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ORIGINAL ARTICLE

Optimization of facility layout design with ambiguity by an efficient fuzzy multivariate approach

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Abstract This paper presents an integrated fuzzy simulation-fuzzy data envelopment analysis (FDEA)-analytic hierarchy process (AHP) approach to deal with a flow shop facility layout design (FSFLD) problem with ambiguous inputs and outputs. Ambiguous inputs and outputs are defined as noncrisp operational, qualitative, and dependent indicators. At first, feasible layout alternatives are generated by a software package. Then, fuzzy AHP is used for weighting noncrisp qualitative data (maintainability, accessibility, and flexibility). Fuzzy simulation is then used to incorporate the ambiguity associated with processing times in the flow shop by considering all generated layout alternatives with uncertain inputs. The outputs of fuzzy simulation or noncrisp operational indicators are average waiting time-in queue, average time-in system, and average machine utilization. Finally, FDEA is used for finding the optimum layout alternative among all feasible generated alternatives with respect to operational, qualitative, and layout-dependent indicators (distance, adjacency, and shape ratio). The integrated approach of this study is more precise and efficient than previous studies with ambiguous inputs. It also provides a comprehensive analysis on the FSFLD problems by using operational and subjective and fuzzy indicators. The results have been verified and validated by DEA, principal component analysis, and numerical taxonomy. The unique features of this study are the ability of dealing with multiple noncrisp inputs and outputs. It also uses fuzzy mathematical programming for optimum layout alternatives. Moreover, it is a practical tool and may be applied in real cases by considering uncertain and ambiguous aspects of the manufacturing process within FSFLD problems.

Keywords Facility layout design · Flow shop · Fuzzy simulation · Fuzzy analytic hierarchy process · Fuzzy data envelopment analysis · Ambiguous data

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1 Motivation and significance

There are usually missing data, incomplete data, or lack of data with respect to layout problems in general and FSFLD problems in particular. This means that data could not be collected and analyzed by deterministic or stochastic models and new approaches for tackling such problems are required. This gap motivated the authors to develop a unique approach to handle such gaps in FSFLD problems.

The integrated fuzzy simulation-fuzzy DEA-fuzzy AHP presents exact solution to the FSFLD problems with ambiguity, whereas previous studies present incomplete and nonexact alternatives. Also, it provides a comprehensive analysis on the FSFLD problems with uncertainty by incorporating noncrisp operational, dependent, and qualitative indicators. Moreover, it provides complete and exact rankings of the plant layout alternatives with uncertain and fuzzy inputs. The superiority and effectiveness of the proposed integrated approach are compared with previous DEA-simulation-AHP, AHP-DEA, AHP-principal component analysis (PCA), and numerical taxonomy (NT) methodologies through a case study. The unique features of the proposed integrated approach are the ability of dealing with multiple fuzzy inputs and outputs (operational, qualitative, and dependent) and optimization through fuzzy DEA and applicability in real cases due to considering

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operational aspects of the manufacturing process within FSFLD problems.

2 Introduction

Facility layout design (FLD) is a crucial task in redesigning, expanding, or designing the manufacturing systems, e.g., flow shop systems. The FSFLD problem involves determining the arrangement and the location of equipments, workstations, offices, etc. within a flow shop system by considering the interconnections through sequential facilities as well as walks and vehicle transportations. The most common objectives of layout problems in literature are minimization of the transportation costs of raw material, parts, tools, work-in-process, and finished products among the facilities [31, 32, 34], facilitating the traffic flow and minimizing the costs of it [7], maximization of the layout performance [47], minimization of the dimensional and form errors of products depending on the fixture layout [15, 36], minimization of the total number of loop traversals for a family of products [39] increasing the employee morale, and minimization of the risk of injury of personnel and damage to property, providing supervision and face-to-face communication [24].

Algorithmic approaches usually simplify both design constraints and objectives in reaching a total objective to obtain the solution of the problems. These approaches lead to generation of efficient layout alternatives, especially when commercial software (e.g., Spiral®) is available. Nevertheless, the obtained quantitative results of these tools often do not capture all of the design objectives. On the other hand, procedural approaches are used in FLD processes which are able to incorporate both qualitative and quantitative objectives. To do so, the FLD process is divided into several steps to be sequentially solved. However, the success of this process strongly depends on the generation of quality design alternatives provided by an expert designer. Deb and Bhattacharyya [17] proposed a fuzzy multiple-criteria decision-making methodology in which flow rates between facilities are ambiguous and vague. Considering material handling costs as the main objective, several heuristic and meta-heuristic approaches have been presented in the literature for various facility layout problems [19, 26, 27, 42, 45].

Layout generation and evaluation are often a challenging and time-consuming task due to its inherent multiple objective natures and its difficult data collection process [29]. Different methodologies have been presented in the literature to deal with such problems. The algorithmic approaches have mainly focused on minimizing flow distance in order to minimize material handling costs, and the procedural approaches have heavily relied on the experience and judgment of expert designers. In this regard, Yang et al. [43] showed that neither algorithmic nor procedural FLD methodology is necessarily effective in solving FLD problems. Following this idea, different studies have been conducted to cover the existent gap in the FLD problems [12, 21, 43]. Azadeh et al. [6] proposed an integrated fuzzy simulation-fuzzy data envelopment analysis (FSFDEA) algorithm to cope with a special case of single-row facility layout problem. The proposed FSFDEA algorithm is capable of modeling and optimizing small-sized SRFLP's in stochastic, uncertain, and nonlinear environments.

On the other hand, several studies have attempted to determine the efficiency of different layout alternatives and rank these decision-making units (DMUs) in a better fashion. In order to rank the DMUs, Yang and Kuo [44] and Azadeh and Izadbakhsh [2] considered three quantitative performance indicators in an FSFLD problem including distance, adjacency, and shape ratio, and three qualitative performance indicators including flexibility, accessibility, and maintenance. Nevertheless, neither Yang and Kuo [44] nor Azadeh and Izadbakhsh [2] provided a comprehensive decision-aiding tool for FLD problems. Therefore, a more comprehensive approach should be developed to incorporate all required features of manufacturing system to the ranking models and so provide a thorough and more real decision-aiding tool for decision-making processes.

Simulation is a tool with the ability to use data to evaluate a current facility layout, show potential improvement areas, and objectively evaluate various alternatives, and it is used widely in the literature [3, 33, 35, 40, 48]. Zhou et al. [48] integrated general purpose simulation to model the space, logistics, and resource dynamics with genetic approaches (GAs) for optimizing the layout based on various constraints and rules, and implementing a site layout optimization system within a simulation environment. Jithavech and Krishnan [25] presented a simulation-based method for predicting the uncertainty associated with the layout and validated their simulation approach against analytical procedures. Braglia et al. [10] proposed the adoption of indices that will help in identifying the layout design strategy to be preferred.

FDEA is the most important category of literature related to this work, which has been widely used in different research works in the literature for operation evaluation and ranking of DMUs [20, 44]. Andersen and Petersen [1] proposed a procedure called the superefficiency method for ranking DEA-efficient units. Superefficiency models are used to determine critical outputs. Different superefficiency DEA models are introduced in Seiford and Zhu [41]. A complete list of superefficiency DEA models is provided, in which the necessary and sufficient conditions are developed for the infeasibility of various superefficiency DEA models. Superefficiency models have been deeply researched in the DEA literature [8, 9, 13, 14, 22, 28, 30]. An integrated multivariate and multiattribute analysis approach based on AHP and PCA was proposed by Azadeh and Izadbakhsh [2] for solving plant FLD problems. Using the integrated AHP-PCA, they presented exact solution to the FLD problems by providing complete and exact rankings of the plant layout alternatives. However, up to knowledge of the authors, none of the previous studies considered and presented a unique methodology for FSFLD problems with noncrisp inputs and outputs. Moreover, there are usually missing data, incomplete data, or lack of data with respect to layout problems in general and FSFLD problems in particular. This means that data could not be collected and analyzed by deterministic or stochastic models, and new approaches for tackling such problems are required. This gap motivated the authors to develop a unique approach to handle such gaps in FSFLD problems.

Based on this motivation, an integrated fuzzy simulation-fuzzy DEA multiattribute approach is presented in this paper to locate the optimum layout through a set of feasible solutions. First, Spiral®, as a well-known computer-aided layout planning tool, is used to generate different layout alternatives. Then, discrete-event-simulation, as a robust performance evaluation and modeling tool, is used to model the generated layout alternatives, with respect to a set of operational data. Simulation is a flexible and powerful tool for visualizing and manipulating the system under study and can be used in different situations to make the company agile in implementing changes in a swift and effective manner based on a confident analysis. The results of the simulation model include the average waiting times in the queues and the average utilization of each machine (i.e., stage), and the average time-in system for a given number of products. Thus, having ten stages, we have 21 additional quantitative performance indicators (ten average machine utilizations and ten average queue lengths, and one average time-in system), to the three mentioned ones (i.e., distance, adjacency, and shape ratio), and three qualitative indicators (flexibility, accessibility and maintainability). Thus, 27 performance indicators are considered for different layout alternatives in order to find the best one. AHP is applied to collect qualitative performance data. All 27 performance indicators are then imported to DEA in order to determine the technical efficiency and rank of each layout alternative (DMU). The results show that the proposed integrated computer simulation-DEA approach yields a more comprehensive and applicable framework for FSFLD in comparison with the previous studies. To the best of our knowledge, this is the first study in literature that presents such integrated approach based on computer simulation and DEA for FSFLD problems.

3 The approach

3.1 System description

A practical case presented by Yang and Kuo [44] which is in regard to IC packaging process is used in this study to illustrate the efficiency and effectiveness of the proposed approach. The IC packaging process consists of ten stages. Figure 1 presents the existing layout of the ten stages [44].

The manager of the plant would like to assure that their future plant layout is efficient in supporting production activities. If the current layout is not efficient, the company would like to know what layout alternatives are efficient. The experience learned from this study will provide the guidelines for future FSFLD optimization and planning. The following assumptions are considered in the proposed approach:

- Due to the low inventory cost of IC packaging process, the most desirable layout is the one that produces the most quantity of products within a given period of time.
- The manufacturing system is flow shop which consists of ten sequential stages (i.e., machines).
- The material flow is initiated from each stage.
- The processing times are modeled based on fuzzy logic and the nature of the manufacturing system such that the processing times can be obtained by fuzzy probability theory. Moreover, it is assumed that quantitative data is not available, and therefore, fuzzy logic is used in computer simulation and multivariant analysis.
- Layout alternatives consist of noncrisp indicators.

Considering the above assumptions, the fuzzy simulation-fuzzy DEA multiattribute approach can be expressed as follows.

3.2 The integrated approach

This paper presents an integrated fuzzy simulation-fuzzy DEA multiattribute approach to deal with the FSFLD problems with ambiguous inputs and outputs. Figure 2 presents a schematic view of the proposed approach. In the following section, the steps of the proposed approach have been applied to the IC packaging process. In summary, the proposed approach is achieved as follows:

Step 1: Collect the required data for designing the layout of the manufacturing plant such as the total space of the plant and space of each machine

Step 2: Generate different layout alternatives with respect to the collected data using a computer-aided layout planning tool such as Spiral®.

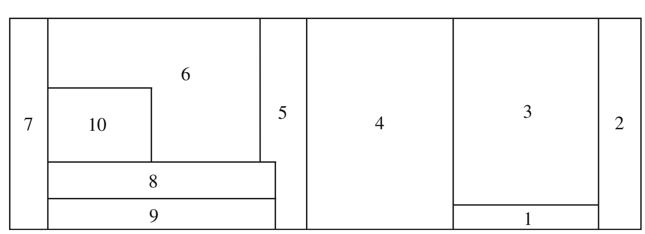

Fig. 1 The current plant layout for the IC packaging process

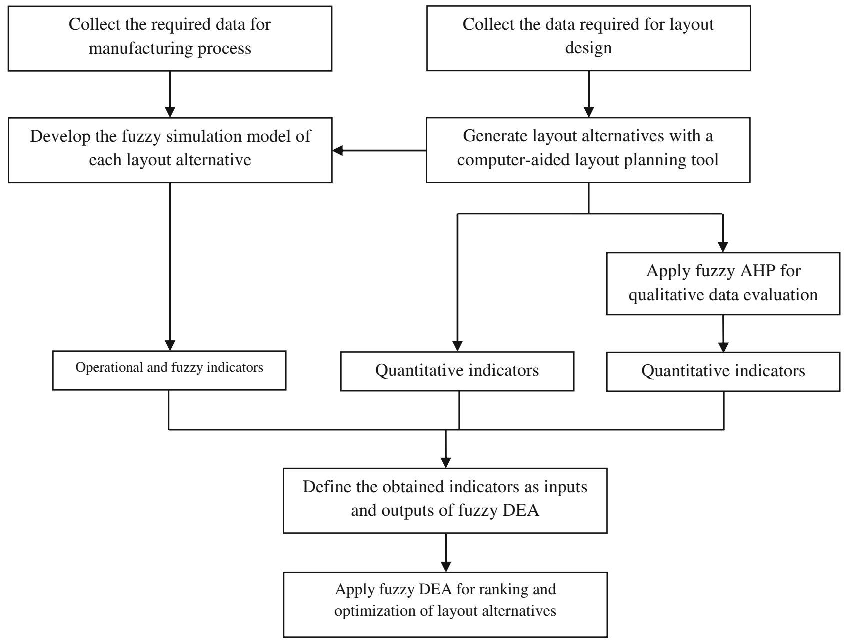

Fig. 2 Schematic view of the integrated fuzzy simulation-fuzzy DEA-AHP approach

Step 3: Collect the required data for the manufacturing process such as processing times and travelling times between sequential machines, which can be obtained from expert judgments and history of the manufacturing plant by fuzzy statistics.

Step 4: Develop the fuzzy simulation network model of each layout alternative using some additional information such as machines' processing times, which can be obtained from historical data and the experts of manufacturing plant by fuzzy probability and statistics.

Step 5: Analyze and retrieve three operational indicators from fuzzy simulation model to be used for further analysis in fuzzy DEA.

Step 6: Apply AHP for evaluation of qualitative performance indicators including flexibility, accessibility, and maintainability.

Step 7: Incorporate layout-dependent indicators (distance, adjacency, and shape ratio), qualitative indicators (flexibility, accessibility, and maintainability), and operational indicators (average waiting time in the queues, average machine utilization, and average time-in system) to the fuzzy DEA models to rank the generated layout alternatives and identify the optimum alternative. The fuzzy operational indicators, shape ratio, and distance are considered as inputs, while qualitative indicators and adjacency are considered as outputs of fuzzy DEA models.

Step 8: Compare fuzzy DEA rankings with previous studies to see if there is a significant difference between results.

4 Experiments: approach implementation

4.1 Data collection for FSFLD

Data collection should include characteristics of products, quantities, routing, support, and time considerations in order to assure the validity of the input data at the design stage. The outputs of this step are used in generating different layout alternatives. Table 1 presents the facility sizes of the ten stages. Also, the available width and length of the plant are 99.25 and 27 m, respectively.

As mentioned, operational indicators are defined as average waiting time in the queues, average machine utilization, and average time-in system. They are retrieved as outputs of fuzzy simulation models. Furthermore, minimizing average

Table 1 Facilities (stages) sizes

No.	Name	Size (m^2)
1	Wafer sawing	89.21
2	Die bond	181.51
3	Wire bond	577.38
4	Molding	599.57
5	De-junk/trimming and curing	183.71
6	Electro de-flash/solder platting	500.13
7	Marking	199.94
8	Forming and singulation	186.40
9	Lead scanning/inspection	110.78
10	Packaging	51.09

time-in system essentially would guarantee to produce the most quantity of products within a given period of time. In addition, qualitative indicators are weighted and retrieved from AHP. Hence, the qualitative and quantitative performance indicators can be defined as follows:

- Layout-dependent indicators:

– *Flow distance*: the sum of the products flow volume and rectilinear distance between the centroids of two facilities
– *Adjacency score*: the sum of all positive relationships between adjacent departments
– *Shape ratio*: the maximum of the depth-to-width and width-to-depth ratio of the smallest rectangle which can completely surround the facility

- Qualitative indicators:

– *Flexibility*: the capability of performing various tasks under various operating conditions and the sufficiency for future expansions
– *Accessibility*: the ease of material handling and operator movement between facilities
– *Maintenance*: the required space for maintenance actions and tool movements

4.2 Generating layout alternatives

A computer-aided layout planning tool (i.e., Spiral®) is used to efficiently investigate a large number of design alternatives to assure solution quality. The inputs of Spiral® in this problem are from–to matrix obtained from flow routing and the facilities sizes. Spiral® generates a layout alternative based on its embedded approach and then improves on the basis of three-way pair-wise interchange to generate a large number of alternatives ranked by flow distance in ascending order, and the preferred alternatives could be selected [23, 44].

4.3 Multiattribute analysis

The role of AHP in the proposed integrated approach is to identify the significance of the qualitative indicators. AHP cannot handle the uncertainty and imprecision of the decision-maker's perception to exact numbers [18]. A fuzzy AHP (FAHP) is capable to tolerate vagueness or ambiguity associated with fuzziness and vagueness, which are common characteristics in many decision-making problems. Technically, FAHP is a multicriteria decision-making (MCDM) method that allows decision makers to model a complex problem in a hierarchical structure which consists of the goal, objectives (criteria), sub-objectives, and alternatives [38]. The process encounters various options in decision making and gives the criteria sensitiveness analysis possibility. The decision maker should determine the weight of all criteria in order to do pair-wise comparison between them. The main procedure of AHP is as follows [16]:

1. Determining the objective and evaluation attributes
2. Developing hierarchical structure levels with goals, contracture, criteria, and the alternatives
3. Finding out the importance of different attributes considering the goals

Fuzzy number can be applied for mapping uncertain comparison judgment. A triangular fuzzy number that is the special class of fuzzy number is used. Fuzzy membership is defined by three numbers as most optimistic, most pessimistic, and average values [46].

4.4 Data collection for the manufacturing process

To illustrate the efficiency of the proposed approach in evaluating the generated layout alternatives from operational viewpoints, a set of operational data from a case study in Azadeh et al. [5] are applied to the IC packaging process. The required data for modeling the IC packaging process are shown in Table 2. The historical production data are collected from the company's shop floor control system. The setup times, mean time between failures (MTBF), and mean time to repair (MTTR) are stochastic data analyzed by commercial curve fitting software, ExpertFit. The resulting distributions for each machine type are validated by both chi-square and Kolmogorov-Smirnov tests for their goodness of fit. There are neither historical data nor robust time studies on processing times.

Moreover, expert judgment is used to derive to processing times. Therefore, fuzzy theory may be applied for this instance. Triangular-shaped fuzzy numbers with different α-cuts are used to establish confidence intervals. This is because of lack of proper documented or quantitative data. Furthermore, expert judgment is used to establish triangular fuzzy numbers. Thus, all processing times are noncrisp as shown in Tables 3 and 4. The computed triangular fuzzy numbers are modeled for α=0.001, 0.01, 0.2, 0.4, 0.6, and 0.8, but only results of α=0.001 are shown in Tables 3 and 4. The processing time for the stages in Table 3 is dependent on material type, regardless of product size, while the processing time for the stages in Table 4 is independent of product type. The notation for product size and material types is a convention of the case study company. There are 24 product types as a combination of six material types and four product size.

The sample of MATLAB for generating an exponential distribution with the parameter λ=1 is shown in Appendix I. Pessimistic and optimistic values (based of expert judgments) are used for establishing the confidence intervals. The

Table 2 Setup times, MTBF, and MTTR for machines

Stage	Number of machines	Setup time (min)	MTBF (min)	MTTR (min)
1	2	Uniform (27, 33)[a]	Exp (300)	Exp (130)
2	1	0	0	0
3	1	Uniform (25, 33)[b]	Exp (200)	Exp (80)
4	6	0	0	0
5	2	Constant (1440)[a]	0	0
6	1	0	Exp (540)	Exp (150)
7	1	Uniform (29, 35)[b]	Exp (250)	Exp (30)
8	1	Constant (1440)[a]	Exp (350)	Exp (45)
9	1	Uniform (1, 2)[a,b]	Exp (720)	Exp (70)
10	1	Uniform (20, 29)[b]	Exp (200)	Exp (60)

[a] Setup needed for the material change

[b] Setup needed for the size change

distances between each two sequential stages are calculated by a computer-aided layout planning tool for all 18 layout alternatives. It is assumed that the flow of work-in-process (WIP) between sequential stages has approximately 0.5 m/min velocity (considering all waste times). Thus, the time taken to transfer WIP between each two sequential stages can be calculated by dividing the distance into the flow velocity as shown in Table 5.

4.5 Simulation network modeling

Six product types and ten resources are considered as entities and servers in this model, respectively. Each product type has two attributes identifying its type and starting time and is emanated in network by a CREATE node, and also the type and starting time of it are determined by an ASSIGN node positioned after the CREATE node.

It is assumed that all product types have equal percents of the overall demand. Hence, the simulation network is modeled with 50 entities for each product type. A product (entity) is sent to original network. If the specific machine processing this product is available, then it is assigned to the machine for during the processing time. Otherwise, this material must be awaited in the file number of the stage. This process is done with ten AWAIT nodes. Processing time of each product on each machine in each step is defined during the activity. After entering all 200 entities to the TERMINATE node, the simulation will be

Table 3 Material-type dependent fuzzy processing time data (min) with α=0.001

Stage		Material type					
		A	B	C	D	E	F
1	OV	1031.1	717.2355	481.1773	1180.9	847.6458	598.7394
	PV	453.4489	274.4959	167.7388	458.97	321.0706	222.566
2	OV	27.0933	45.3498	45.3501	49.1857	49.2389	76.4505
	PV	8.11	19.8775	19.7741	18.887	18.8881	22.6836
3	OV	524.4302	246.7524	246.7633	316.7419	250.9155	161.8067
	PV	176.1557	94.9543	94.8955	126.738	102.403	66.62
4	OV	5217.7	4759.3	5217.8	4068.9	3381.6	4759.3
	PV	2050.9	1833.2	2051.7	1223.7	1260.4	1832.2
6	OV	547.477	409.1516	533.6557	700.3589	599.0052	848.9364
	PV	213.2199	176.6249	230.3617	272.1089	213.242	289.0328
9	OV	397.6682	397.6682	397.6682	397.6682	397.6682	397.6682
	PV	236.2484	236.2484	236.2484	150.6	236.2484	236.2484
10	OV	1199.6	764.9157	764.9157	1144.3	1121.6	1121.6
	PV	383.225	269.38	269.38	395.85	347.83	347.83

PV pessimistic value, *OV* optimistic value

Table 4 Single fuzzy processing time data (min) with α=0.001

Stage	Pessimistic value	Processing time	Optimistic value
5	719.5	1593	2055.3
7	48.803	105.02	146.710
8	31.9293	62.28	84.0229

completed. The fuzzy operational indicators are average waiting times in the queues, average machine utilization in each stage, and average time-in system. Fuzzy simulation is performed by considering pessimistic and optimistic values in addition to central point for the nine indicators. There are three qualitative, three layout dependent, and three operational indicators (obtained from fuzzy simulation model). As stated, there are 18 layout alternatives. This means that fuzzy simulation was run 18 times for each mode (pessimistic, central, and optimistic), which would be a total of 54 runs for each α-cut. The reader should note that the fuzzy simulation was replicated ten times, and the average of ten runs was used for each fuzzy DEA model. Triangular fuzzy shape is used to decrease the relative error in comparison with the other models. For the details of fuzzy simulation, readers are referred to Buckley [11].

4.6 Applied fuzzy DEA model

It is interested to investigate the efficiency of different layouts. The fuzzy data is inputted to fuzzy DEA model to obtain the ranking results. In most general decision-making cases, the decisions are based on concurrent quantitative and qualitative data. Fuzzy DEA seems to be convenient for problems associated with uncertainty pertinent to existent of qualitative data set. This is because most indicators for layout alternatives are judgmental and are of noncrisp nature. Saati et al. (2002) proposed a new method for ranking the efficient units based on CCR model. This was achieved by adding the constraint $\sum_{j=1}^{n}\tau_j=1$ to the CCR model and obtaining the results for the BCC model. The fuzzy BCC model for ranking the layout alternatives is as follows:

$$\begin{aligned} & \min\theta \\ s.t.\quad & \tilde{y}_{rp} \le \sum_{j=1}^{n} \tau_j \tilde{y}_{rj} \qquad \forall r = 1, \ldots, 5 \\ & \theta\tilde{x}_{rp} \ge \sum_{j=1}^{n} \tau_j \tilde{x}_{ij} \qquad \forall i = 1, \ldots, 4 \\ & \sum_{j=1}^{n} \tau_j = 1 \qquad \forall j = 1, \ldots, 18 \end{aligned} \tag{1.1}$$

Table 5 The material transfer time between stages for different layout alternatives (min)

Layout alternative	From–to								
	1–2	2–3	3–4	4–5	5–6	6–7	7–8	8–9	9–10
1	35.6	36.6	39.4	38.2	91.8	26.8	32.6	37	24
2	13.8	136.4	44.4	61.6	23.2	53.8	32.8	22.4	11.8
3	27.8	54	61.8	41	76.8	54	36.2	42.2	16
4	36	34.6	36.6	41.6	93.2	38.6	17	41.6	24.8
5	27	78.2	37.4	34.6	74.6	72.8	19	52.8	26.2
6	26.6	26.8	129.8	39.6	107	38.8	59	29.6	54.6
7	43.6	51	32.8	99	76.8	74.6	23.4	54.2	30.4
8	43	19.4	27	103.6	37.2	42	23.2	48.6	26
9	26.6	81.2	33.6	39.8	80.2	49.8	18.2	31.4	21.6
10	26.8	19.4	40.8	30.6	73.4	47.4	20.4	33.8	130
11	27.2	27.8	71.2	61.4	55.4	33.2	74.4	39	16.4
12	64	13.2	77.4	15.6	94.2	42.8	25.6	49	43
13	30.8	72	60.2	58.4	65.4	83	43	41.6	17
14	27.4	57.8	58.6	40.8	76.6	54.6	35.6	42.2	17
15	34.6	25.4	49.8	37	77.6	23.8	33.4	34.2	22.2
16	46	94.4	36.4	17.4	77.8	28	43.2	27.6	52
17	32.2	25.6	49.8	34.8	83	52.8	18	36.6	20.8
18	57.2	32.2	50	32.6	37.2	58.8	58.4	11	45.6

In the above model, indices i, r, and j represent the inputs, outputs, and layout alternatives, respectively. The fuzzy input indicators are average waiting time in the queues, average machine utilization in each stage, average time-in system, shape ratio, and distance. The fuzzy output indicators are the three qualitative indicators (accessibility, flexibility, and maintenance) and adjacency. This is because inputs should be reduced, while outputs should be increased in optimization problems. $\tilde{x}_{ij}$ and $\tilde{y}_{ij}$ are respectively input and output variables of FDEA which are triangular-shaped fuzzy numbers as discussed before, and $\tilde{x}_{ip}$ and $\tilde{y}_{rp}$ are the optimistic value for input variables $\tilde{x}_{ij}$ and pessimistic value for output variables $\tilde{y}_{ij}$, respectively. Substituting fuzzy values $\tilde{x}_{ij}$ and $\tilde{y}_{ij}$ with $\tilde{x}_{ij}=\left(x^p_{ij},x^m_{ij},x^o_{ij}\right)$ and $\tilde{y}_{ij}=(y^p_{ij},y^m_{ij},y^o_{ij})$, respectively, and using α-cuts method, model (1.1), can be expressed as follows:

$$\begin{aligned}
&\min\theta\\
&s.t.\,\theta\left(\alpha x^m_{ip}+(1-\alpha)x^p_{ip}\right)\geq\sum\nolimits_{j=1}^{n}\tau_j\left(\alpha x^m_{ij}+(1-\alpha)x^p_{rj}\right)\quad\forall i=1,\ldots,5\\
&\alpha y^m_{rp}+(1-\alpha)y^o_{rp}\leq\sum\nolimits_{j=1}^{n}\tau_j\left(\alpha y^m_{rj}+(1-\alpha)x^p_{rj}\right)\qquad\forall r=1,\ldots,4\\
&\sum\nolimits_{j=1}^{n}\tau_j=1\tau_j\geq 0\quad\forall j=1,\ldots,18
\end{aligned}\tag{1.2}$$

In model (1.2), α is a parameter belonging to the interval [0 1]. Model (1.2) is a parametric linear programming model which can be used for obtaining the optimum solution for each given value of α (Saati et al. 2002). Since the objective of this study is to analyze the efficiency of layouts based on output indicators, the output-oriented BCC model has been utilized, and the efficiency and rank of each layout are determined based on model (1.2) for different α values. Also, since α represents the certainty of the given indicators, as α gets closer to zero, the certainty of the given indicators gets lower, and the system becomes fuzzier. In contrast, as α goes to one, the more certainty of the given indicators increases and the fuzzy system goes to the certain system [4].

5 Computational results

In this paper, an integrated computer simulation-DEA approach is presented to deal with the FSFLD problem in an IC packaging process. As mentioned previously, Yang and Kuo [44] and Azadeh and Izadbakhsh [2] considered three quantitative and three qualitative indicators for evaluating the performance of feasible layout alternatives provided by a computer-aided layout planning tool. Consequently, 18 layout alternatives have been generated. The quantitative measures for those design alternatives are converted to

Table 6 Fuzzy quantitative indicators

Layout alternative	PV	Distance (m)	OV	PV	Adjacency	OV	PV	Shape ratio	OV
DMU 1	72.48	185.95	250.91	3.11	8	8.09	4.47	8.28	15.62
DMU 2	119.8	207.37	325.65	2.31	9	10.18	2.13	3.75	6.01
DMU 3	57.21	206.38	327.29	3.26	8	8.09	3.98	7.85	12.87
DMU 4	106.98	189.66	251.37	3.11	8	8.91	3.64	8.28	10.42
DMU 5	121.86	211.46	333.1	3.11	8	8.09	4.9	7.71	12.73
DMU 6	137.46	264.07	383.07	2.44	5	5.89	1.06	2.07	4.77
DMU 7	145.51	228.00	382.01	3.15	8	8.09	6.01	14.00	17.53
DMU 8	76.91	185.59	283.61	4.78	9	12.12	3.64	6.25	8.03
DMU 9	51.52	185.85	294.74	4.44	9	4.79	4.14	7.85	11.12
DMU 10	164.93	236.15	486.57	3.11	8	8.94	4.14	7.85	11.12
DMU 11	95.35	183.18	265.73	3.11	8	8.09	0.83	2.00	2.83
DMU 12	84.61	204.18	309.84	3.11	8	8.09	6.16	13.30	15.96
DMU 13	99.27	225.26	309.35	3.11	8	8.08	4.42	8.14	11.08
DMU 14	104.13	202.82	279.11	3.11	8	8.09	3.77	8.00	14.62
DMU 15	49.9	170.14	309.05	4.26	9	12.79	3.77	8.28	11.05
DMU 16	118.51	216.38	369.16	5.48	9	13.53	3.62	7.71	11.51
DMU 17	50.29	179.80	338.33	3.11	8	8.09	4.96	10.30	14.21
DMU 18	94	185.75	308.28	9	10	10.11	4.35	10.16	16.62

PV pessimistic value, *OV* optimistic value fuzzy triangular numbers as shown in Table 6 in which the noncrisp values of distance and shape ratio are presented due to the larger-the-better criterion for layout alternatives. When it is not expected that one point estimate is exactly equal to a parameter such as θ, a (1 − β)100 % confidence interval is often defined for θ, where β represents the confidence level. Consider X as a random variable with probability density function of f(x,θ) for parameter θ. Assume that θ is unknown estimated from a random sample (X1, …, Xn). Let Y = u(X1, …, Xn) be a statistic for estimation of θ. Given the values of these random variables Xi ≤ xi, 1 ≤ i ≤ n, a point estimate θ* = y = u(x1, …, xn) is obtained for θ. It is not expected that this point estimate is exactly equal to θ. Thus, a (1 − β)100 % confidence interval is often computed for θ. The (1 − β)100 % confidence intervals can be generated for all 0.001 ≤ β ≤ 1. These confidence intervals are denoted as [θ1 (β), θ2 (β)] for 0.001 ≤ β ≤ 1. Also, the confidence interval for β = 1 could be represented as [θ*1, θ*2]. Subsequently, placing these confidence intervals one on top of the others leads to producing a triangular shaped fuzzy number q whose α-cuts are the confidence intervals. As a result, θ [α] = [θ1(α),θ2(α)] for all 0.001 ≤ α ≤ 1. The results are obtained for α-cuts 0.001, 0.2, 0.4, 0.6, 0.8, and 1, but only the results of α=0.001 are shown for simplicity. Moreover, due to severe ambiguity that exists in the manufacturing process, the results for α=0.001 is more reliable than other α-cuts. In addition, the experts identified 99.9 % level of uncertainty for the layout systems due to severe ambiguity that exists in various activities.

5.1 Fuzzy AHP results

Table 7 shows the weight of final privilege scores of each qualitative indicator by fuzzy triangular numbers. After determining the indicators weights using AHP, the final privilege score can be determined by multiplying the weights in their privilege scores. Therefore, the indicators will be converted into quantitative forms. Note that the weight of final privilege score of each indicator lies between zero and one, and the sum of all final privilege score value is equal to one. A consistency ratio (CR) is defined in order to prevent potential comparative inconsistency between pairs of categories and assure the appropriateness of the comparisons. The obtained CR values for central modes of flexibility, accessibility, and maintenance are 0.097, 0.088, and 0.098, respectively. Since the obtained CR is smaller than the critical value of 0.1, it can be concluded that there is no inconsistency.

5.2 Fuzzy simulation results

The fuzzy operational data for the IC packaging process have been presented in Tables 2, 3, and 4, in which six material and ten resources have been considered in order to test the model. Machines priorities and processing times for each stage are modeled and analyzed by fuzzy simulation. Data entering for each mode (pessimistic, center, and optimistic) is carried out by suitable control statements. By analyzing the output of fuzzy simulation, product sequences on each machine will be determined. The control statements are used to equalize the variables used in the network in Visual SLAM. Moreover, the array statements make a table with seven rows. The required information about the product type-dependent processing times and stages sequencing have to be read from this table. The processing time of products on stages is determined for the model by array statements. Column number is the same as the product number.

After defining the control statements, the simulation model will be ready to run. The simulation network has been modified based on the flow distances between each two sequential stages obtained by a computer-aided layout planning tool for all 18 layout alternatives. The simulation output shows information given in the nodes of the model, such as the average waiting time in the queues, average utilization of resources for each machine, and the average time-in system. Tables 8, 9, and 10 present the average waiting times in the queues, average machine utilization, and average time-in system, respectively, for all 18 layout alternatives.

5.3 Fuzzy DEA results

FDEA model discussed in previous section is used to evaluate the efficiency of each layout alternative and optimize the FSFLD problem with ambiguous inputs and outputs. As mentioned, 18 layout alternatives and 9 performance indicators including distance, adjacency, shape ratio, flexibility, accessibility, maintenance, average waiting time, average machines utilization, and average time-in system are considered and analyzed by the fuzzy DEA model. The FDEA model performs a full ranking on all 18 DMUs. Thus, optimal layout alternative could be obtained. Moreover, the output-oriented BCC model (1.2) has been utilized, and the efficiency and rank of each layout are determined based

Table 7 Qualitative indicators

Layout alternative	PV	Flexibility	OV	PV	Accessibility	OV	PV	Maintenance	OV
DMU 1	0.024	0.0494	0.074	0.011	0.0294	0.039	0.006	0.0130	0.016
DMU 2	0.024	0.0494	0.074	0.004	0.0147	0.023	0.015	0.0519	0.094
DMU 3	0.027	0.0370	0.067	0.004	0.0147	0.023	0.021	0.0519	0.066
DMU 4	0.027	0.0370	0.067	0.004	0.0147	0.023	0.032	0.0519	0.100
DMU 5	0.033	0.0617	0.113	0.004	0.0147	0.023	0.031	0.0390	0.091
DMU 6	0.024	0.0494	0.074	0.004	0.0147	0.023	0.015	0.0519	0.094
DMU 7	0.009	0.0247	0.033	0.042	0.0735	0.041	0.032	0.0649	0.107
DMU 8	0.027	0.0370	0.067	0.023	0.0441	0.064	0.031	0.0390	0.091
DMU 9	0.029	0.0741	0.108	0.023	0.0441	0.064	0.015	0.0519	0.094
DMU 10	0.029	0.0741	0.108	0.021	0.0588	0.0.057	0.032	0.0649	0.107
DMU 11	0.037	0.0864	0.102	0.042	0.1029	0.0156	0.031	0.0909	0.091
DMU 12	0.029	0.0370	0.108	0.042	0.0588	0.057	0.012	0.0260	0.03
DMU 13	0.009	0.0247	0.033	0.022	0.0735	1.019	0.015	0.0519	0.066
DMU 14	0.009	0.0247	0.033	0.042	0.0588	0.057	0.015	0.0519	0.066
DMU 15	0.051	0.0864	0.14	0.081	0.1176	0.202	0.062	0.1169	0.157
DMU 16	0.029	0.0741	0.108	0.041	0.0735	0.105	0.015	0.0519	0.094
DMU 17	0.053	0.0988	0.166	0.081	0.1324	0.203	0.044	0.0909	0.149
DMU 18	0.029	0.0741	0.108	0.042	0.0588	0.057	0.31	0.0390	0.091

PV pessimistic value, *OV* optimistic value

on the stated mathematical program. As mentioned before, in this study, the experts identified 99.9 % level of uncertainty for the layout systems due to severe ambiguity that exists in various activities. Therefore, α=0.001 is used for the FDEA analysis. The results of FDEA are computed for α=0.001 by using AutoAssess® (Table 11). In addition, the results of various α-cuts are shown in Table 12. This table shows that different α-cuts or different level of uncertainty would result into different decision-making process for the layout problems.

The results of FDEA are compared with previous studies as shown in Table 11. It is observed that by incorporating the fuzzy and noncrisp indicators to the FSFLD problem, the ranking results have been considerably changed. For instance, layout alternative 14 is recognized as the most efficient layout by the proposed integrated approach, while the obtained ranks by simulation-DEA-AHP, AHP-DEA, AHP-PCA, and NT methods were 13, 10, 10, and 11, respectively. On the other hand, layout alternative 15 that took the best rank among all alternatives using AHP-DEA, AHP-PCA, and NT methods has been recognized as the fifth ranked alternative by the proposed integrated approach. It is concluded that the existent difference between the results of the integrated fuzzy simulation-fuzzy DEA-AHP approach and the previous studies is due to its comprehensive standpoint in fuzzy modeling the FSFLD problems. The ranking results show that considering fuzzy operational indicators (waiting times in

Table 8 Fuzzy simulation result for the average time-in system with α=0.001

Layout	Time-in system	
	Pessimistic value	Optimistic value
DMU 1	133,692.498	138,386.209
DMU 2	133,713.382	138,349.082
DMU 3	133,810.202	138,356.949
DMU 4	133,745.716	138,390.501
DMU 5	133,764.759	138,446.515
DMU 6	133,898.811	138,505.243
DMU 7	133,809.294	138,510.757
DMU 8	133,721.920	138,417.509
DMU 9	133,757.368	138,387.553
DMU 10	133,765.389	135,541.384
DMU 11	135,083.628	138,444.844
DMU 12	133,811.162	138,346.222
DMU 13	133,859.483	138,342.205
DMU 14	133,832.735	138,427.163
DMU 15	133,715.288	136,814.254
DMU 16	133,854.942	138,421.959
DMU 17	133,691.261	138,421.959
DMU 18	133,728.682	138,394.664

Table 9 Fuzzy simulation results for the average waiting times in the queues (min) with α=0.001

Layout alternative		Stage (machine)									
		1	2	3	4	5	6	7	8	9	10
DMU 1	OV	0	82.824	0	0	0	164,980.253	0	0	0.561	0
	PV	0	1.703	0	0	0	160,283.198	5034.897	0.313	4.741	0
DMU 2	OV	0	82.496	0	0	0	164,935.572	0	0.008	0.546	0
	PV	0	1.673	0	0	0	160,269.767	4948.159	0.269	4.650	0
DMU 3	OV	0	82.28	0	0	0	165,049.707	0	0.008	0.549	0
	PV	0	1.578	0	0	0	160,306.628	4946.666	0.336	4.751	0
DMU 4	OV	0	82.205	0	0	0	165,025.208	0	0.005	0.565	0
	PV	0	1.612	0	0	0	160,319.137	5008.000	0.332	4.805	0
DMU 5	OV	0	82.753	0	0	0	165,008.337	0	0.006	0.572	0
	PV	0	1.785	0	0	0	160,316.490	5014.767	0.311	4.797	0
DMU 6	OV	0	82.828	0	0	0	165,081.139	0	0.006	0.563	0
	PV	0	1.640	0	0	0	160,313.805	5011.175	0.332	4.851	0
DMU 7	OV	0	82.495	0	0	0	164,986.564	0	0.009	0.55	0
	PV	0	1.784	0	0	0	160,295.734	5049.965	0.318	4.612	0
DMU 8	OV	0	82.174	0	0	0	165,011.580	0	0.010	0.583	0
	PV	0	1.793	0	0	0	160,295.393	5063.576	0.308	4.571	0
DMU 9	OV	0	81.929	0	0	0	165,044.366	0	0.010	0.558	0
	PV	0	1.523	0	0	0	160,315.675	4980.267	0.268	4.546	0
DMU 10	OV	0	82.945	0	0	0	165,011.837	0	0.006	0.578	0
	PV	0	1.656	0	0	0	160,327.908	4986.918	0.313	4.739	0
DMU 11	OV	0	83.397	0	0	0	164,988.947	0	0.007	0.567	0
	PV	0	1.591	0	0	0	160,312.439	5056.540	0.358	4.760	0
DMU 12	OV	0	82.065	0	0	0	165,063.571	0	0.005	0.554	0
	PV	0	1.639	0	0	0	160,319.607	4923.127	0.281	4.615	0
DMU 13	OV	0	82.444	0	0	0	165,043.692	0	0.007	0.578	0
	PV	0	1.695	0	0	0	160,342.174	4851.984	0.341	4.666	0
DMU 14	OV	0	83.077	0	0	0	165,092.790	0	0.011	0.568	0
	PV	0	1.531	0	0	0	160,287.84	5039.161	0.289	4.603	0
DMU 15	OV	0	81.020	0	0	0	165,035.274	0	0.01	0.565	0
	PV	0	127.0	0	0	0	165,235.949	2.194	0.114	3.045	0
DMU 16	OV	0	82.569	0	0	0	165,082.130	0	0.008	0.557	0
	PV	0	1.788	0	0	0	160,294.037	4963.006	0.313	4.787	0
DMU 17	OV	0	83.108	0	0	0	164,989.952	0	0.004	0.600	0
	PV	0	1.788	0	0	0	160,294.037	4963.006	0.313	4.787	0
DMU 18	OV	0	82.851	0	0	0	165,007.080	0	0.014	0.573	0
	PV	0	1.665	0	0	0	160,310.659	5037.811	0.295	4.552	0

PV pessimistic value, *OV* optimistic value

queues, machine utilization, and fuzzy time-in system), noncrisp layout-dependent indicators (distance, adjacency and shape ratio), and fuzzy qualitative indicators (flexibility, maintainability, and accessibility) provide more comprehensive insight to the decision-making process in FSFLD problems with ambiguous inputs and outputs. Moreover, it should be noted that performing exact ranking among all layout alternatives could help policy makers and top managers to have precise understanding and improve existing systems with respect to facility layout performance.

6 Conclusion

There are usually missing data, incomplete data, or lack of data with respect to layout problems. This means data could not be collected and analyzed by

Table 10 Fuzzy simulation results for the average machine utility with α=0.001

Layout alternative		Stage (machine)									
		1	2	3	4	5	6	7	8	9	10
DMU 1	OV	0.947	0.047	0.384	4.374	1.966	0.608	0.196	1.018	0.465	0.744
	PV	0.48	0.02	0.213	1.662	1.087	0.368	0.196	1.029	0.26	0.31
DMU 2	OV	0.095	0.047	0.384	4.373	1.966	0.609	0.195	1.018	0.465	0.744
	PV	0.48	0.017	0.213	1.662	1.987	0.368	0.196	1.029	0.26	0.315
DMU 3	OV	0.946	0.047	0.384	4.373	1.966	0.608	0.196	1.018	0.466	0.744
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.029	0.26	0.315
DMU 4	OV	0.946	0.0473	0.384	4.374	1.96	0.608	0.196	1.018	0.465	0.754
	PV	0.017	0.479	0.213	1.663	1.987	0.368	0.196	1.029	0.26	0.314
DMU 5	OV	0.946	0.047	0.384	4.374	1.966	0.608	0.195	1.018	0.465	0.754
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.029	0.26	0.315
DMU 6	OV	0.946	0.047	0.384	4.372	1.966	0.608	0.195	1.018	0.465	0.744
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.028	0.26	0.315
DMU 7	OV	0.946	0.047	0.384	4.372	1.966	0.607	0.195	1.018	0.465	0.744
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.028	0.26	0.315
DMU 8	OV	0.946	0.047	0.384	4.374	1.966	0.608	0.195	1.018	0.465	0.754
	PV	0.48	0.017	0.213	1.663	1.987	0.368	0.196	1.029	0.26	0.315
DMU 9	OV	0.946	0.047	0.384	4.373	1.966	0.608	0.196	1.018	0.465	0.754
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.029	0.26	0.315
DMU 10	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 11	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.47	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 12	PV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 13	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.368	0.196	1.029	0.26	0.315
DMU 14	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 15	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 16	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 17	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314
DMU 18	OV	0.946	0.047	0.384	4.373	1.967	0.608	0.196	1.018	0.465	0.745
	PV	0.479	0.017	0.213	1.662	1.987	0.369	0.196	1.029	0.26	0.314

PV pessimistic value, *OV* optimistic value

deterministic or stochastic models, and new approaches for tackling such problems are required. This gap motivated the authors to develop a unique approach to handle such gaps in FSFLD problems. This study presented a unique approach based on fuzzy simulation, fuzzy DEA, and fuzzy AHP to tackle the FSFLD problems with data ambiguity in manufacturing systems. Moreover, this study considered operational, qualitative, and dependent indicators (distance, adjacency, and shape ratio) for evaluating the generated layout alternatives. Fuzzy AHP was used for weighting the fuzzy qualitative indicators (maintainability, accessibility, and flexibility). An integrated fuzzy simulation approach was then used to model the IC packaging process with respect to the operational data (average waiting time-in queue, average time-in system, and average machine

Table 11 Layout alternatives ranks by the proposed integrated approach and recent studies

Layout alternative	Technical efficiency for proposing FDEA	FDEA ranks by the proposed approach	Simulation-DEA-AHP ranks [4]	PCA ranks [2]	NT ranks [2]	DEA ranks ([44]
1	118.167	11	3	16	15	8
2	159.218	17	9	8	8	2
3	150.359	4	2	14	14	13
4	156.225	8	6	13	12	9
5	290.194	10	14	11	13	12
6	99.6750	7	16	15	18	4
7	214.389	3	4	17	16	16
8	178.287	6	17	9	9	5
9	232.285	2	1	4	4	6
10	165.264	15	11	6	7	10
11	134.653	16	10	2	2	1
12	111.135	12	18	18	17	15
13	132.041	18	5	12	11	14
14	1413.66	1	13	10	10	11
15	115.983	5	12	1	1	1
16	136.185	9	8	5	5	3
17	141.249	13	7	3	3	7
18	185.513	14	15	7	6	1

utilization). Finally, the BCC output-oriented fuzzy DEA model was used to find the optimal layout design. In the proposed DEA, each layout alternative has been considered as a DMU. The results show that the proposed integrated approach provides an efficient approach in solving FSFLD problems with ambiguity and uncertainty by incorporating a set of fuzzy operational, qualitative, and dependent indicators. Moreover, the integrated approach presented in this study yields exact rankings, whereas previous studies present incomplete and nonexact plant layout alternatives. The superiority and effectiveness of the proposed approach were quantitatively compared with previous DEA-simulation, AHP-DEA, AHP-PCA, and NT studies through a case study. The proposed approach would help policy makers and top managers to have a more comprehensive and thorough understanding the layout design aspects with respect to the operational features of the manufacturing processes. Although the proposed approach might be relatively time-consuming, it could be applied in real-world problem due to its aforementioned advantages. Furthermore, benefits of facility layout design optimization will justify time and work which is used to implement the proposed approach.

Table 12 FDEA ranks by different α-cut levels

Layout alternative	α=0	α=0.2	α=0.4	α=0.6	α=0.8	α=1
1	11	3	3	3	3	3
2	17	9	6	6	6	6
3	4	13	13	12	13	13
4	8	5	4	4	4	4
5	10	4	5	5	5	5
6	7	1	1	1	1	1
7	3	14	15	15	14	14
8	6	18	18	18	18	17
9	2	11	10	9	8	7
10	15	10	12	14	17	18
11	16	15	14	13	12	12
12	12	7	8	7	7	8
13	18	16	16	16	15	15
14	1	12	11	10	10	10
15	5	6	7	8	9	9
16	9	17	17	17	16	16
17	13	8	9	11	11	11
18	14	2	2	2	2	2

The integrated fuzzy simulation-fuzzy DEA-fuzzy AHP approach is also compared with some of the relevant studies and methodologies in the literature. Its features are compared with previous models to show its advantages over previous models (Table 13). The approach is capable of dealing with operational indicators as well as fuzzy-dependent and qualitative indicators. It can handle complex layout problems in manufacturing systems due to utilization

Table 13 The features of the integrated fuzzy simulation-fuzzy DEA-AHP approach

Studies	Feature								
	Multiple inputs and outputs	Data ambiguity	Operational indicators	Weighing fuzzy qualitative indicators	Handling complex layout problems	Optimization	Exact ranking	Multicriteria decision-making	Practicability in real-world cases
Fuzzy simulation-FDEA-AHP	✓	✓	✓	✓	✓	✓	✓	✓	✓
Azadeh and Moghaddam [4]	✓		✓		✓	✓	✓	✓	✓
Conventional simulation	✓	✓							✓
Yang and Kuo [44]				✓				✓	✓
Ertay et al. [20]				✓		✓		✓	✓
Azadeh and Izadbakhsh [2]				✓			✓		✓
Jithavech and Krishnan [25]	✓	✓					✓		✓
Zhou et al. [48]	✓	✓					✓		✓

of discrete-event-simulation. Also, it has the ability of optimization layout problems due to utilization of fuzzy DEA which is able to find the optimal layout solution through ranking DMUs (i.e., layout alternatives) based on various inputs and outputs. In addition, it provides a comprehensive and robust approach in solving real-world FSFLD problems.

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Appendix

The sample of MATLAB code for generating an exponential distribution with the parameter λ=1:

```
i=50
b=[0.001,0.2,0.4,0.6,0.8,1]
for j=1:1:6
z=rand(1,i)
X=-1×reallog(z)
aver=mean(X)
variance=var(X)
standard_deviation=sqrt(variance)
t=tinv(1-b(j)/2,i-1)
    Upper(j)=aver+t×standard_deviation/sqrt(i)
    Lower(j)=aver×t×standard_deviation/sqrt(i)
End
Upper
Lower
```

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