Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 5836663, 19 pages
https://doi.org/10.1155/2022/5836663

Research Article

Selecting the Optimal LoA to Prevent the Expansion of COVID-19 in the Chemical Industry considering Sustainability Factors: A Fuzzy Mathematical Optimization Approach

Mahtab Hajghasem,[1] **Amir-Reza Abtahi**,[2] **Kaveh Khalili-Damghani**,[1] **and Reza Yousefi-Zenouz**[2]

[1]*Department of Industrial Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran*
[2]*Department of Operations Management and Information Technology, Kharazmi University, Tehran, Iran*

Correspondence should be addressed to Amir-Reza Abtahi; abtahi@khu.ac.ir

Received 4 June 2022; Revised 21 July 2022; Accepted 28 July 2022; Published 10 September 2022

Academic Editor: Reza Lotfi

Automation has attracted interest from the industry sector for its potential to improve energy efficiency, cost efficiency, and environmental performance. By elevating the LoA to the highest degree, associated costs will grow accordingly and its implementation will be far more complicated. This will also result in losing workers and decreasing environmental pollutants. On the other hand, increasing power consumption at high levels of automation leads to the production of greenhouse gases. This paper aims to increase the level of automation (LoA) considering the concept of sustainability. This study presents fuzzy multi-objective programming to determine the optimal LoA considering sustainability factors to achieve competitive advantages. To solve the model, the Zimmermann max-min approach was adopted and a cosmetics factory in Iran was chosen to optimize LoA according to this model. The results showed that it is possible to improve the LoA and also consider sustainability factors with the available resources without using the highest LoA. This study can help managers optimize the LoA in their organizations considering the current resources and sustainability issues, and control the company's return on investment and cost of overhead. They can run the model with every definition of LoA proposed till now. This research can benefit the environment and the workers' health in the production line by reducing environmental pollutants and prevent the dismissal of all personnel due to its negative social effects. It also reduces the risk of COVID-19 by minimizing the number of workers. So far, a mathematical model for selecting optimal LoA in the chemical industry considering sustainability has not been presented.

1. Introduction

The high competition among producers and a variety of products has caused organizations to optimize LoA which entails benefits like an increase in quality as well as the production speed, more accurate and faster quality control (QC), a reduction in production waste, better interaction with business systems, an increase in the productivity of industrial units, an increase in the safety factor for manpower and the reduction of mental and physical stress among workers [1].

The implementation of high LoA is a very important issue due to the decrease in dangerous gases emitted from chemical interactions and the transportation hazards of chemicals that threaten the workers in the chemical industry [2]. However, implementing automation at high levels entails heavy expenditure which most organizations cannot afford. Moreover, performing the jobs manually prolongs the production process that in turn increases the chance of infiltration of microbes into the product and can damage the environment and the consumers; therefore, chemical industries can reduce these hazards and the production time by increasing the LoA [3]. Although, at high levels of automation, the number of workers reduces which causes social concerns in the chemical industry. Due to the prevalence of COVID-19 as a pandemic, customer health has become more important than before, and to prevent the risk of this disease, manufacturers are forced to use high LOA in the process of production to prevent endangering the health of customers. It should be mentioned that COVID-19 spreads not only from person to person via close contact respiratory droplet transfer but also on contaminated surfaces. Coronavirus can persist on inanimate surfaces including metal, glass, or plastic for days. Another important reason to increase LoA is to decrease the danger of transferring COVID-19 and avoid transferring viruses to workers and customers. Also implementing optimal LoA can help organizations attain the goals of sustainability. Sustainability is a multifaceted concept. It forces organizations to set goals in three fully interrelated aspects as below:

(i) Providing social responsibility in which the needs of all stakeholders are met;
(ii) Effective protection of the environment and accurate use of natural resources;
(iii) Providing economic growth and economic prosperity.

Few studies have focused on a specific aspect of the problem, such as environmental, social, and economic factors. This separates the model from the real world because these issues need to be considered together. Therefore, the main objective of this research is to determine the optimal LoA for the chemical industry considering three dimensions of sustainability. So the main questions are: What is the optimal LoA in the chemical industry considering the different aspects of sustainability in the chemical industry? Which criteria and parameters should be considered for environmental and social objectives? To answer these questions we developed a bi-objective mathematical model that suggests the optimal LoA considering the concept of sustainability. Also, it keeps some workers in workstations and uses the current budget considering net present value (NAV). The model also reduces pollution in the factory.

(i) The main contribution of this work lies in developing a bi-objective mathematical model that suggests the optimal LoA considering current resources and the concept of sustainability.

The remainder of the paper is as follows. The related literature is reviewed in Section 2 and in Section 3, the problem is discussed. The mathematical model is defined and the objective functions, constraints, and solution approach are described. In Section 4, the implementation of the model is presented, respectively, in an Iranian cosmetics factory. Section 5 provides managerial insights and practical implications. In conclusion, the findings and recommendations for further research are presented in Section 6.

2. Literature Review

2.1. Automation and Autonomy. The term automation was coined in the early 1940s to determine the different mechanisms for the assignment of tasks requiring human monitoring, control, and intervention to automated machines and systems. The degree to which tasks are performed automatically in an industrial or service unit is called levels of automation [4]. The first definition of LoA presented by Sheridan and Verplank [5] defined ten levels of automation for industries. It is based on six activities that humans and systems do in the production process that involves getting, selecting, starting, requesting, approving, and telling. Many other definitions were given till now [6–16]. After that, Riley [17] offered a different definition. He considered a 2-D matrix, in which rows show the levels of automation while the columns correspond to the dimensions of automation. Vagia et al. [18] reviewed all research papers about LoA and developed a new taxonomy. In contrast to a conventional automated system designed to carry out a limited set of preprogrammed supervised tasks on behalf of the user, autonomy is the technology (either hardware or software) designed to carry out a user's goals and does not require supervision [1]. In this sense, successful autonomy is considered to be well designed and highly capable of automation and can adapt to a wider variety of conditions better [19]. This concept is in agreement with Hancock's idea [20] who described autonomy as a later evolution of automation which was historically more restricted in capability and scope than autonomy. Most authors do not differentiate between automation and autonomy but Fereidunian [21] and Parasuraman [14] made a difference between the levels of autonomy and automation. Determining the LoA has a wide range of applications in different industries for example in avionics, teleportation systems, remote control operations, and aircraft control.

In recent research on LOA, Mostafa et al. [22] reviewed 171 research papers and provided a fundamental understanding of adjustable autonomy and its application. Also, Malek [23] considered various definitions of the term automation. His paper aimed at the study, analysis, and discussion of several definitions of the LoA proposed in the literature. On the grounds of this analysis, a set of requirements to be gained by an accurate indicator was given out to propound a new definition of the LoA to be applied in the manufacturing domain to optimize workstations. At the end of this bibliographical study, a table summarizing the list of different definitions and the requirements that each of them meets is drawn. A proposal for a new definition of LoA as a time ratio is also presented. By studying the literature review, we developed a fuzzy multi-objective model that can improve LoA in the chemical industry by considering any one dimensions (1D) or two dimensions (2D) definition of LoA that has been defined before.

2.2. Appropriate LoA. Despite the large benefits of automation, it should be mentioned that the highest LoA is not necessarily the best option and the most appropriate level for many industries; therefore, the optimal LoA for each industry should be determined by considering some issues [5]. The main research for optimizing LoA was done by Frohm [5] that proposed Dynamo's methodology to determine the levels of automation in organizations. This methodology consists of the following stages: planning steps, a preliminary study for identifying activities, documenting the flow of products and activities, identifying the main activity of each production workstation, identifying the sub-activities of each production workstation, measuring the LoA, evaluating the LoA, and analyzing the results. Fasth et al. [9] followed Frohm's research [5] by presenting the Dynamo++ methodology in 12 steps that can measure the current LoA and provide suggestions for increasing the LoA and eventually help the executives to select the optimal LoA. The Dynamo and Dynamo ++ methodologies are time-consuming in terms of implementation and need to simulate the optimal scenario for their implementation. Many types of research are also done using Dynamo and Dynamo++ methodologies: Fasth and Stahre [9] examined six industrial groups that needed to change their automation level and used Dynamo methodology to evaluate the current LoA. In these industrial groups, the main parameter for changing the LoA was the flexibility or production time. They concluded that it is not always necessary to change the LoA. Stahre and Fasth [24] calculated and analyzed the levels of automation in the assembly industry using Dynamo++ in 12 stages so that the best LoA could be determined considering efficiency and cost. The impact of automation on human resources, waste reduction, efficiency, and cost in different industries was investigated in a study by Wang [25], too.

Choe et al. [26] used the Dynamo++ methodology to calculate the LoA in a truck manufacturing factory and simulated the impact of automation on flexibility in the material transportation system. Before this study, the Dynamo methodology was used in assembling systems. Mehta and Subramanian [27] investigated and explored the barriers that a company would face while increasing the LoA in the preassembly production unit. To achieve the primary goal of investigating the barriers, their study took a threefold approach. They measured first the current LoA for the preassembly workstations. This measurement was conducted by incorporating an existing methodology adapted from the Dynamo++ methodology. They concluded that this methodology could be incorporated in measuring and analyzing the current LoA of the preassembly workstations. Hadi and Brillinger [28] declared that achieving high quality and high variety batch size production could be quite expensive. The focus of their research lies on high adaptive and cognitive aspects in the assembly along with qualitative aspects. They presented a level of practical application matrix of all the possible adaptive technologies that were feasible to implement in the preassembly line using Frohm's [5] Dynamo methodology.

By studying the literature review, it can be said that there is no need to use the highest LoA in an organization, and according to the current conditions of organizations in terms of human resources, equipment, and financial resources, the optimal LoA can be selected to suit them. Most research studies show that the used Dynamo methodology is too complex and time-consuming. For this purpose, we have selected the optimal LoA in the desired factory for our case study using mathematical modeling that is user-friendly and can be run fast and considers sustainability. This model has not been used till now.

Recently, some researchers have been done in LoA such as:

Krishnamoorthi [29] demonstrated a methodology for evaluating multiple construction processes and selecting an optimal solution. The methodology combined compositional modeling, case-based reasoning, and stochastic search. Potential solutions consisting of automated construction processes were explored by generating various combinations of process fragments. Malek [30] aimed to propose a new methodology for organizing and identifying the assembly operations that ought to be automated in an automotive assembly line. The different requirements of the methodology were defined, which led to a proposal for a method that respects all the requirements and allows not only the grouping of operations but also the analysis of the automation and the line balancing. Imset Marius [31] studied a drilling unit (MODU) from a subsea oil and gas well. He applied a framework for levels of automation to explore the critical decision process leading to an EQD. He also provided an overview of the benefits and drawbacks of existing automation and decision support systems vs. manual human decision-making. This paper summarizes the growth of Industry 4.0 during the last 5 years and provides a concise background overview of Industry 4.0-related works and its various application areas. Shastri [32] developed a model for Levels of automation for IT services based on Bloom's taxonomy taken as the reference and assessed the automation scope for all the processes of ITIL. Aryal [33] studied heating, ventilation, and air conditioning (HVAC) systems. In this article, he described the development and implementation of an Internet-of-Things (IoT)-based intelligent agent that learns individual occupant comfort requirements and controls the thermal environment using PCS (i.e., a local fan and a heater). The results showed that PCS used improved occupant satisfaction and including some LoA can improve occupant satisfaction further than what is possible with manually operated PCS. Among the levels of automation investigated, inquisitive automation, where the user approves/declines the control actions of the intelligent agent before execution, led to the highest occupant satisfaction with the thermal environment. References [34–37] studied LoA and social impacts on Self-Driving Vehicles.

2.3. Selecting Optimal LoA considering Sustainability Goals: A Research Gap. Usually, Dynamo and Dynamo ++ methodologies have been adopted to select the optimal LoA. The implementation of these methodologies is extremely complex and time-consuming. To the best of our knowledge, no research has ever been conducted to determine the optimal LoA by using a mathematical modeling approach. Also, sustainable development factors (cost, social, and environmental factors) have not yet been considered in selecting the optimal level and dimension of automation. In this study, a mathematical model will be presented to determine the optimal LoA based on both one dimension (1D) and two

Table 1: A review of all research down till now and a research gap.

Writer	Methodology	Case study	Automation	LoA	Cost	Environment	Social
Stayton	Literature review	Self-driving Vehicles	*	*			
Hadi et al.	Dynamo	Industrial groups	*	*			
Fasth et al.(2008)	Dynamo++	Six industrial groups	*	*			
Fasth et al.(2010)	Dynamo++	Assembly industry	*	*	*		
Wang et al.	Dynamo++	different industries	*	*	*		
Choe et al.	Dynamo++	Truck manufacturing factory	*	*			
Mehta et al.	Dynamo++	Preassembly production unit	*	*			
Hadi	Dynamo	Assembly industry	*	*			
Krishnamoorthi	Stochastic Search algorithm	Construction processes	*				
Malek	Literature review	Automotive assembly line	*	*			
Imset Marius	Design a framework	Drilling unit from a subsea oil and gas	*	*			
Shastri	Bloom's taxonomy	IT services	*	*			
Aryal	Heating, ventilation, and air conditioning (HVAC) systems	Implementation an IoT	*	*		*	
Burtnyk, Endsley, FakhrHosseini, Fereidunian, Frohm, Fasth, Frohm, Hancock, Lorenz, Mostafa, Parasuraman, Di Nocera, Sheridan, Simmler, Xu, Vagia	LoA definition	Literature review	*	*			
Frank, abbas, Gopinath, Stayton	Literature review	Self-driving Vehicles	*	*			*
This research	Modeling	Chemical manufacturing	*	*	*	*	*

dimensions (2D) definitions of LoA considering the three dimensions of sustainability. In brief, the research gaps are as follows:

Many studies have focused on a specific aspect of the problem, such as environmental, social, and economic aspects. This separates the model from the real world because these issues need to be considered together;

A large number of studies have used examples generated with random numbers to validate their models, but it is better to validate models using real-world examples and to write models for real case studies;

(ii) There was no research conducted to determine the optimal LoA by using a fuzzy multi-objective model approach.

The goal of this research is to present a mathematical model for selecting the optimal LoA in the chemical industry based on sustainability considerations to reduce the danger of transmitting viruses like COVID-19. The research has been done in the chemical industry in Iran. In Table 1, a review of the LoA has been done and the research gap is shown.

In this study the researchers studied the previous research in LoA optimization, optimized LoA considering sustainable factors with a Fuzzy mathematical optimization approach, defuzzilized the model using LHS, used the Zimmermann max-min approach, conducted a sensitivity analysis (SA) to evaluate the importance of model inputs, and then examined the model in a case study. The differences between this study and the previous studies are as follows. This study optimizes LoA with modeling, considers sustainable factors, and uses a case study.

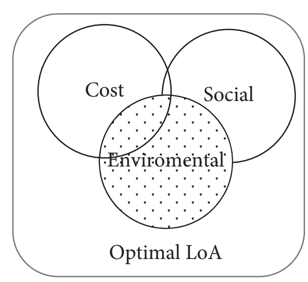

Figure 1: A picture of the problem statement.

3. Problem Statement

During chemical production, if the process of production is long and manually performed, which is usually done at low levels of automation, there is a high probability of infiltration of microbes and viruses like COVID-19 into the product and causing damage to workers and consumers. Consequently, to lessen the level of expected harm chemical manufacturing industries have to reduce the production time by increasing the LoA. It should be mentioned that using full automation has a high cost and most organizations cannot afford it [38]. Full automation

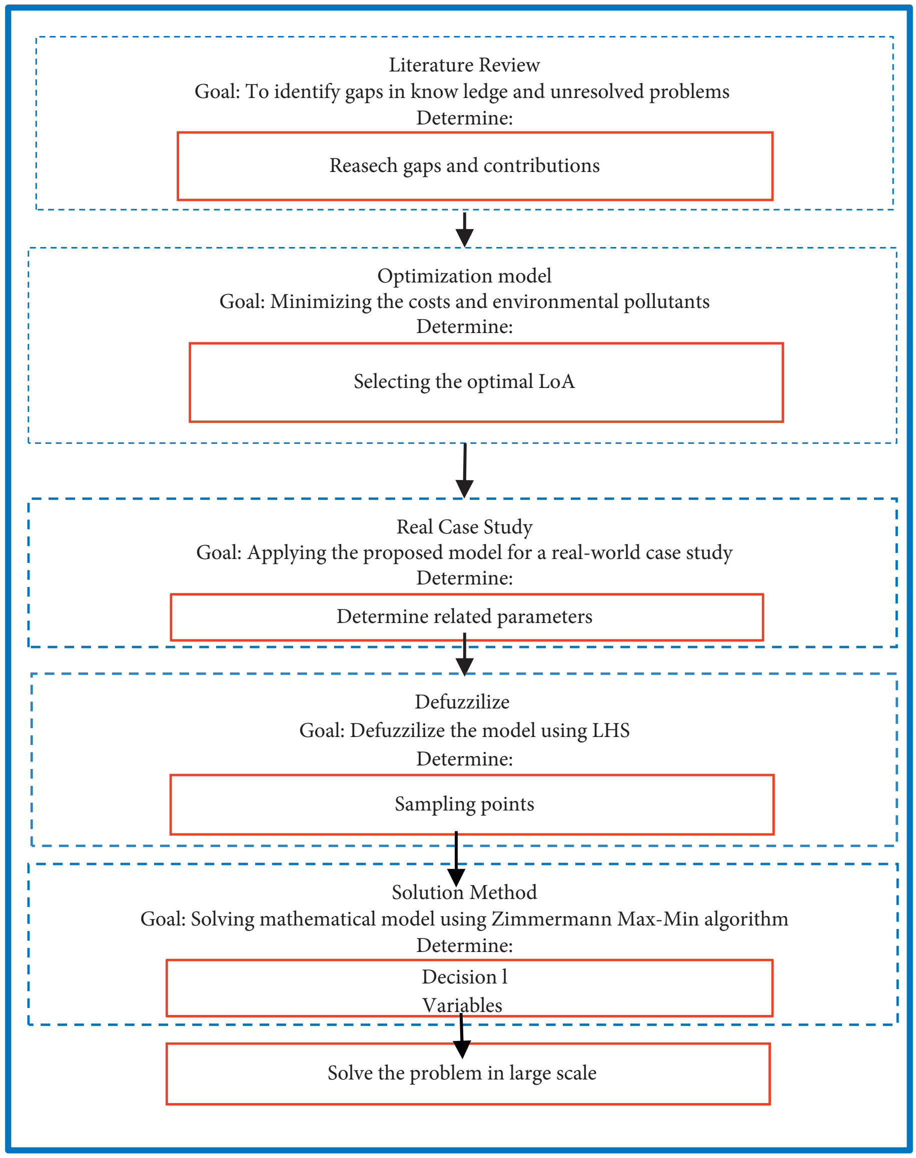

Figure 2: Research framework.

also leads to the downsizing of workers and has negative social effects, consumes more electricity, and produces greenhouse gases. Environmental pollution, in its place, is one of the main problems in society and governmental agencies impose heavy rules and fines for it. There is even a risk of closure of the organization which cannot manage it as well. Taking these issues into account, it is essential to select the optimal LoA in chemical industries by considering the existing financial resources of organizations and maintaining a certain number of workers in production lines which reduces the social damage caused by downsizing the workforce and decreases the environmental pollutants. According to the mentioned issues, the major concern in this research is selecting the optimal LoA in the chemical industry considering sustainability as follows:

Reducing production costs in different production workstations, including the costs of raw materials, labor costs, and overhead costs, maintaining a certain number of production line workers, and reducing environmental pollutants.

A picture of the problem statement is shown in Figure 1.

In this research, first, the literature review is done. The purpose of this section is to determine the research gap. In the second step, a mathematical model is designed. In this model, which was run for a long time, the Net Present Value (NPV) or the current value of cash flows with the desired return rate on the project will be positive relative to the initial capital. Also, the selection of the level and dimension of automation will be measurable with one of the taxonomies. The model applies to all taxonomies of LoA including one-dimensional taxonomy (1D) [39] or two-dimensional (2D) [17]. If the 2D taxonomy is used, the LoA in different dimensions is homogenous; for example, in one dimension it is not fully automatic and in the other dimension it is manual. In this study, the method developed by McKay [40]

Table 2: Parameters, variables, and constants of the model.

Sets	
I	Index of automation dimensions, $i = 1,2,\ldots,$ im
J	Index of automation levels, $j = 1,2,\ldots.,$ jm
F	Index of activities, $f = 1,2,\ldots,$ fm
M	Index of raw materials, $m = 1,2,\ldots$mm
E	Index of the specialists with different skill levels, $e = 1,2,\ldots,$ em
N	Index of environmental pollutants, $n = 1,2,\ldots,$ nm
T	Return on investment period, $t = 1,2,\ldots,$ tm
Parameters	
Upper indexes M, F and P refer to manufacturing workstations, filling workstations, and packaging workstations	
$\tilde{c}_{mt}^{M}$	The unit cost of raw material m in manufacturing workstation M in period t
$\tilde{c}_{mt}^{F}$	The unit cost of raw material m in filling workstation F in period t
$\tilde{c}_{mt}^{P}$	The unit cost of raw material m in packaging workstation P in period t
u_{ijm}	The usage of raw material m at level j and dimensiIn i of LoA
$\tilde{d}_{ft}^{M}$	The overhead costs of activity f in manufacturing workstation M in period t
$\tilde{d}_{ft}^{F}$	The overhead costs of activity f in filling workstation F in period t
$\tilde{d}_{ft}^{P}$	The overhead costs of activity f in packaging workstation P in period t
s_{ije}^{M}	The Number of specialists required with skill level e at the level j and dimensIon i in manufacturing workstation M
s_{ije}^{F}	The Number of specialists required with skill level e at the level j and dimenIion i in filling workstation F
s_{ije}^{P}	The Number of specialists required with skill level e at the level j and dimeIsion i in packaging workstation P
sc_{et}^{M}	The labor cost of each expert with skill level e in manufacturing workstation M in period t
sc_{et}^{F}	The labor cost of each expert with skill level e in filling workstation F in period t
sc_{et}^{P}	The labor cost of each expert with skill level e in packaging workstation P in period t
mb_{ij}^{M}	Total machinery cost in manufacturing workstation M at level j and dimension i
mb_{ij}^{F}	Total machinery cost in filling workstation F at level j and dimension i
mb_{ij}^{P}	Total machinery cost in packaging workstation P at level j and dimension i
λ_{f}^{M}	The number of activities f for production in manufacturing workstation M
λ_{f}^{F}	The number of activities f for production in filling workstation F
λ_{f}^{P}	The number of activities f for production in packaging workstation P
Constants	
pv^{M}	Production volume in manufacturing workstation M (bulk)
pv^{F}	Production volume in filling workstation F (bottle)
pv^{P}	Production volume in packaging workstation P (carton)
b	The change rate of bulk to bottle
p	The change rate of the bottle to carton
d	The difference between the LoAs in different dimensions
$\exp n^{t}$	Environmental impact n in period t
MAXCM	The budget for purchasing machinery
MAXCR	The budget for raw material
MAXCO	The budget for overhead costs
DEMAND	Maximum product demand
NOWCM	The current cost of machinery in manufacturing workstation M
NOWCF	The current cost of machinery in filling workstation F
NOWCP	The current cost of machinery in packaging workstation P
NOWCRM	The current cost of raw materials in manufacturing workstation M
NOWCRF	The current cost of raw materials in filling workstation F
NOWCRP	The current cost of raw materials in packaging workstation P
NOWCSM	The current cost of the specialists in manufacturing workstation M
NOWCSF	The current cost of the specialists in filling workstation F
NOWCSP	The current cost of the specialists in packaging workstation P
NOWCOM	The current labor costs in manufacturing workstation M
NOWCOF	The current labor costs in filling workstation F
NOWCOP	The current labor costs in packaging workstation P
ml	The Number of automation levels permitted to use full automation(without operator)in manufacturing workstation M
fl	The Number of automation levels permitted to use full automation(without operator)in filling workstation F
pl	The Number of automation levels permitted to use full automation(without operator)in packaging workstation P
R_t	Net cash flow in period t
Decision variables	
x_{ij}^{M}	$\begin{cases} 1, & \text{If dimension } i, \text{ level } j \text{ is selected for } LoA \text{ in manufacturing workstation } M, \\ 0, & \text{Otherwise,} \end{cases}$
x_{ij}^{F}	$\begin{cases} 1, & If \text{ dimension } i, \text{ level } j \text{ is selected for } LoA \text{ in filling workstation } F, \\ 0, & \text{Otherwise,} \end{cases}$
x_{ij}^{P}	$\begin{cases} 1, & \text{If dimension } i, \text{ level } j \text{ is selected for } LoA \text{ in packaging workstation } P, \\ 0, & \text{Otherwise,} \end{cases}$

is employed to defuzzilize the model due to its effectiveness and computational efficiency.

Then, a case is stated and in the last step, to solve the mathematical model, the Zimmermann max-min approach is used and the results are analyzed. Finally, a sensitivity analysis (SA) is conducted to evaluate the importance of model inputs. The steps are shown in Figure 2.

3.1. Assumption of the Model

The amount of material consumption in each workstation is specified and predefined, and it is definite in each dimension and for every level of automation in a specific period;

The number of specialists in each workstation is specific, definite, and predefined in each dimension and every LoA;

The cost of materials is uncertain due to changes in exchange rates and world prices;

The cost of specialists and workers in each workstation is certain in each dimension and for every level of automation in a specific period;

(v) Overhead costs are uncertain because they vary in different geographical areas and different seasons;

(vi) The chemical production process includes three workstations-manufacturing, filling, and packaging;

(vii)The model runs for a long time.

3.2. Mathematical Formulation

3.2.1. Notations. The sets, parameters, and variables used in the mathematical model are given as follows (see Table 2):

3.2.2. Objective Functions. The first objective function (1) minimizes all costs associated with the implementation of the automation. Four different costs consist of fixed costs(line one), raw material costs(line two), overhead costs(line three), and labor costs(line four) formulated as follows:

Line one represents the total fixed costs (purchasing machinery) at different levels and different dimensions in manufacturing workstations, filling workstations, and packaging workstations. Line two shows the total cost of raw material at different levels and different dimensions in manufacturing workstations, filling workstations, and packaging workstations.

Line three shows the total overhead costs that are equal to the multiplication of the overhead cost, activity cost driver, and the volume of product at different levels and different dimensions in manufacturing workstations, filling workstations, and packaging. Line four represents the total labor cost at different levels and different dimensions in manufacturing workstations, filling workstations, and packaging workstations. The equation is as follows:

$$
Min\left(\begin{array}{c}
\sum_{i=1}^{im}\sum_{j=1}^{jm} mb_{ij}^{M}x_{ij}^{M}+\sum_{i=1}^{im}\sum_{j=1}^{jm} mb_{ij}^{F}x_{ij}^{F}+\sum_{i=1}^{im}\sum_{j=1}^{jm} mb_{ij}^{P}x_{ij}^{P}\\
-\left(\left(\sum_{t=1}^{tm}\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{m=1}^{mm} u_{ijm}\tilde{c}_{mt}^{M}x_{ij}^{M}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{m=1}^{mm} u_{ijm}\tilde{c}_{mt}^{F}x_{ij}^{F}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{m=1}^{mm} u_{ijm}\tilde{c}_{mt}^{P}x_{ij}^{P}\right)-\right.\\
\left(\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{f=1}^{fm}\tilde{d}_{ft}^{M}\lambda_{f}^{M}pv^{M}x_{ij}^{M}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{f=1}^{fm}\tilde{d}_{ft}^{F}\lambda_{f}^{F}pv^{F}x_{ij}^{F}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{f=1}^{fm}\tilde{d}_{ft}^{P}\lambda_{f}^{P}pv^{P}x_{ij}^{P}\right)-\\
\left.\left(\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{e=1}^{em} s_{ije}^{M}sc_{et}^{M}x_{ij}^{M}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{e=1}^{em} s_{ije}^{F}sc_{et}^{F}x_{ij}^{F}+\sum_{i=1}^{im}\sum_{j=1}^{jm}\sum_{e=1}^{em} s_{ije}^{P}sc_{et}^{P}x_{ij}^{P}\right)\right)
\end{array}\right). \quad (1)
$$

In the second objective function (2), the amounts of pollution in the manufacturing workstation, filling workstation, and packaging workstation during the period t are minimized, as can be seen in this equation:

$$
\text{Min}\sum_{t=1}^{tm}\sum_{i=1}^{im}\sum_{j=1}^{jm}\left(\left(\sum_{n=1}^{nm} enp_{nt}x_{ij}^{M}\right)+\left(\sum_{n=1}^{nm} enp_{nt}x_{ij}^{F}\right)+\left(\sum_{n=1}^{nm} enp_{nt}x_{ij}^{P}\right)\right). \quad (2)
$$

3.2.3. Constraints

$$
\sum_{j=1}^{jm} x_{ij}^{M}=1; \quad i=1,2,\ldots,im, \quad (3)
$$

$$
\sum_{j=1}^{jm} x_{ij}^{F}=1; \quad i=1,2,\ldots,im, \quad (4)
$$

$$\sum_{j=1}^{jm} x_{ij}^{P} = 1; \quad i = 1, 2, \dots, im, \tag{5}$$

$$\sum_{i=1}^{im} \sum_{j=jm}^{jm} x_{ij}^{M} \le ml, \tag{6}$$

$$\sum_{i=1}^{im} \sum_{j=jm}^{jm} x_{ij}^{F} \le fl, \tag{7}$$

$$\sum_{i=1}^{im} \sum_{j=jm}^{jm} x_{ij}^{P} \le pl, \tag{8}$$

$$\sum_{i=1}^{im} \sum_{j=1}^{jm} mb_{ij}^{M} x_{ij}^{M} + \sum_{i=1}^{im} \sum_{j=1}^{jm} mb_{ij}^{F} x_{ij}^{F} + \sum_{i=1}^{im} \sum_{j=1}^{jm} mb_{ij}^{P} x_{ij}^{P} \lesssim MAXCM, \tag{9}$$

$$\sum_{t=1}^{tm} \left(\sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{M} x_{ij}^{M} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{F} x_{ij}^{F} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{P} x_{ij}^{P} \right) \lesssim MAXCR, \tag{10}$$

$$\sum_{t=1}^{tm} \left(\sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{M} \lambda_{f}^{M} pv^{M} x_{ij}^{M} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{F} \lambda_{f}^{F} pv^{F} x_{ij}^{F} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{P} \lambda_{f}^{P} pv^{P} x_{ij}^{P} \right) \lesssim MAXCO, \tag{11}$$

$$pv^{P} \ge \mathrm{DEMAND}, \tag{12}$$

$$pv^{F} = p.pv^{P}, \tag{13}$$

$$pv^{M} = b.pv^{F}, \tag{14}$$

$$\begin{gathered}
\sum_{i=1}^{im} \sum_{j=1}^{jm} \left(mb_{ij}^{M} x_{ij}^{M} - \mathrm{NOWCM} \right) + \sum_{i=1}^{im} \sum_{j=1}^{jm} \left(mb_{ij}^{F} x_{ij}^{F} - \mathrm{NOWCF} \right) + \sum_{i=1}^{im} \sum_{j=1}^{jm} \left(mb_{ij}^{P} x_{ij}^{P} - \mathrm{NOWCP} \right) \\
- \sum_{t=1}^{tm} \left[\left(\begin{gathered} \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{M} x_{ij}^{M} - \mathrm{NOWCRM} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{F} x_{ij}^{F} - \mathrm{NOWCRF} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{m=1}^{mm} u_{ijm} \tilde{c}_{mt}^{F} x_{ij}^{F} - \mathrm{NOWCRP} + \\
\sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{M} \lambda_{f}^{M} pv^{M} x_{ij}^{M} - \mathrm{NOWCOM} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{F} \lambda_{f}^{F} pv^{F} x_{ij}^{F} - \mathrm{NOWCOF} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{f=1}^{fm} \tilde{d}_{ft}^{P} \lambda_{f}^{P} pv^{P} x_{ij}^{P} - \mathrm{NOWCSP} + \\
\sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{e=1}^{em} s_{ije}^{M} sc_{et}^{M} x_{ij}^{M} - \mathrm{NOWCSM} + \sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{e=1}^{em} s_{ije}^{F} sc_{et}^{F} x_{ij}^{F} - \mathrm{NOWCSF} + \frac{\sum_{i=1}^{im} \sum_{j=1}^{jm} \sum_{e=1}^{em} s_{ije}^{P} sc_{et}^{P} x_{ij}^{P} - \mathrm{NOWCSP})]}{(1 + R_t)} \gtrsim 0
\end{gathered} \right. \right.
\end{gathered} \tag{15}$$

$$\sum_{i=1}^{im} \sum_{\substack{j'=1 \\ j' \ne j}}^{jm} \sum_{\substack{i'=1 \\ i' \ne i}}^{im} \left(x_{ij}^{M} \times x_{i'j'}^{M} \right) (j - j') \le d; \quad j = 1, 2, \dots, jm \tag{16}$$

$$\begin{gathered}
\sum_{i=1}^{im} \sum_{\substack{j'=1 \\ j' \ne j}}^{jm} \sum_{\substack{i'=1 \\ i' \ne i}}^{im} \left(x_{ij}^{F} \times x_{i'j'}^{F} \right) (j - j') \le d; \quad j = 1, 2, \dots, jm \sum_{i=1}^{im} \sum_{\substack{j'=1 \\ j \ne j'}}^{jm} \left(x_{ij}^{F} + x_{ij'}^{F} \right) (j - j') \le - \ d + M(1 - Z); \quad j = 1, 2, \dots, \\
jm \sum_{i=1}^{im} \sum_{\substack{j'=1 \\ j \ne j'}}^{jm} \left(x_{ij}^{F} + x_{ij'}^{F} \right) (j - j') \ge d - MZ; \quad j = 1, 2, \dots, jm,
\end{gathered} \tag{17}$$

$$\sum_{i=1}^{im} \sum_{\substack{j'=1 \\ j' \ne j}}^{jm} \sum_{\substack{i'=1 \\ i' \ne i}}^{im} \left(x_{ij}^{P} \times x_{i'j'}^{P} \right) (j - j') \le d; \quad j = 1, 2, \dots, jm, \tag{18}$$

Table 3: Positive and negative ideal solution.

	Positive ideal solution					Negative ideal solution			
	Z_1	Z_2	. . ...	Z_g		Z_1	Z_2	. . ...	Z_g
Max Z_1	z_1^u	$z_2(x_1)$	. . .	$z_g(x_1)$	$Min\, Z_1$	z_1^u	$z_2(x_1)$	. . .	$z_g(x_1)$
Max Z_2	$z_1(x_2)$	z_2^u	. . ..	$z_g(x_2)$	$Min\, Z_2$	$z_1(x_2)$	z_2^l	. . .	$z_g(x_2)$
. . ...	. . ...	. . ...	. . ...	. . ...	. . ...	. . ...	. . ..	. . ...	. . ...
Max Z_g	$z_1(x_g)$	$z_2(x_g)$	. . ..	z_g^u	$Min\, Z_g$	$z_1(x_g)$	$z_2(x_g)$	. . ..	z_g^l
Best Value	z_1^u	z_2^u	. . ..	z_g^u	Best Value	z_1^l	z_2^l	. . .	z_g^l

Table 4: The membership function.

For minimization	For maximization
$\mu(g(x))\begin{cases} 1, & if\ Zg(x) \le Z_g^l, \\ 1-(Z_g^u - Zg(x)/Z_g^u - Z_g^l), & if\ Z_g^l < Zg(x) < Z_g^u, \\ 0, & if\ Zg(x) \ge Z_g^u, \end{cases}$	$\mu(g) = \begin{cases} 1, & if\ Zg(x) \ge Z_g^u, \\ 1-(Zg(x) - Z_g^l/Z_g^u - Z_g^l), & if\ Z_g^l < Zg(x) < Z_g^u, \\ 0, & if\ Zg(x) \le Z_g^l, \end{cases}$

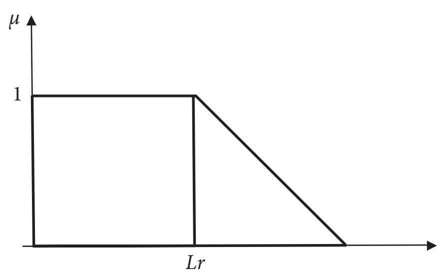

Figure 3: Linear membership function.

$$\sum_{i=1}^{im}\sum_{\substack{j'=1\\ j'\neq j}}^{jm}\sum_{\substack{i'=1\\ i'\neq i}}^{im}\left(x_{ij}^{M}\times x_{i'j'}^{F}\right)(j-j')\le d;\quad j=1,2,\ldots,jm, \tag{19}$$

$$\sum_{i=1}^{im}\sum_{\substack{j'=1\\ j'\neq j}}^{jm}\sum_{\substack{i'=1\\ i'\neq i}}^{im}\left(x_{ij}^{M}\times x_{i'j'}^{P}\right)(j-j')\le d;\quad j=1,2,\ldots,jm, \tag{20}$$

$$\sum_{i=1}^{im}\sum_{\substack{j'=1\\ j'\neq j}}^{jm}\sum_{\substack{i'=1\\ i'\neq i}}^{im}\left(x_{ij}^{F}\times x_{i'j'}^{P}\right)(j-j')\le d;\quad j=1,2,\ldots,jm, \tag{21}$$

$$\sum_{i=1}^{im}x_{i1}^{M}=0;\sum_{i=1}^{im}x_{i1}^{F}=0;\sum_{i=1}^{im}x_{i1}^{P}=0, \tag{22}$$

$$x_{ij}^{M},x_{ij}^{F},x_{ij}^{P}\in\{0,1\};\quad i=1,2,\ldots,im;i,j=1,2,\ldots,jm. \tag{23}$$

Constraints (3)–(5) ensure that only one LoA can be selected in each dimension in the manufacturing workstation, filling workstation, and packaging workstation. Constrain (7) is introduced to consider social damage and states that the maximum fully automated level (without the operator) in the manufacturing workstation is ml LoA. Constrain (8) is introduced to consider social damage and states that the maximum fully automated level (without the operator) in the manufacturing workstation is fl LoA. Constrain (9) is

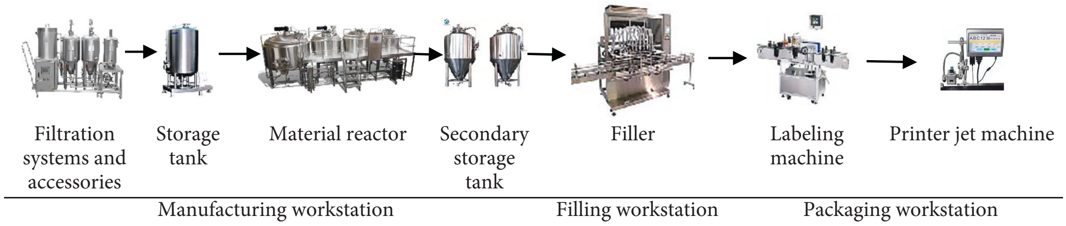

Figure 4: The production process in the cosmetics factory.

introduced to consider social damage and states that the maximum fully automated level (without the operator) in the manufacturing workstation is pl LoA. Constraints (9)–(11) monitor that fixed costs (purchase of machinery) do not exceed the intended budget of the organization (MAXCM), the consumption of raw materials does not exceed the intended budget of the organization (MAXCR), and overhead costs do not exceed the budget of the organization (MAXCO), respectively. Constraint (13) states that market demand should be met. Constraint (14) is the relationship between the number of products in the filling as well as the packaging workstation (i.e., the number of bottles in each carton packaging). Constraint (14) is the relationship between the number of products in the manufacturing and filling workstations (i.e., the amount of bulk used in each bottle that is filled in the filling workstation). Constraint (15) controls the company's return on investment during tm years. Constraints (16)–(18) are to keep the levels of automation in each workstation homogenous in different dimensions. Constraints (19)–(21) are to keep the levels of automation in all workstations homogenous. The difference in the LoA in the three workstations of manufacturing, filling, and packaging should not be great. For example, if the LoA in a manufacturing workstation is high but the LoA in the filling workstation is low, the filling workstation will not respond properly.

Constraint (22) determines that the manual levels in workstations are not allowed. Constraint (23) determines the type of decision variables of the model.

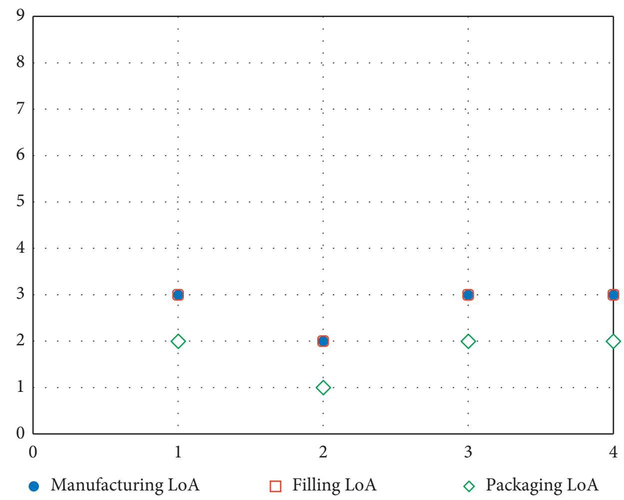

Figure 5: The current LoA in the case study.

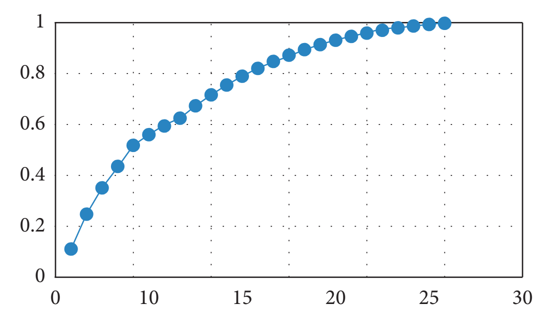

Figure 6: Cumulative distribution of raw materials.

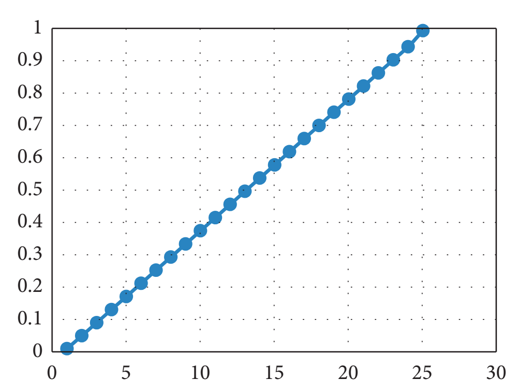

Figure 7: Cumulative distribution of D1, D2.

3.3. Solution Approach

3.3.1. Zimmermann Max-Min Approach. To solve the problem, not all goals may be achieved simultaneously under system constraints. In this situation, some tolerance is defined in the model and for this reason, Zimmermann max-min approach [41]is used to solve the bi-objective problem. This method has the following steps:

(1) Start

(2) Solve first and second objective functions separately

(3) Create a pay-off table for the first and second objective functions separately as follows Table 3:

(4) Define the membership function for the first and second objective functions separately Table 4:

(5) Figure 3 shows the linear membership function for minimizing the goal.

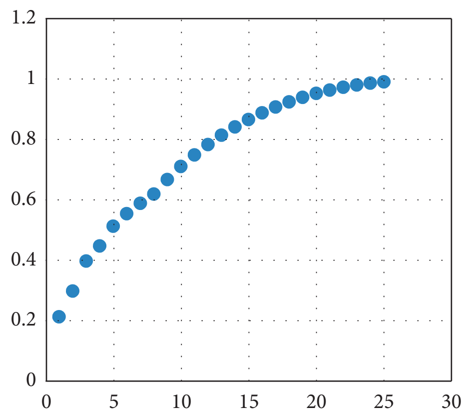

Figure 8: Cumulative distribution of D3, D4.

(6) Transform fuzzy multi-objective linear programming to deterministic linear programming using Latin Hypercube Sampling (LHS).

(7) The new objective function shows the satisfaction level for all objective functions ($Z = Max$ℷ). Then, the membership functions are added to constraints for each objective function as follows:

(8) $\lambda \leq \mu g(x) = Z_g^u - Zg(x)/Z_g^u - Z_g^l$ It should be noted that with the introduction of the Zimmermann max-min and Lp-Metric methods, the introduced multi-objective model becomes a single-objective model. Then, the model was run using the GAMS software on a system with a Corei7 processor.

3.3.2. Lp-Metric Method. In this research, the Lp-metric method has been used to integrate objective functions. In this method, the deviation of the objective functions from their optimal value is considered. At first, the individual answers are calculated for the optimization of each objective function and then the objective function is minimized as follows:

$$\begin{gathered}\text{Min}\left(\sum_{k=1}^{q}\left[w_k\left|\frac{f*_k - f_k(x)}{f*_k}\right|\right]^p\right)^{1/p},\\ s.t. X_\alpha = \left\{\frac{x}{g(x)} \leq b_h, \quad h = 1, 2, \ldots, g\right\},\end{gathered} \tag{24}$$

where w_k is the degree of importance for the i-th objective function and $1 \leq p < \infty$ is the parameter defining the Lp-metric method. The value of p determines the degree of emphasis on the existing deviations so that the larger the value of p, the greater the emphasis on the largest deviation. Usually, the values of $p = 1$, $p = 2$, and $p = \infty$ are used in calculations; $p = 1$ indicates that the same importance is considered for all deviations and $p = 2$ indicates that each deviation has its weight so that the largest deviation takes the most weight. When p tends to infinity, the largest deviation indicates distance.

This method is converted to the Min-Max approach for the value $p = \infty$. The variable λ is defined as follows:

$$\lambda = \text{Max}\left(\sum_{k=1}^{q}\left[w_k\left|\frac{f*_k - f_k(x)}{f*_k}\right|\right]\right). \tag{25}$$

Therefore, the multi-objective model can be written as a single-objective model, as to the following relations:

$$\begin{gathered}\text{Min } Z = \lambda s.t.\lambda \geq w_1\left|\frac{Z_1 - Z*_1}{Z*_1}\right|,\\ \lambda \geq w_1\left|\frac{Z_2 - Z*_2}{Z*_2}\right|,\\ \lambda \geq w_q\left|\frac{Z_q - Z*_q}{Z*_q}\right|,\\ X_\alpha = \left\{\frac{x}{g(x)} \leq b_h, \quad h = 1, 2, \ldots, g\right\}.\end{gathered} \tag{26}$$

4. Results

The case is a cosmetic factory that produces different types of hygienic-chemical products in Iran. The products manufactured at the factory include lipstick, eyeliner, mascara, creams, shampoos, varnishes, powder creams, and other products. Some workstations use a low LoA and employ many workers. However, in the Covid-19 epidemic, the managers have to reduce the number of workers to prevent transmission of the Coronavirus to other workers and customers. Also, due to the costly nature of chemical production and the competitive business environment in this industry concerning the quality level, increasing LoA is very important for reducing the final product's manufacturing costs and increasing the amount and quality of production. But using full automation has a very high cost and its implementation is too complex and time-consuming so the factory cannot perform it. Also, they have to fire many workers and pay a lot of penalties which can result in very negative social effects. On the other hand, it is important to reduce environmental pollutants due to the controls practiced by governmental agencies and the social responsibilities thereof in a way that if the rules are not observed, they will have to pay heavy penalties. Therefore, the aim of implementing the proposed model in this factory is to determine the optimal LoA so that costs and environmental pollution are minimized and several workers are retained with a specific budget. Moreover, in the long run, the Net Present Value (NPV) or the current value of cash flows with the desired return rate on the project will be positive relative to the initial capital. To better understand the content, we examine the production processes as follows:

The production line includes three workstations of production-manufacturing, filling, and packaging. The process flow of cosmetics manufacturing under study is shown in Figure 4.

Proud's definition [15] was used for the implementation of the model. This definition has four dimensions (observe, orient, decide, and act) and eight

Table 5: Best value of Z1, and Z2 in Zimmermann max-min approach.

Scenario	MinZ1		MinZ2		Best Value	
	Z1	Z2	Z1	Z2	Z1	Z2
1	4158692	0.000728049760	4159993	0.000721040600	4158692	0.000721040600
2	4552350	0.000031456810	4557125	0.00003052111	4552350	0.00003052111
3	5558692	0.000001250007	5559123	0.00000101204	5558692	0.00000101204

Table 6: Z and λ values were gathered using Zimmermann max-min approach in Scenario 1.

New objective Function	$Z = \text{ma } x^{\lambda}$		$\lambda = 0.5$
New constraint1	$\lambda \leq (4159993 - z1/4159993 - 4158692)$	SOLUTION	$\lambda 1 = 0.57$
New constraint2	$\lambda \leq (0.000728049760 - z2/0.000728049760 - 0.000721040600)$		$\lambda 2 = 0.5$

LoAs. The LoA in the manufacturing workstation and filling workstation in dimensions observe, decide, and act is 3 and in the orient dimension is 2. The LoA in the packaging workstation in the orient dimension is 2 and in the other dimensions is 3. The current LoA in this factory is shown in Figure 5.

The raw material is added to the reactor in the manufacturing workstation. Unit costs of raw materials in manufacturing workstation, filling workstation, and packaging workstation are fuzzy variables. Also, overhead costs in workstations are fuzzy variables. We considered four overhead costs including the cost of electricity, the cost of water, depreciation cost, and repair cost as D1, D2, D3, and D4.

To deal with uncertainty, the LHS method was used to generate the scenario. Data from the last two years were used and the number of samples was 25 according to Morgan's table. Using the data, a cumulative distribution diagram was drawn and random scenarios were generated using coding in MATLAB as shown in Figures 6–8.

We used the data of three types of specialists who participated in the production processes at different automation levels including simple workers, excellent workers, and specialists. In manufacturing cosmetics, the mixing reactor is regarded as the heart of the process. In this process, the purified and deionized water is transferred into the mixer tank first. Then, the materials are pumped or manually fed into the reactor to be mixed, being simultaneously heated. The amount and duration of heating depend on the process. The next phase is storing the materials in a large container followed by packaging which includes filling, capping, and labeling. The filling machine is a device with at least one tank and a nozzle for filling different bottles. After that, the final phases are packaging and putting the bottles in cartons, which can be performed manually or automatically. It should be noted that in low levels of automation, the workers are present in all production processes, especially packaging and for this reason the risk of transmission of viruses is high. During the manufacturing process, chemical reactions produce several gases including primary pollutants. The pollutants in the cosmetics industry include particulate matter (PM), oxides of carbon, sulfur, nitrogen, ozone, free radicals, and other airborne chemicals like pesticides, chemical sprays, and hydrocarbons. A secondary pollutant is not directly emitted as such but is formed when other

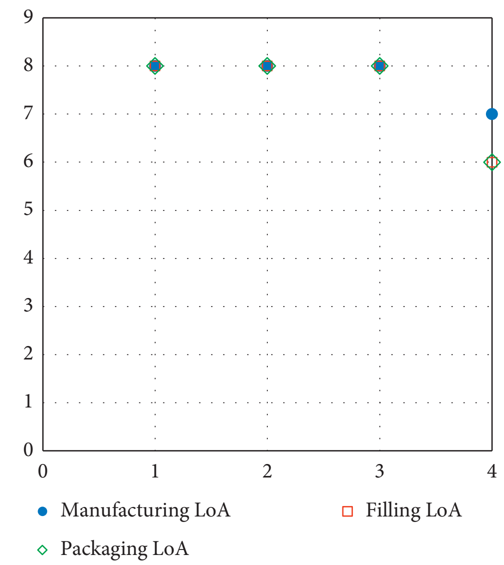

Figure 9: The results of implementing scenario3.

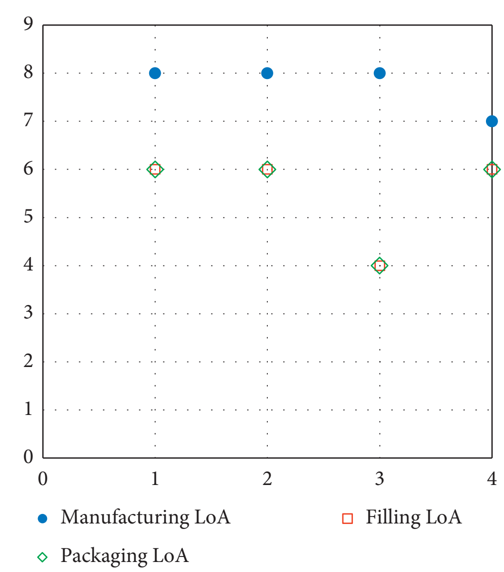

Figure 10: The results of implementing scenario1.

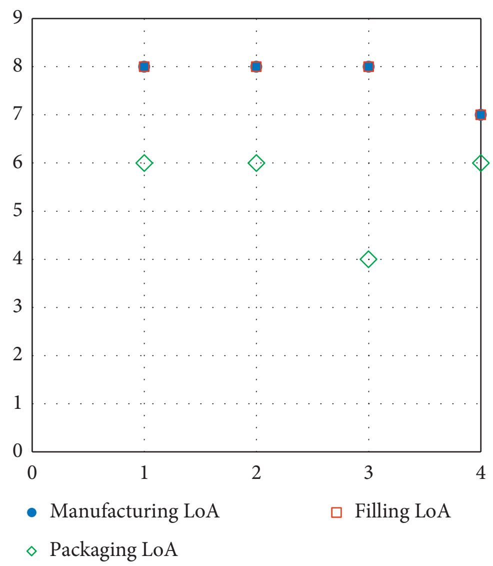

Figure 11: The results of implementing scenario2.

pollutants (primary pollutants) react. Examples of secondary pollutants include ozone which is formed when hydrocarbons (HC) and nitrogen oxides (NOx) combine in the presence of sunlight, NO2 which is formed as NO combined with oxygen in the air, and acid rain which is formed when sulfur dioxide or nitrogen oxides react with rain. Another type of pollutant is the sewage made as the result of production processes, the most serious of which include surfactants, detergents, and phosphorus. Major pollutants comprise surfactants, detergents, and phosphorus which are required to be recycled according to environmental standards. In this study, we pay attention to CO2 emissions and greenhouse gases in the production process.

4.1. Discussion. The developed model was coded in GAMS 24.9.2/CPLEX 12.7.1.0 as solver and all cases were run on a computer with a 3.00 GHz processor Intel® core™ i7 processor and 64 GB memory RAM 64 bit. For running the model, three scenarios were selected. The results of implementing various scenarios are presented here:

Scenario 1. The planning horizon is 5 years (tm = 5). The number of workers in the manufacturing workstation is 1 (nm = 1), the number of workers in the filling workstation is 4 (nf = 4), and the number of workers in the packaging workstation is 4 (np = 4). The cost of buying machinery is $ 100,000 ($b = 4$; $p = 6$; $d = 3$).

Scenario 2. The planning horizon is 4 years (tm = 4). The number of workers in the manufacturing workstation is 1 (nm = 1), the number of workers in the filling workstation is 1 (nf = 1), and the number of workers in the packaging workstation is 5 (np = 4). The cost of buying machinery is $ 200,000 ($b = 4$; $p = 6$; $d = 3$).

Scenario 3. The planning horizon is 3 years (tm = 3). The number of workers in the manufacturing workstation is 0 (nm = 0), the number of workers in the filling workstation is 1 (nf = 1), and the number of workers in the packaging workstation is 1 (np = 1). The cost of buying machinery is $ 400,000 ($b = 4$; $p = 6$; $d = 3$).

It can be concluded from the scenario1 that if the organization is not able to pay the costs of purchasing machinery with a high LoA, it can compensate for it by increasing the production level over five years with a low LoA, but the number of production workers will still be really large. In scenario 2, with an increase in investment, the organization will be able to compensate for its costs for four years and some workers are maintained in packaging and filling workstations. On the contrary, in the manufacturing workstation which causes the greatest damage to workers and the environment, there is only one worker in the production lines and the number of pollutants in the environment is relatively low. By reducing the number of workers, we can reduce the danger of the microbial conditional of the product, which results in less damage to the environment. In scenario 3, with an increase in investment compared with scenario 2, the organization will be able to compensate for its costs over three years, and a few workers are maintained in packaging and filling workstations. On the contrary, in the manufacturing workstation that causes the greatest damage to workers and the environment, the completely automated level is used. At the full automated level, there is no worker in production lines and the amount of pollutants in the environment is almost zero. Also, the microbial potential of the product is almost zero and hence there will be no damage to the environment. It is suggested that scenario 3 be used in the factory. This does low damage to the environment and some production workers remain in production lines. It is proportionate to the rich organization's budget. If it is not possible, an increase in the investment amount of scenario 2 is proposed due to the short term of its return on investment. As it is seen, higher fixed costs bring about higher levels of automation with higher profitability and the period of return on investment will be shorter. But, the number of workers is reduced at a high LoA. To prevent social damage caused by downsizing the workers, medium levels of automation are proposed in the packaging workstation because there is no environmental pollution in these lines at lower levels of automation. However, we usually use high levels of automation in the manufacturing workstations because they have beneficial environmental impacts. It must be considered that LoA in different workstations must be homogenous. In running these scenarios, the difference between LoAs in workstations should be less or equal to 4.

The results of implementing scenarios 1, 2, and 3 with the Zimmermann max-min approach in three workstations are given in Tables 5 and 6. In the third scenario, the implementation cost is high, but the amount of environmental pollutants is very low.

Results show that the best scenario is scenario 3. Figure 9 shows that in scenario 3 in the manufacturing workstation in all dimensions the LoA is eight and in the filling workstation and packaging workstation in four dimensions it is seven. In scenarios 1 and 2, the LoA is lower than in scenario 3 and the manufacturing workstation tries to use upper LoA because

Table 7: Detailed results of the implementation of different scenarios.

Scenario	For one day of production (8 hours)							Cost for one product			Profit$	Equipment cost $	Training cost$
	QC time	Break down time	Setup time	Time out	Production time	Production number	No. of workers	Direct material cost $	Labor cost $	overhead costs $			
1. Before the change	4.5	3	0.5	0.5	22	289	10	0.375	0.15	0.1	275	0	0
2. Expert	4.5	2	0.25	0.25	9	326	8	0.3625	0.125	0.075	329	5,000	100
3. Low-cost	4.5	2	0.5	0.5	19.5	714	9	0.375	0.145	0.1	279	1,250	25
4. Costly but profitable	1.5	0	0	0	5	1514	2	0.325	0.0125	0.05	960	250,000	250

Table 8: The data for implementing the three scenarios.

Scenarios	1- Before the change			2- Expert			3- Low-cost			4- Costly but profitable		
	T	P	W	T	P	W	T	P	W	T	P	W
Manufacturing workstation	6.0	64	6	4.0	64	6	6.0	64	6	2.0	64	0.2
Filling workstation	4.0	572	8	2.0	574	6	3.5	572	8	1.0	637	2
Packaging workstation	12.0	550	22	3.0	556	18	10.0	550	22	2.0	635	2
QC workstation	3.0	0	20	1.0	0	20	3.0	0	20	1.0	0	2
Warehouse		530			536			530			631	

T: Time; P: Product quantity; W: Waste quantity

Table 9: The number of experts required in each scenario.

Scenario	The number of experts		
	Simple worker	Excellent worker	Expert
Scenario 1	8	1	0
Scenario 2	5	0	2
Scenario 3	0	0	2

Table 10: Current overhead costs.

Time	Overhead costs: D1			Overhead costs: D2			Overhead costs: D3			Overhead costs: D4		
	Manufacturing	Filling	Packaging	Manufacturing	Filling	Packaging	Manufacturing	Filling	Packaging	Manufacturing	Filling	Packaging
1	450	800	100	300	800	100	22000	17000	12000	22000	17000	12000

Table 11: The result of sensitivity analysis in the scenario1 after changing raw material cost.

Run	Z1	Z2	Increase%	Z1 after change	Z2 after change
1	4158692	0.000721040602	10%-	3382016	0.000721040601
2	4158692	0.000721040601	10%-	3382125	0.000721040602
3	4158692	0.000721040600	10%-	3382126	0.000721040601
4	4158692	0.000721040601	10%	4550578	0.000721040600
5	4158692	0.000721040600	10%	4550569	0.000721040600
6	4158692	0.000721040600	10%	4550592	0.000721040600
7	4158692	0.000721040600	20%	5276520	0.000721040601
8	4158692	0.000721040600	20%	5276516	0.000721040600
9	4158692	0.000721040602	20%	5276520	0.000721040600
10	4158692	0.000721040600	30%	5354012	0.000721040603
11	4158692	0.000721040600	30%	5354016	0.000721040600
12	4158692	0.000721040601	30%	5354012	0.000721040603

of danger in the production process as shown in Figures 9–11.

Table 7 presents the results of the running of the proposed scenarios and the initial state of production. As can be seen, in the costly but profitable scenario, the production time, the amount of waste, and the number of workers in the production line are lower but the production quantity and profitability are significantly higher.

Other results of the implementation of the proposed scenarios are given in Table 8. Table 9 shows that in the low-cost scenario, the production time and the amount of product waste are slightly reduced. In the expert scenario, the amount of waste and the time of production are further reduced. In the costly but profitable scenario, the production time and the amount of waste are significantly reduced. In Figures 12(a,b,c, and d), the variations of production time, the amount of waste, production quantity, and profit in the initial state of production before the change (s0), and the three proposed scenarios (s1, s2, s3) are compared; it was found that the s3 scenario, i.e., costly but profitable, has the least waste, the least productive time, and the maximum profit as shown in Figure 13.

After increasing the number of experts, the results show that the amount of Z1 increases and the LoA decreases. The number of three types of experts is shown in three workstations in Table 9 and Figure 10; the amounts increased and the Z1 value increased, too.

4.2. Sensitivity Analysis. The results show that the amount of Z1 increases after increasing the overhead costs. The results

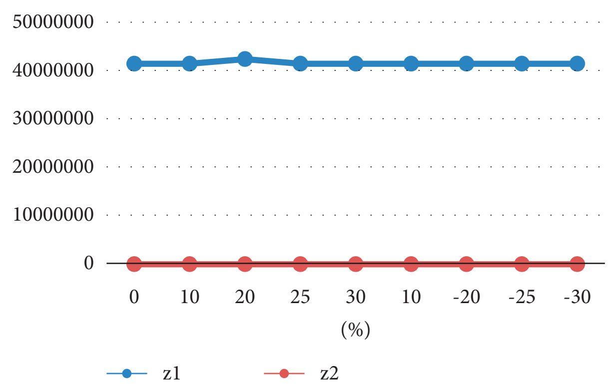

Figure 12: The changes in the overhead costs and a change in Z.

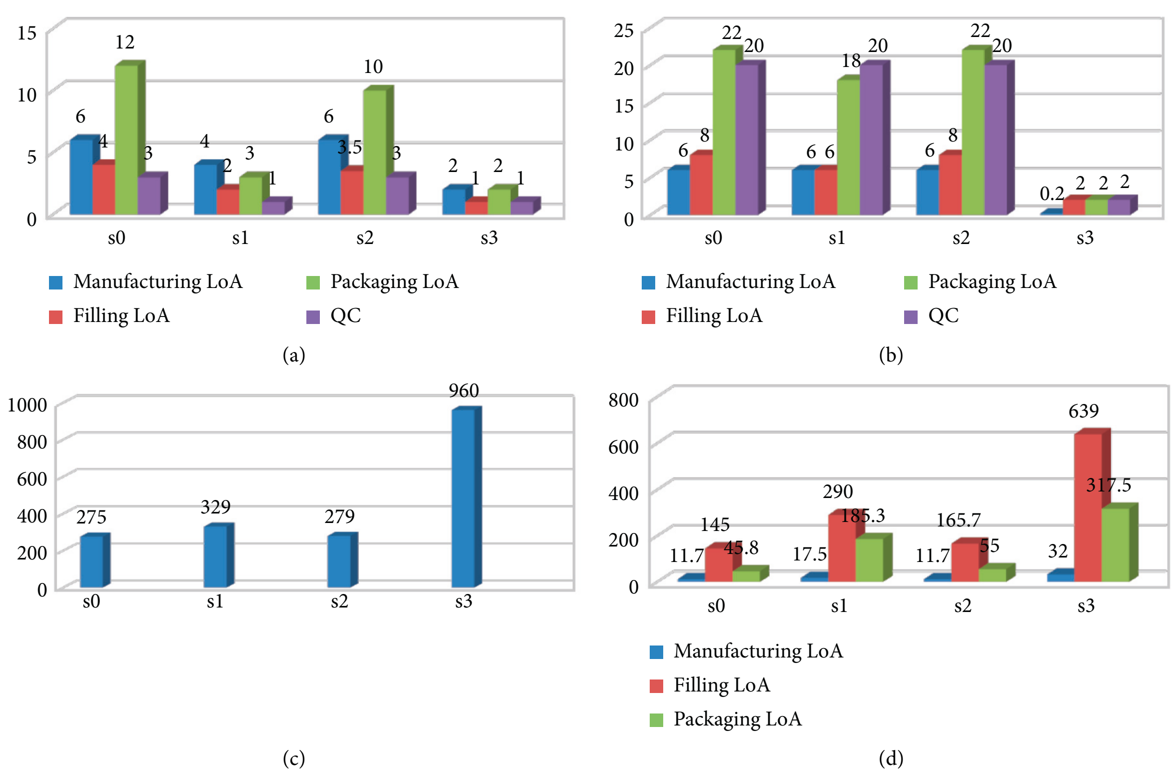

Figure 13: Changes in production parameters after implementing different scenarios s0(Before change), s1(Expert), s2(Low-cost), s3(Costly but profitable) (a) Changes in production time after implementing different scenarios (s0, s1, s2, s3) in the manufacturing, filling, and packaging workstations (b) Changes in production waste after implementing different scenarios (s0, s1, s2, s3) in the manufacturing, filling, packaging, and QC workstations. (c). Changes in profit after implementing different scenarios (s0, s1, s2, s3). (d). Changes in production quantity after implementing different scenarios (s0, s1, s2, s3) in the manufacturing, filling, and packaging workstations.

are shown in Table 10. The results of sensitivity analysis show that increasing the cost of raw materials, the number of workers, and overhead costs leads to an increase in the value of Z1, but it is almost ineffective on the value of Z2 as shown in Table 11 and Figures 12, 14 and 15.

(i) Discussion: The Dynamo method that was previously used to determine the optimal LoA was very complicated and time-consuming, and simulation should be used to implement it, but the model in this research is very practical, simple, and low-cost and it also covers all aspects of sustainability.

5. Managerial Insights and Practical Implications

This model can help executives to select the appropriate level and dimension of automation proportionate to organization resources and requirements. Before optimizing LoA in

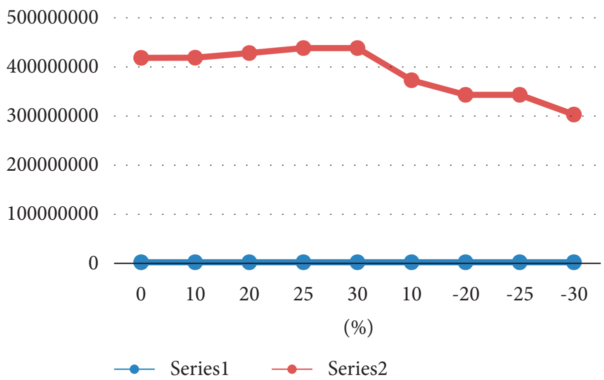

Figure 14: The changes in raw material costs and a change in Z.

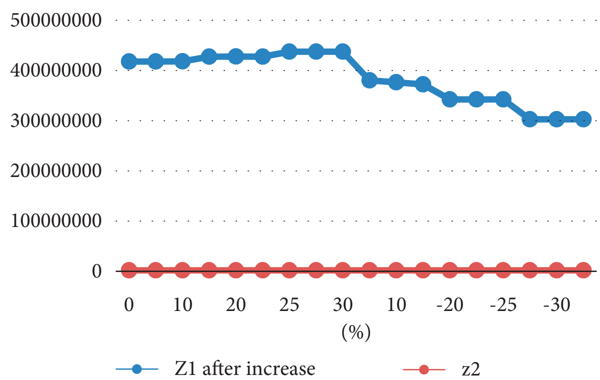

Figure 15: The changes in the labor costs and a change in Z.

chemical industries, the level of environmental pollutants is high and may involve factory closure, heavy penalties, and environmental tax policies. This model helps managers to solve this problem as well. Due to the high cost of full implementation of automation, this model helps managers to create the best performance by choosing the optimal LoA and the dismissal of all workers is also prevented. By using the definition of LoA (2D), it is possible to improve the LoA in different dimensions according to the needs of the organization.

6. Conclusion

In this paper, a mathematical model is developed to determine the optimal LoA in the chemical industry considering triple aspects of sustainability, namely, economic, environmental, and social aspects. The chemical industry process contains three workstations manufacturing, filling, and packaging. Unit costs of raw materials and overhead costs in manufacturing workstations, filling workstations, and packaging workstations are fuzzy variables. The cost of specialists and workers in each workstation is certain.

This research develops a fuzzy multi-objective model that can improve the LoA by considering any one-dimensional (1D) or two-dimensional (2D) definition of LoA. The danger of transactions of COVID-19 is an important reason to increase LoA to avoid virus infection to workers and customers. To achieve these objectives, an organization was asked to consider the existing financial resources and try to maximize the net present value, minimize the environmental damage and maintain a certain number of production line workers to reduce the social damage of downsizing. In our model, NPV should be positive in the long run. By using a two-dimensional definition of LoA, automation levels can be defined in more precise dimensions, such as the definition proposed by Proud et al. [15]. Also, it should be noted that the proposed levels and dimensions of automation should be homogenous; for example, it cannot be completely manual in one dimension and completely automated in another dimension, and it should also be implementable. A bi-objective mathematical model is developed for this purpose. The first objective of the model is to minimize the cost function including the cost of materials, labor cost, and overhead costs, and the second objective is to minimize the number of environmental pollutants. The model is solved using Zimmermann max-min approach. Finally, to validate the model, it is implemented in a real case in Iran and three scenarios are developed to cover the uncertainties that are present in some parameters.

(i) The results show that the optimal LoA can be improved with the available resources and the benefits of increasing the LoA can be used for reducing the social damage caused by downsizing the workforce and decreasing the environmental pollutants.

For further research, the authors can refer to optimizing LoA in other industries and optimizing LoA in the supply chain. They can also consider recycling and optimizing LoA to improve profitability and reduce the related defects. Measuring manufacturing performance parameters can also be measured after improving LoA in organizations.

Data Availability

The data in the article are available in full in the tables.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] P. Brown, T. Ly, H. Pham, and P. Sivabalan, "Automation and management control in dynamic environments: m," *The British Accounting Review*, vol. 52, no. 2, Article ID 100840, 2020.

[2] H. Hashemi, A. M. Shaharoun, S. Izman, B. Ganji, Z. Namazian, and S. Shojaei, "Fixture design automation and optimization techniques: review and future trends," *International Journal of Engineering (IJE), TRANSACTIONS B: Applications*, vol. 27, no. 11, pp. 1787–1794, November 2014.

[3] J. Kim, A. M. Stockton, E. C. Jensen, and R. A. Mathies, "Pneumatically actuated microvalve circuits for programmable automation of chemical and biochemical analysis," *Lab on a Chip*, vol. 16, no. 5, pp. 812–819, 2016.

[4] S. FakhrHosseini, C. Lee, and J. F. Coughlin, "Home as a platform: levels of automation for connected home services," in *Proceedings of the International Conference on Human-*

Computer Interaction, pp. 451–462, Springer, Cham, New York, NY, USA, July, 2020.

[5] E. Stayton and J. Stilgoe, "It's time to rethink levels of automation for self-driving vehicles," *IEEE Technology and Society Magazine*, vol. 39, 2020.

[6] M. R. Endsley, "The application of human factors to the development of expert systems for advanced cockpits," in *Proceedings of the Human Factors Society Annual Meeting*, vol. 31, no. No. 12, pp. 1388–1392, SAGE Publications, Los Angeles, CA, September, 1987.

[7] N. Burtnyk and M. A. Greenspan, *Supervised Autonomy-Partitioning Telerobotic Responsibilities between Human Machine*, National Research Council of Canada, Institute for Information Technology, Ottawa, Canada, 1991.

[8] J. Frohm, *Levels of Automation in Production Systems*, Chalmers University of Technology, Göteborg, Sweden, 2008.

[9] A. Fasth, J. Stahre, and K. Dencker, "Analyzing changeability and time parameters due to levels of Automation in an assembly system," in *Proceedings of the 18th Conference on Flexible Automation and Intelligent Manufacturing-FAIM*, Wayne State University, Detroit, MI, USA, January 2008.

[10] J. Frohm, V. Lindström, and M. Bellgran, "A model for parallel levels of automation within manufacturing," in *Proceedings of the 18th International Conference on Production Research*, pp. 1–6, DYNAMO, Salerno, Italy, July, 2005.

[11] B. Lorenz, F. Di Nocera, S. Röttger, and R. Parasuraman, "The effects of LoA on the out-of-the-loop unfamiliarity in a complex dynamic fault-management task during simulated spaceflight operations," in *Proceedings of the Human Factors and Ergonomics Society - Annual Meeting*, vol. 45, no. No. 2, pp. 44–48, SAGE Publications, Los Angeles, CA, October, 2001.

[12] R. Parasuraman, "Designing automation for human use: empirical studies and quantitative models," *Ergonomics*, vol. 43, no. 7, pp. 931–951, 2000.

[13] F. Di Nocera, B. Lorenz, and R. Parasuraman, "Consequences of shifting from one LoA to another: main effects and their stability," *Human factors in design, safety, and management*, pp. 363–376, Shaker Publishing, Maastricht, Germany, 2005.

[14] R. Parasuraman, M. Barnes, K. Cosenzo, and S. Mulgund, *Adaptive Automation for Human-Robot Teaming in Future Command and Control Systems*, Army research lab aberdeen proving ground md human research and engineering directorate, 2007.

[15] R. W. Proud, J. J. Hart, and R. B. Mrozinski, *Methods for Determining the Level of Autonomy to Design into a Human Spaceflight Vehicle: A Function-specific Approach*, National Aeronautics And Space Administration Houston Tx Lyndon B Johnson Space Center, Texas, TX, USA, 2003.

[16] M. Simmler and R. Frischknecht, "A Taxonomy of Human-Machine Collaboration: Capturing Automation and Technical Autonomy," *AI & SOCIETY*, vol. 36, pp. 1–12, 2020.

[17] V. Riley, "A general model of mixed-initiative human-machine systems," in *Proceedings of the Human Factors Society Annual Meeting*, vol. 33, pp. 124–128, , no. No. 2, SAGE Publications, Los Angeles, CA, 1989, October.

[18] M. Vagia, A. A. Transeth, and S. A. Fjerdingen, "A literature review of the levels of automation during the years. What are the different taxonomies that have been proposed?" *Applied Ergonomics*, vol. 53, pp. 190–202, 2016.

[19] W. Xu, *From Automation to Autonomy and Autonomous Vehicles: Challenges and Opportunities for Human-Computer Interaction*, Association for Computing Machinery, New York, NY, USA, 2020.

[20] K. Schaefer and P. Hancock, "A meta-analysis of factors influencing the development of trust in automation: implications for understanding autonomy in future systems," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 58, no. 3, pp. 377–400, 2016.

[21] A. Fereidunian, C. Lucas, H. Lesani, M. Lehtonen, and M. Nordman, "Challenges in the implementation of human-automation interaction models," in *Proceedings of the 2007 Mediterranean Conference on Control & Automation*, pp. 1–6, IEEE, Athens, Greece, June, 2007.

[22] S. A. Mostafa, M. S. Ahmad, and A. Mustapha, "Adjustable autonomy: a systematic literature review," *Artificial Intelligence Review*, vol. 51, no. 2, pp. 149–186, 2019, þ.

[23] H. Ait Malek, A. Etienne, A. Siadat, and T. Allavena, "A literature review on the LoA and new approach proposal," in *Proceedings of the IFIP International Conference on Advances in Production Management Systems*, pp. 408–417, Springer, Cham, New York, NY, USA, August, 2020.

[24] J. Stahre and A. Fasth, "Concept model towards optimizing Levels of Automation (LoA) in assembly systems," in *Proceedings of the 3rd CIRP Conference on Assembly Technologies and Systems*, pp. 1–3, International Academy of Production Engineering CIRP, Paris, France, June, 2010.

[25] Y. Wang, X. Wang, H. Yu et al., "Optimal design of integrated energy system considering economics, autonomy, and carbon emissions," *Journal of Cleaner Production*, vol. 225, pp. 563–578, 2019.

[26] P. Choe, J. D. Tew, and S. Tong, "Effect of cognitive automation in a material handling system on manufacturing flexibility," *International Journal of Production Economics*, vol. 170, pp. 891–899, 2015.

[27] A. Mehta and M. Subramanian, *Investigating the Barriers to Increase Levels of Automation.: A Case Study in Pre-assembly of Tap Changer Assembly Line*, Paper Within Production Systems, Jonkoping, Sweden, 2019.

[28] M. Abdul Hadi, M. Brillinger, M. Bloder et al., "Implementing cognitive technologies in an assembly line based on two case studies," *Procedia CIRP*, vol. 97, pp. 520–525, 2021.

[29] S. Krishnamoorthi and B. Raphael, "Identifying the right level of automation through model composition and stochastic search," *CSIT*, vol. 10, no. 2, pp. 85–95, 2022.

[30] H. A. Malek, A. Etienne, A. Siadat, and T. Allavena, "Proposal of a methodology to improve the LoA of an assembly line," in *Proceedings of the IFIP International Conference on Advances in Production Management Systems*, pp. 433–441, Springer, Cham, New York, NY, USA, September, 2021.

[31] I. Marius, F. Kristin, K. Marianne, and N. Salman, "The level of automation in emergency quick disconnect decision making," *Journal of Marine Science and Engineering*, vol. 6, no. 1, p. 17, 2018.

[32] A. Shastri and G. T. Thampi, "Automation of IT service management processes," in *2021 International Conference on Advances in Computing, Communication, and Control (ICAC3)*, pp. 1–4, IEEE, Mumbai, India, December, 2021.

[33] A. Aryal, B. Becerik-Gerber, G. M. Lucas, and S. C. Roll, "Intelligent agents to improve thermal satisfaction by controlling personal comfort systems under different levels of automation," *IEEE Internet of Things Journal*, vol. 8, no. 8, pp. 7089–7100, 2021.

[34] U. Frank, "Increasing the level of automation in organisations: some remarks on formalisation, contingency and the social construction of reality," *Systemist*, vol. 20, no. 113, 1998.

[35] H. A. Abbass, "Social integration of artificial intelligence: functions, automation allocation logic and human-autonomy

trust," *Cognitive Computation*, vol. 11, no. 2, pp. 159–171, 2019.

[36] K. Gopinath and G. Narayanamurthy, "Early bird catches the worm! Meta-analysis of autonomous vehicles adoption–Moderating role of automation level, ownership and culture," *International Journal of Information Management*, vol. 66, Article ID 102536, 2022.

[37] E. Stayton and J. Stilgoe, "It's time to rethink levels of automation for self-driving vehicles [opinion]," *IEEE Technology and Society Magazine*, vol. 39, no. 3, pp. 13–19, 2020.

[38] L. F. Wang, "A fault diagnosis method for automaton based on morphological component analysis and ensemble empirical mode decomposition," *International Journal of Engineering (IJE), IJE TRANSACTIONS C: Aspects*, vol. 32, no. 6, pp. 877–883, June 2019.

[39] T. B. Sheridan and W. L. Verplank, *Human and Computer Control of Undersea Teleoperators*, Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab, Massachusetts, MA, USA, 1978.

[40] M. D. Mckay, R. J. Beckman, and W. J. Conover, "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics*, vol. 42, no. 1, pp. 55–61, 2000.

[41] H. J. Zimmermann, "Fuzzy programming and linear programming with several objective functions," *Fuzzy Sets and Systems*, vol. 1, pp. 45–55, 1978.