), 59–80.

De Matta, R., Hsu, V. N., & Feng, C. X. J. (2001). Short-term capacity adjustment with offline production for a flexible manufacturing system under abnormal disturbances. *Annals of Operations Research, 107*(1), 83–100. https://doi.org/10.1023/A:1014942830746

Demirbag, M., Tatoglu, E., & Glaister, K. W. (2009). Equity-based entry modes of emerging country multinationals: Lessons from Turkey. *Journal of World Business, 44*(4), 445–462.

Dhafr, N., Ahmad, M., Burgess, B., & Canagassababady, S. (2006). Improvement of quality performance in manufacturing organizations by minimization of production defects. *Robotics and Computer-Integrated Manufacturing, 22*(5–6), 536–542.

Diaz-Elsayed, N., Jondral, A., Greinacher, S., Dornfeld, D., & Lanza, G. (2013). Assessment of lean and green strategies by simulation of manufacturing systems in discrete production environments. *CIRP Annals, 62*(1), 475–478.

Dillon, A. P., & Shingo, S. (1985). *A revolution in manufacturing: The SMED system*. CRC Press.

Doğan, N. Ö., & Unutulmaz, O. (2016). Lean production in healthcare: A simulation-based value stream mapping in the physical therapy and rehabilitation Department of a Public Hospital. *Total Quality Management & Business Excellence, 27*(1–2), 64–80.

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of Manufacturing Systems, 39*, 79–100.

Gijo, E. V., & Antony, J. (2014). Reducing patient waiting time in outpatient department using lean six sigma methodology. *Quality and Reliability Engineering International, 30*(8), 1481–1491.

Greinacher, S., Moser, E., Freier, J., Müller, J., & Lanza, G. (2016). Simulation-based methodology for the application of lean and green strategies depending on external change driver influence. *Procedia CIRP, 48*, 242–247.

Gurumurthy, A., & Kodali, R. (2008). A multi-criteria decision-making model for the justification of lean manufacturing systems. *International Journal of Management Science and Engineering Management, 3*(2), 100–118.

Gustavsson, S. O. (1984). Flexibility and productivity in complex production processes. *International Journal of Production Research, 22*(5), 801–808. https://doi.org/10.1080/00207548408942500

He, J., Chu, F., Zheng, F., & Liu, M. (2020). A green-oriented bi-objective disassembly line balancing problem with stochastic task processing times. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03558-z

Helgeson, W. B., & Birnie, D. P. (1961). Assembly line balancing using the ranked positional weight technique. *Journal of Industrial Engineering, 12*(6), 394–398.

Hines, P., & Rich, N. (1997). The seven value stream mapping tools. *International Journal of Operations & Production Management*.

Hopp, W., & Spearman, M. (2000). *Factory physics*. McGraw-Hill/Irwin.

Jordon, K., Dossou, P. E., & Junior, J. C. (2019). Using lean manufacturing and machine learning for improving medicines procurement and dispatching in a hospital. *Procedia Manufacturing, 38*, 1034–1041.

Kilic, H. S., & Durmusoglu, M. B. (2013). A mathematical model and a heuristic approach for periodic material delivery in lean production environment. *The International Journal of Advanced Manufacturing Technology, 69*(5), 977–992. https://doi.org/10.1007/s00170-013-5082-y

Kull, T. J., Yan, T., Liu, Z., & Wacker, J. G. (2014). The moderation of lean manufacturing effectiveness by dimensions of national culture: Testing practice-culture congruence hypotheses. *International Journal of Production Economics, 153*, 1–12.

Li, Y., Diabat, A., & Lu, C. C. (2020). Leagile supplier selection in Chinese textile industries: A DEMATEL approach. *Annals of Operations Research, 287*(1), 303–322. https://doi.org/10.1007/s10479-019-03453-2

Mao, Z., Huang, D., Fang, K., Wang, C., & Lu, D. (2019). Milk-run routing problem with progress-lane in the collection of automobile parts. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03218-x

Markarian, J. (2004). Six sigma: Quality processing through statistical analysis. *Plastics, Additives and Compounding, 6*(4), 28–31. https://doi.org/10.1016/S1464-391X(04)00236-3

Meyers, F. E., & Stewart, J. R. (2002). *Motion and time study for lean manufacturing*. Pearson College Division.

Meza, D., & Jeong, K. Y. (2013). Measuring efficiency of lean six sigma project implementation using data envelopment analysis at NASA. *Journal of Industrial Engineering and Management (JIEM), 6*(2), 401–422.

Monden, Y. (1984). A simulation analysis of the Japanese just-in-time technique (with Kanbans) for a multiline, multistage production system': A comment. *Decision Sciences, 15*(3), 445–447.

Monkman, S. K., Morrice, D. J., & Bard, J. F. (2008). A Production scheduling heuristic for an electronics manufacturer with sequence-dependent setup costs. *European Journal of Operational Research, 187*(3), 1100–1114. https://doi.org/10.1016/j.ejor.2006.06.063

Naylor, J. B., Naim, M. M., & Berry, D. (1999). Leagility: Integrating the lean and agile manufacturing paradigms in the total supply chain. *International Journal of Production Economics, 62*(1–2), 107–118.

Negahban, A., & Smith, J. S. (2014). Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems, 33*(2), 241–261.

Nemati, M., Kazemi Matin, R., & Toloo, M. (2020). A two-stage DEA model with partial impacts between inputs and outputs: Application in refinery industries. *Annals of Operations Research, 295*, 285–312.

Nicholas, J. (2015). *Lean production for competitive advantage: A comprehensive guide to lean methodologies and management practices*. CRC Press.

Ohlmann, J. W., Fry, M. J., & Thomas, B. W. (2008). Route design for lean production systems. *Transportation Science, 42*(3), 352–370.

Ohno, T. (1988). *Toyota production system: Beyond large-scale production*. CRC Press.

Porter, M. E. (1989). How competitive forces shape strategy. *Readings in strategic management* (pp. 133–143). Palgrave.

Rahani, A. R., & Al-Ashraf, M. (2012). Production flow analysis through value stream mapping: A lean manufacturing process case study. *Procedia Engineering, 41*, 1727–1734.

Rekiek, B., Dolgui, A., Delchambre, A., & Bratcu, A. (2002). State of art of optimization methods for assembly line design. *Annual Reviews in Control, 26*(2), 163–174.

Robinson, S. (2004). *Simulation: The practice of model development and use*. Wiley Chichester.

Scholl, A., Boysen, N., & Fliedner, M. (2009). Optimally solving the alternative subgraphs assembly line balancing problem. *Annals of Operations Research, 172*(1), 243. https://doi.org/10.1007/s10479-009-0578-4

Singh, B. J., & Khanduja, D. (2010). SMED: For quick changeovers in foundry SMEs. *International Journal of Productivity and Performance Management*.

Soroush, H., Sajjadi, S. M., & Arabzad, S. M. (2014). Efficiency analysis and optimisation of a multi-product assembly line using simulation. *International Journal of Productivity and Quality Management, 13*(1), 89–104.

Suarez, F. F., Cusumano, M. A., & Fine, C. H. (1995). An empirical study of flexibility in manufacturing. *MIT Sloan Management Review, 37*(1), 25.

Sullivan, W. G., McDonald, T. N., & Van Aken, E. M. (2002). Equipment replacement decisions and lean manufacturing. *Robotics and Computer-Integrated Manufacturing, 18*(3–4), 255–265.

Susilawati, A., Tan, J., Bell, D., & Sarwar, M. (2015). Fuzzy logic based method to measure degree of lean activity in manufacturing industry. *Journal of Manufacturing Systems, 34*, 1–11.

Trovinger, S. C., & Bohn, R. E. (2005). Setup time reduction for electronics assembly: Combining simple (SMED) and IT-based methods. *Production and Operations Management, 14*(2), 205–217.

Van Goubergen, D. (2008). Setup reduction for lean cells and multi-machine situations. *Lean business systems and beyond* (pp. 295–303). Springer.

Villarreal, B., Garza-Reyes, J. A., Kumar, V., & Lim, M. K. (2017). Improving road transport operations through lean thinking: A case study. *International Journal of Logistics Research and Applications, 20*(2), 163–180.

Vinodh, S., & Balaji, S. R. (2011). Fuzzy logic based leanness assessment and its decision support system. *International Journal of Production Research, 49*(13), 4027–4041.

Vinodh, S., & Chintha, S. K. (2011). Leanness assessment using multi-grade fuzzy approach. *International Journal of Production Research, 49*(2), 431–445.

Womack, J. P., & Jones, D. T. (1997). Lean thinking—Banish waste and create wealth in your corporation. *Journal of the Operational Research Society, 48*(11), 1148–1148.

Wu, Z., Xu, J., & Xu, Z. (2016). A multiple attribute group decision making framework for the evaluation of lean practices at logistics distribution centers. *Annals of Operations Research, 247*(2), 735–757. https://doi.org/10.1007/s10479-015-1788-6

Yang, T., Kuo, Y., Su, C. T., & Hou, C. L. (2015). Lean production system design for fishing net manufacturing using lean principles and simulation optimization. *Journal of Manufacturing Systems, 34*, 66–73.

Zaim, S., Bayyurt, N., Turkyilmaz, A., Solakoglu, N., & Zaim, H. (2008). Measuring and evaluating efficiency of hospitals through total quality management. *Journal of Transnational Management, 12*(4), 77–97.

Zarrin, M., & Azadeh, A. (2017). Simulation optimization of lean production strategy by considering resilience engineering in a production system with maintenance policies. *SIMULATION, 93*(1), 49–68.

Zhou, Z., Wang, M., Ding, H., Ma, C., & Liu, W. (2013). Further study of production possibility set and performance evaluation model in supply chain DEA. *Annals of Operations Research, 206*(1), 585–592.