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An Application of Data Envelopment Analysis and Machine Learning Approach to Risk Management

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ABSTRACT An integrated method comprising DEA and machine learning for risk management is proposed in this paper. Initially, in the process of risk assessment, the DEA cross-efficiency method is used to evaluate a set of risk factors obtained from the FMEA. This FMEA-DEA cross-efficiency method not only overcomes some drawbacks of FMEA, but also eliminates several limitations of DEA to offer a high discrimination capability of decision units. For risk treatment and monitoring processes, an ML mechanism is utilized to predict the degree of remaining risk depending on simulated data corresponding to the risk treatment scenario. Prediction using ML is more accurate since the predictive power of this model is better than that of DEA which potentially contains errors. The motivation for this study is that the combination of the DEA and ML approaches gives a flexible and realistic choice in risk management. Based on a case study of logistics business, the results ascertain that the short-term and urgent solutions in service cost and performance are necessary to sustainable logistics operations under the COVID-19 pandemic. The prediction findings show that the risk of skilled personnel is the next concern once the service cost and performance strategies have been prioritised. This approach allow decision-makers to assess the risk level for handling forthcoming events in unusual conditions. It also serves as a useful knowledge repository such that appropriate risk mitigation strategies can be planned and monitored. The outcome of our empirical evaluation indicates that the proposed approach contributes towards robustness in sustainable business operations.

INDEX TERMS Data envelopment analysis (DEA), DEA cross-efficiency, machine learning (ML), artificial neural network (ANN), failure mode and effect analysis (FMEA), risk management.

I. INTRODUCTION

The significant transformation of the business world due to globalization leads to rapid changes in operations and customer demands. Business organizations nowadays face intense competition and arduous challenges. Indeed, in today's dynamic environments, organizations need to tackle various uncertainties and handle them effectively. In this respect, risk management is a robust approach to becoming prepared to face risks and their consequences [1]. Identification and assessment of risks are a crucial aspect of the risk management process [2]. Risk assessment includes the analysis and evaluation processes. It requires a sensible technique to ascertain the qualitative and/or quantitative risk levels and examine the prospective outcomes of possible failures with respect to an organization's resources [3].

Data Envelopment Analysis (DEA) has been broadly used for evaluating the efficiency of decision-making units (DMUs) in many areas [4] for organizational performance improvement, such as financial institutions, manufacturing companies, hospitals, airlines, and government agencies. DEA has also been applied to assess organizational risks [5]. There are many studies on deterministic DEA methods for examining the relationship between efficiency and various risk aspects [6]. Indeed, DEA (DEA extension or DEA integrated with other methods) offers a logical approach to analyze and determine the risk level of activities in an organization. Nonetheless, when a set of new DMUs is available for analyzing its performance level (represented by the efficiency scores), it is necessary to re-compute the

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DEA procedure [7]. When applying the DEA to risk management in the situation where an organization has already evaluated the current level of risk for a sizable number of DMUs, the subsequent re-application of DEA for risk evaluation renders different results. This is because DEA utilizes dynamic information over time for internal benchmarking computation of the DMUs. If only some DMUs need to be re-computed in terms of its new value of efficiency to represent the new level of risk, usually what managers do is to apply the entire DEA procedure again. This can result in a new set of efficiency scores for all other DMUs. The second round of efficiency scores can be similar or different from those from the first evaluation, which can create confusion in a decision-making process, especially for risk monitoring purposes. In this study, we propose a machine learning (ML) approach to predict the new level of risk embodied by the efficiency scores. Previous studies have considered hybrid DEA-ML methods for estimating or predicting the DMUs efficiency in several fields, but yet in risk management.

Corresponding to the reliability methodologies of risk assessment, the Failure Mode and Effects Analysis (FMEA) offers a qualitative method to recognize and counteract failures, delivering information to support decision-making in risk management [8]. FMEA has been utilized as a useful tool for risk and reliability analysis in various enterprises [9]. Investigations on FMEA cover theoretical enhancement to overcome the drawbacks of conventional FMEA methodology [10] as well as practical evaluation in a variety of applications [9]. A key problem in FMEA is the need to consider the importance level of each factor pertaining to the weight and/or the relationship of various failure modes. In this aspect, DEA offers a utility measurement method to gain more complete weights of the corrective actions in FMEA. However, there are still some limitations in a traditional DEA method, such as a low discriminating power in efficiency evaluation [11]. The cross-efficiency approach increases the discriminatory power of DEA [12]. Extending the cross-efficiency approach to enhance DEA-FMEA for risk analysis is one of the contributions of this study.

Risk treatment and monitoring constitutes a vital process in risk management. Actions involving the selection of appropriate treatment strategies and estimating success of the treatment strategies are the salient aspects of risk treatment and monitoring, respectively [13]. The development of effective methods and tools to predict the potential outcomes of treatment strategies is important to enhance the risk management process towards a more holistic and robust approach. Artificial Intelligence (AI) serves as a useful methodology for monitoring the influence of variations in strategy pertaining to the predicted variables (i.e., scenario prediction) [14]. As an example, neural networks have been shown as an promising tool for periodic risk monitoring purposes [15], [16]. There are two key benefits of utilizing neural networks for estimation or prediction tasks. Firstly, they are proficient in output estimation with massive volume of data. Secondly, they can produce good prediction accuracy. Moreover, the operation speed neural network is rapid [17]. In this study, applying neural network models for prediction in risk treatment and monitoring is another contribution of our work.

The primary goal of this research is to provide methods for assessing the risk level of sustainable operations in the risk assessment process. And to forecast the outcomes of risk treatment based on the scenario of risk treatment mitigation measures and monitoring procedures. In summary, this paper proposes a DEA cross-efficiency model for risk assessment. It allows efficient evaluation of risk data pertaining to the failure modes from FMEA or DMUs from DEA. It exploits the power of DEA classification with respect to the optimal weights of the input and output data based on the risk factors of FMEA. In addition, a ML approach utilizing neural networks is devised for risk management. From the risk treatment and monitoring perspective, ML can predict the results of treatment strategies, in order to facilitate effective implementation and monitoring processes. Note that the predictive power of ML is better than re-running the DEA model for risk treatment and monitoring.

The rest of this paper is organized as follows. In Section 2, a literature review is presented. The review covers risk management and associated methodologies, the applications of FMEA and DEA methods as well as DEA cross-efficiency and ML approaches in risk management. The proposed FMEA-DEA cross-efficiency and ML method is explained in detail in Section 3. A case study is presented Section 4. The results are analyzed and discussed comprehensively. In Section 5, the managerial implications pertaining to risk management and policy recommendations of the proposed method are presented, along with concluding remarks.

II. LITERATURE REVIEW

A. RISK MANAGEMENT AND METHODOLOGIES

Risk management in an enterprise generally involves four primary processes, namely (i) risk identification; (ii) risk assessment (a continuous sub-process of risk analysis and risk evaluation); (iii) risk treatment; and (iv) risk monitoring [13], [18]–[20]. Firstly, risk identification defines the events that can negatively impact the operational objectives [21]. Secondly, risk assessment merges risk analysis and risk evaluation. Risk analysis involves recognizing each risk, as well as its likelihood and consequences. Irrespective of whether the result is stated in a quantitative, semiquantitative, or qualitative manner, performing risk analysis requires considering the effectiveness and reliability of the existing control measures along with any potential controlling gaps [20]. The process continues to risk evaluation that involves deciding the risk level and priority, applying the benchmarking criteria related to the established context area [20]. Thirdly, risk treatment entails plan design, selection and implementation. This is a crucial stage involving the selection of appropriate strategies, and further treatment is required for those that remain unacceptable [22]. Fourthly, risk monitoring continuously scrutinizing and appraising how the sources of risk are expanding and whether any adjustment to the treatment strategies needs to be modified, as risk is not a static phenomenon [13].

Quantitative and qualitative approaches are two aspects of the framework of risk management [23], which are relevant to the risk identification and assessment processes. However, both aspects can generate different recommendations in practice [24]. Quantitative risk assessments are favored when sufficient data are obtainable. Nonetheless, comprehensive quantitative data are often not available. While qualitative approaches may not be ideal, the development of an integrated model for improving qualitative risk management is therefore vital. In this regard, methods like multiple criteria decision- making (MCDM) have been employed in various risk and uncertainty contexts, which are based on the process of risk management [25], [26].

FMEA is a qualitative methodology for risk management and decision-making [27]. It prioritizes the failure modes in the form of a Risk Priority Number (RPN) with respect to each failure [28]. These RPN outputs are used to enhance the production or service performance by controlling, reducing, and/or eliminating the failures [28]. The higher the RPN is, the more urgent the corrective (or preventive) action is [29]. The RPN is computed by multiplying the Occurrence (O), Severity (S), and Detect (D) scores (O × S × D), i.e., the inputs of an FMEA system. Specifically, O is the probability or frequency of a failure, S is the seriousness of the effect of a failure, while D is the probability of a failure being detected before its effect/impact is actualized and propagated to other entities [30].

In the literature, the limitations associated with the crisp RPN scores in a standard FMEA model have been highlighted, such as the questionable mathematical formula for computing the RPN, which results in some non-intuitive statistical properties [30]. Moreover, the RPN technique does not consider both direct and indirect relationships between each failure mode and is inadequate for a system or process with many subsystems and/or components [31], [32]. In this paper, we adopt the DEA method to deal with the mathematical formula issues of the RPN computation. Moreover, the DEA method can handle the weights of risk factors and consider the direct/indirect relationships between the failure modes. A review on FMEA using DEA is presented in the next subsection.

B. DEA-FMEA WITH AN EXTENSION OF DEA CROSS-EFFICIENCY

While FMEA is a useful risk assessment method, it ignores the comparative significance among O, S and D [33]. Countless MCDM practices have been utilized to evaluate the risks of failure modes and enhance the effectiveness of FMEA results [9], and one of them is the DEA. DEA is a performance determination tool for investigating the relative efficiencies of different DMUs. In this regard, the potential risks or failure modes in FMEA can be considered as DMUs, and the O-S-D ratings of FMEA serve as the inputs to the DEA [34], forming a synergized FMEA and DEA model.

From the FMEA perspective, the weights associated with the risk factors are normally assigned directly or verified based on judgement of human experts. In this respect, MCDM methods can be applied to determine the weights of risk factors. While the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) method are widely accepted techniques [9], the DEA offers another useful weighting method. The DEA not only supplements the standard FMEA by enhancing its capability of assessment but also, notably, provides correct information involving the failure factors, O-S-D. It considers multiple criteria and can be used as an appropriate weight assignment method. The DEA does not need to specify or determine the relative importance pertaining to the weights associated with the risk factors subjectively.

The weights are determined by the inter-related processes in the DEA [28]. The evaluation of efficiency of a DMU is characterized by its position comparative to the finest performance formed mathematically based on the ratio of weighted sum of outputs to the weighted sum of inputs [35]. Another distinctive feature of the DEA, in addition to determining the importance of risk factors by weights, is examining the ranking of failure modes by considering not only the direct impact of indices of individual failures but also the influence of these indices relative to the efficiency scores among the DMUs [30]. Therefore, the DEA can be useful for manipulating the weights of risk factors by considering the direct or indirect relationships among the failure modes. This is because the main principle of DEA is to produce optimal weights for each DMU in its set to maximize the ratio of weighted sum of outputs to weighted sum of inputs while preserving all the DMU ratios close to one [36]. In the standard DEA model, one limitation is the lack of ability to differentiate among DMUs with similar efficiency scores. The standard DEA model with total weight tractability appraises numerous DMUs as efficient, and cannot further differentiate among these efficient DMUs [36].

An extension of DEA with a cross-efficiency technique has been developed for assessing and rating DMUs. Sexton, Silkman, and Hogan [37] integrated the peer evaluation perception into DEA and proposed this evaluation method to enrich the discriminating power of DEA. There are three fundamental advantages of the cross-efficiency technique. Firstly, it reduces unrealistic weight schemes without incorporating weight restrictions. Secondly, it efficiently distinguishes good and weak performers among the DMUs. Finally, it can constantly organize the DMUs in a distinctive order [36]. Owing to these benefits, DEA cross-efficiency has been used in many fields including business operations under risk and uncertainty [12] or supply risk for sustainable operations [38]. In this regard, multiple input and output parameters are considered as the inputs, e.g. insufficient resources involving manpower, operation cost, facility, social and environment impact, and management systems. The outputs can include quality level, financial performance, and other items. Linguistic terms can also be used to express the input and output parameters, instead of the original data [38]. To the best of our knowledge, studies on evaluating risk factors related to FMEA integrated with DEA cross-efficiency are yet to exist in the current literature, therefore the contribution of this work.

C. ML IN RISK MANAGEMENT

ML can be applied to various disciplines e.g., statistics, convex analysis, probability, approximation, and algorithm complexity theory. Recent advances in ML deep learning-based approaches are offering excellent results. ML algorithms focus on how computers implement and simulate the learning behaviors of humans, in order to obtain new knowledge and constantly enhance prediction performance [7]. As a branch of Artificial Intelligence (AI), ML models entail many principles by exploiting the rapid growth of data [7]. Predictive or classification analytics is a crucial capability of ML [39]. There is a growing influence of ML in business applications, with several solutions already employed and countless more being developed [40]. Commonly, the main concept of ML is utilizing computerized algorithms to describe and learn from data. ML algorithms generalize the learned knowledge and make predictions when new data are given, facilitating the process of decision-making with respect to new scenarios. ML algorithms cover unsupervised learning, semi-supervised learning, supervised learning, and intensive learning. One of the broadly utilized ML algorithms is supervised learning, which uses a set of known or unknown patterns to train neural networks. It is useful for classification and prediction (or regression) tasks [7]. In prediction, the ML algorithms use previous data to predict the future, and their predictive power grow with additional data, accordingly, improving their prediction accuracy over time [40]. Due to the prediction accuracy is the extremely crucial indicator for the predicting performance [41].

Focusing on the business sector, ML has been applied to risk management, e.g. risk assessment or prediction of probability of risks. Past studies on risk assessment using ML mostly focused on the financial industry, e.g. the review of Leo *et al.* [40] demonstrated ML applications to banking risks management, including credit risk, liquidity risk, operational risk, and market risk. In terms of investment, Chandrinos *et al.*, [42] presented an ML-based risk management system to improve the performance of two portfolios through estimated losses. ML is also embodied in other areas such as industrial risk assessment. A deep neural network (DNN) was applied for risk assessment pertaining to a drive-off scenario in an Oil & Gas drilling rig [43]. The established model could predict risk increase (or decrease) with respect to the change in system conditions, in order to provide proper support for decision-making. For the construction area, the predictive power of ML enables evidence-based decision-making, utilizing interdependent, active, and dynamic risk factors for formulating appropriate strategies in proactive project risk management [44].

III. METHODOLOGY

A. DEA APPROACH FOR FMEA AND THE EXTENSION OF THE DEA CROSS-EFFICIENCY METHOD

In the traditional DEA method, a set of DMUs is formed, utilizing the inputs $X \in x^m$ to deliver the outputs $Y \in y^s$, where m and s are the numbers of the inputs and outputs, respectively. Given a DMU j, x_{ij} denotes the ith input utilized and y_{rj} the rth output delivered. The efficiency score of each DMU, θ, is measured as:

$$\theta = \frac{\sum_{r=1}^{s} \mu_r y_r}{\sum_{i=1}^{m} \nu_i x_i} \tag{1}$$

when μ_r and υ_i are the weights of outputs and inputs, respectively [45]. The multiplier formulation of an input-oriented structure to indicate the constant returns of scale (CRS) situation [46] is shown in model (2):

$$\begin{aligned} &max\ \theta = \sum_{r=1}^{s} \mu_r y_{r0} \\ &s.t.\ \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \nu_i x_{ij} \leq 0 \\ &\sum_{i=1}^{m} \nu_i x_{i0} = 1 \\ &\mu_r, \nu_i \geq 0(\varepsilon) \end{aligned} \tag{2}$$

where subscript $_{i0}$ or $_{r0}$ characterizes the DMU under evaluation, ε is non-Archimedean infinitesimal. Model 2 is an input-oriented DEA model, where the objective function and constraints are maximizing the outputs while maintaining the inputs at their existing levels [46]. With an optimality result ($\theta = 1$), the DMU is said to be CRS-efficient, and is operating at the CRS frontier. Otherwise, the DMU is CRS-inefficient.

In DEA, a DMU is responsible for converting the quantitative inputs to the outputs. Its efficiency can be evaluated with an output-to-input ratio associated with productivity [47], which can be used for comparison purposes. A set of DMUs is used for evaluation of the relative efficiency of DMU. When the standard FMEA is employed with the DEA, the Failure Modes (FM) correspond to the DMUs, while the inputs (O-S-D) correspond to the multiple inputs of the DEA [30]. The RPN output, however, does not conform to the DEA output. In the DEA method, the output is a product of multiple inputs in a ''black box'' process, where the associated transformation function is unknown. The inputs enter and the outputs exit, devoid of transparency in the intermediate steps [48]. In contrast, the RPN output is based on multiplication of O, S and D. To achieve an efficiency score for risk prioritization and to replace the standard RPN computation, previous studies have proposed the DEA model without the outputs, or constant outputs equivalent to one when applying the DEA to FMEA [30], [34], [49], [50].

In the cross-efficiency approach, the DEA model enlargement is executed through two phases, involving self- and peer-evaluation. This extension evaluates the entire performance of every DMU by contemplating not only its individual weights but the weights of all DMUs [51]. Self-evaluation is based on (2), where each DMU j is evaluated with its extremely favorable weights. Specifically, μ_{rj} and v_{ij} are the respective optimal outputs and inputs weights of the self-evaluation stage for a given DMU j ($j \in N$). Under the peer-evaluation stage, it can be simply proved that, by employing the cross-efficiency approach, all DMUs are evaluated corresponding to a similar set of weights. Indeed, the jth DMU value of cross-efficiency (CE_j) is identical to the following model [52]:

$$CE_j = \frac{1}{N}\sum\nolimits_{k=1}^{N} E_{jk} = \frac{1}{N}\sum\nolimits_{k=1}^{N} \left(\frac{\mu_1 y_{1jk}+\mu_2 y_{2jk}+\cdots+\mu_r y_{rjk}}{v_1 x_{1jk}+v_2 x_{2jk}+\cdots+v_m x_{mjk}}\right) \quad (3)$$

Model (3) requires k times of solution, each time for an efficiency score of the target, in order for DMU j (E_{jk}) to acquire the cross-efficiency scores of all DMUs. All these scores can be displayed as a $j \times k$ cross-efficiency matrix where the diagonal parts present the CRS-efficiency scores E^*_{jk}, as shown in Table 1 [51].

TABLE 1. Cross-efficiency matrix of the DMUs.

DMU	Target DMU				Cross-efficiency
	DMU_1	DMU_2	…	DMU_j	(CE_j)
DMU_1	E^*_{11}	E_{12}	…	E_{1k}	$CE_1 = \frac{1}{N}\sum_{k=1}^{N} E_{1k}$
DMU_2	E_{21}	E^*_{22}	…	E_{2k}	$CE_2 = \frac{1}{N}\sum_{k=1}^{N} E_{2k}$
⋮	⋮	⋮	⋮	⋮	⋮
DMU_j	E_{j1}	E_{j2}	…	E^*_{jk}	$CE_j = \frac{1}{N}\sum_{j,k=1}^{N} E_{jk}$

B. ML APPLICATION IN RISK MANAGEMENT CONTEXT

ML can autonomously learn using supervised learning algorithms from a set of the input and output data [17]. An artificial neural network (ANN) is a useful ML model. It generally comprises generally three layers of nodes (neurons) [17], namely input, hidden, and output layers, as indicated in Fig. 1(a). The input layer receives a data sample while the output layer yields the corresponding target category [53].

In Fig. 1(b), a simple ANN structure is shown, covering the neuron connections, biases allocated to neurons, and weights designated to the connections, depicting a multi-layer model [7]. A neuron k can be identified by two equations, as follows [54]:

$$y_k = f(u_k + b_k) \quad (4)$$

$$u_k = \sum\nolimits_{i=1}^{N} w_{ki} x_i \quad (5)$$

where $x_1, x_2, \ldots, x_n$ are the inputs, $w_{k1}, w_{k2}, \ldots, w_{kn}$ are the neuron weights, u_k is the computation outcome of weighted inputs, b_k is the bias term, f is the activation function, and y_k is the output.

When applying DEA-FMEA to ML, there are N DMUs and each DMU j has the three inputs features (O-S-D), and

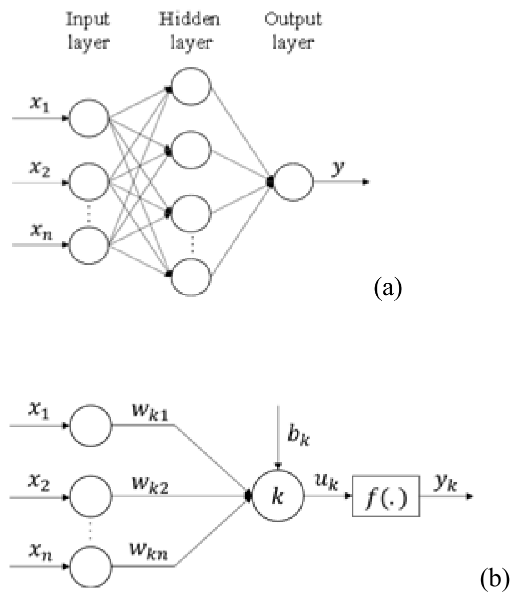

FIGURE 1. Architecture of a neural network.

each DMU j has a target variable of efficiency score obtained by DEA cross-efficiency. For DMU j, the significance of each feature is different, so each feature has distinct weights with varying significance. Subsequently, the sum of weighted O-S-D inputs and efficiency score can determine a mapping relationship via an activation function. By gathering N DMUs with known O-S-D inputs and outputs of efficiency score, the weights and bias term can be computed according to (4) and (5) through model training [7].

In this study, the Neural network toolbox of MATLAB 2020b has been utilized. The ANN was created based on the default settings. Specifically, a feed-forward ANN with backpropagation learning has been established for prediction tasks [55]. TRAINML is selected for a function of network training, which updates the weight and bias values using the Levenberg-Marquardt optimization method. TRAINML is fast, but it requires more memory than other algorithms [56]. LEARNGDM or Gradient descent with momentum weight and bias learning function is used for error minimization. This function computes the change of weight with respect to a certain neuron, covering the input and error terms, weight and bias, learning rate, and momentum term of the neuron, corresponding to gradient descent with momentum backpropagation [57]. A tangent sigmoid function (TANSIG) is used as a transfer function by the following equation for input variable x: [58]:

$$TANSIG\,(x) = \frac{2}{1+e^{-2x}} - 1 \quad (6)$$

TANSIG is utilized for both hidden and the output layers. They compute the output from its net input. This activation function provides output from -1 to $+1$ [59]. After obtaining the trained model, the ANN can be applied to a new DMU (efficiency improvement scenario), whose new inputs

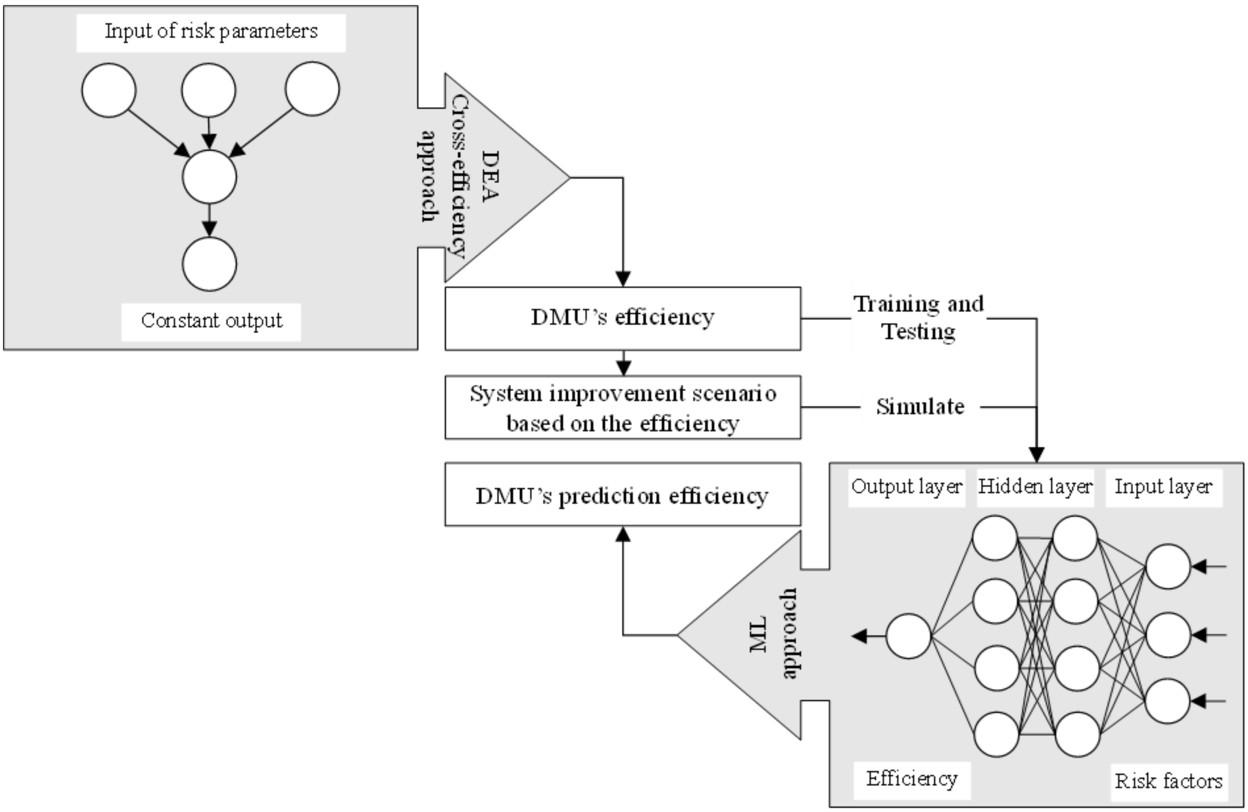

FIGURE 2. A study framework.

of O-S-D are known but the outputs of efficiency score are unknown. The predicted output can be obtained through the ANN model. Fig. 2 depicts the integration of DEA-FMEA and ANN model used in this study. When evaluating the improvement of organizational performance, nevertheless, if a new improved data set of DMU needs to be determined for its efficiency score, the DEA evaluation process has to be re-conducted. The result includes the prediction error because the weight assigned to the DMU is rearranged, causing changes in the efficiency score of non-improvement DMUs as well. Consequently, we predict the efficiency score employing the ANN, which provide more robust prediction. To demonstrate the usefulness of the proposed method, a discussion on an illustration and a case study is presented in the next section.

IV. COMPUTATION AND DISCUSSION

A. ILLUSTRATION

Obtained from Karatop, Taşkan, Adar, and Kubat [60], twenty sub-criteria with respect to the risk of five renewable energy sources (hydropower, wind, solar, geothermal and biomass) according to the risk factors are selected for illustration, as shown in Table 2.

Based on Table 2, the risk of the main criterion is analyzed under 5 dimensions. They are cost, political, technology, environmental, and management of construction, which are also related to the sustainable dimension. Risk analyses are performed according to a 10-scale pertaining to the probability of occurrence, detectability, and severity. The RPN is calculated based on the standard FMEA method.

As shown in Fig. 2, the DEA cross-efficiency approach (Model (3)) is applied. All three risk factors (O-S-D) are considered as the input, due to this indicator is expected to be as low as possible while a dummy or constant output is considered. The dummy output is set at one, and this number is applied to all DMUs. All sub-criteria depend on the five types of renewable energy sources that constitute the DMUs in the DEA cross-efficiency approach, producing a total of 100 DMUs. The results comparing the DEA cross-efficiency and the traditional or CRS approach are shown in Table 3. The selected DEA cross-efficiency model can compute the precise efficiency scores of different DMUs, as compared with those of the CRS. Eight highest efficient DMUs (efficiency score = 1) of CRS are reduced to three DMUs, which reach the highest efficiency score of 0.96. Moreover, 31 DMUs with the highest frequency risk score (= 0.5) of CRS are changed to a more diverse value by the DEA cross-efficiency method. Generally, a low RPN is tagged with a high efficiency score when DEA is applied. However, the efficiency scores of DMUs of this method do not completely rely upon the RPN value, as can be observed in Fig. 3 (fluctuation of the line chart). From this

TABLE 2. Data set of risk factors of renewable energy resources (from Karatop *et al.* [60]).

Risk criterion	Sources of renewable energy																			
	Hydropower				Wind				Solar				Geothermal				Biomass			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
Cost																				
C1-Operating	3	2	2	12	4	6	6	144	3	5	6	90	5	5	6	150	6	5	3	90
C2-Territory	2	3	2	12	7	4	2	56	8	6	3	144	3	3	3	27	3	2	3	18
C3-Investment	6	6	4	144	5	7	3	105	6	6	4	144	9	7	4	252	8	6	4	192
Political																				
P1-Terror	2	8	8	128	2	4	8	64	3	5	8	120	2	7	8	112	2	7	7	98
P2-Civil/external war-unrest	4	7	5	140	2	6	6	72	4	6	6	144	3	7	7	147	4	7	6	168
P3-Change of laws and regulations	2	2	2	8	3	4	3	36	3	4	3	36	6	5	3	90	7	6	2	84
Technology																				
T1-Design defects	3	8	6	144	3	5	3	45	4	5	2	40	3	7	5	105	4	5	3	60
T2-Development of alternative Technologies	5	3	5	75	4	4	5	80	5	6	5	150	6	8	5	240	4	7	5	140
T3-Incorrect material selection	2	7	6	84	2	6	3	36	2	6	3	36	2	7	5	70	2	6	6	72
Environmental																				
E1-Noise	2	2	2	8	2	3	3	18	2	1	1	2	2	2	2	8	6	5	3	90
E2-Odor	1	1	2	2	1	1	2	2	1	1	2	2	3	3	4	36	9	6	2	108
E3-Emission	1	2	2	4	1	2	2	4	1	2	2	4	3	5	3	45	8	7	2	112
E4-Waste	1	2	2	4	2	2	3	12	4	3	2	24	5	4	2	40	7	6	2	84
E5-Harm to living things	2	6	8	96	5	5	3	75	2	4	2	16	3	3	3	27	3	5	3	45
Construction – management																				
M1-Occupational accidents	2	2	3	12	4	3	4	48	4	3	3	36	3	4	4	48	3	4	4	48
M2-Failures during construction and operation	3	4	3	36	4	4	3	48	4	4	3	48	4	3	2	24	3	4	3	36
M3-Extending periodic maintenance times	3	5	6	90	4	4	6	96	4	4	6	96	3	5	6	90	5	4	6	120
M4-Extension of construction times	4	4	8	128	3	4	7	84	3	5	7	105	3	5	7	105	3	4	8	96
M5-Low productiveness	3	6	3	54	2	4	4	32	5	5	3	75	8	6	4	192	7	4	4	112
M6-Physical workload/ need for a qualified employee	2	3	3	18	3	3	3	27	4	3	3	36	5	3	3	45	6	6	4	144

TABLE 3. The result of DEA approach.

Hydropower			Wind			Solar			Geothermal			Biomass		
DMU	CRS-eff.	Cross-eff.	DMU	CRS-eff.	Cross-eff.	DMU	CRS-eff.	Cross-eff.	DMU	CRS-eff.	Cross-eff.	DMU	CRS-eff.	Cross-eff.
1. HC1	0.6	0.5473	21. WC1	0.3	0.2787	41. SC1	0.3333	0.3173	61. GC1	0.2727	0.2512	81. BC1	0.3333	0.304
2. HC2	0.75	0.6817	22. WC2	0.5	0.3145	42. SC2	0.3333	0.2518	62. GC2	0.5	0.4567	82. BC2	0.5	0.46
3. HC3	0.3	0.272	23. WC3	0.375	0.339	43. SC3	0.3	0.272	63. GC3	0.25	0.2114	83. BC3	0.25	0.2283
4. HP1	0.5	0.3145	24. WP1	0.5	0.317	44. SP1	0.3333	0.2692	64. GP1	0.5	0.3149	84. BP1	0.5	0.341
5. HP2	0.3333	0.3055	25. WP2	0.5	0.3742	45. SP2	0.3	0.2787	65. GP2	0.3333	0.2896	85. BP2	0.3	0.2782
6. HP3	0.75	0.685	26. WP3	0.5	0.455	46. SP3	0.5	0.455	66. GP3	0.3333	0.304	86. BP3	0.5	0.3129
7. HT1	0.3333	0.3158	27. WT1	0.5	0.454	47. ST1	0.5	0.454	67. GT1	0.375	0.3497	87. BT1	0.4286	0.3878
8. HT2	0.3333	0.2767	28. WT2	0.3333	0.3077	48. ST2	0.3	0.2733	68. GT2	0.2727	0.247	88. BT2	0.3333	0.3055
9. HT3	0.5	0.3737	29. WT3	0.6	0.554	49. ST3	0.6	0.554	69. GT3	0.5	0.416	89. BT3	0.5	0.3742
10. HE1	0.75	0.685	30. WE1	0.6	0.5573	50. SE1	1	0.92	70. GE1	0.75	0.685	90. BE1	0.3333	0.304
11. HE2	1	0.96	31. WE2	1	0.96	51. SE2	1	0.96	71. GE2	0.4286	0.3971	91. BE2	0.5	0.2629
12. HE3	1	0.95	32. WE3	1	0.95	52. SE3	1	0.95	72. GE3	0.5	0.454	92. BE3	0.5	0.2849
13. HE4	1	0.95	33.WE4	0.6	0.5607	53. SE4	0.5	0.4567	73. GE4	0.5	0.3941	93. BE4	0.5	0.3129
14. HE5	0.5	0.3153	34. WE5	0.375	0.3402	54. SE5	0.75	0.68	74. GE5	0.5	0.4567	94. BE5	0.5	0.454
15. HM1	0.6	0.5607	35. WM1	0.375	0.3442	55. SM1	0.4286	0.3905	75. GM1	0.4286	0.3955	95. BM1	0.4286	0.3955
16. HM2	0.5	0.455	36. WM2	0.4286	0.3888	56. SM2	0.4286	0.3888	76. GM2	0.5	0.4567	96. BM2	0.5	0.455
17. HM3	0.3333	0.3173	37. WM3	0.3	0.2803	57. SM3	0.3	0.2803	77. GM3	0.3333	0.3173	97. BM3	0.2727	0.2522
18. HM4	0.25	0.24	38. WM4	0.3333	0.2918	58. SM4	0.3333	0.2908	78. GM4	0.3333	0.2908	98. BM4	0.3333	0.2702
19. HM5	0.5	0.4533	39. WM5	0.5	0.475	59. SM5	0.375	0.3402	79. GM5	0.25	0.2283	99. BM5	0.2727	0.2497
20. HM6	0.6	0.5573	40. WM6	0.5	0.4567	60. SM6	0.4286	0.3905	80. GM6	0.375	0.3428	100. BM6	0.3	0.272
Average	0.5717	0.5108	Average	0.5060	0.45	Average	0.5022	0.4587	Average	0.4118	0.3629	Average	0.4043	0.3253

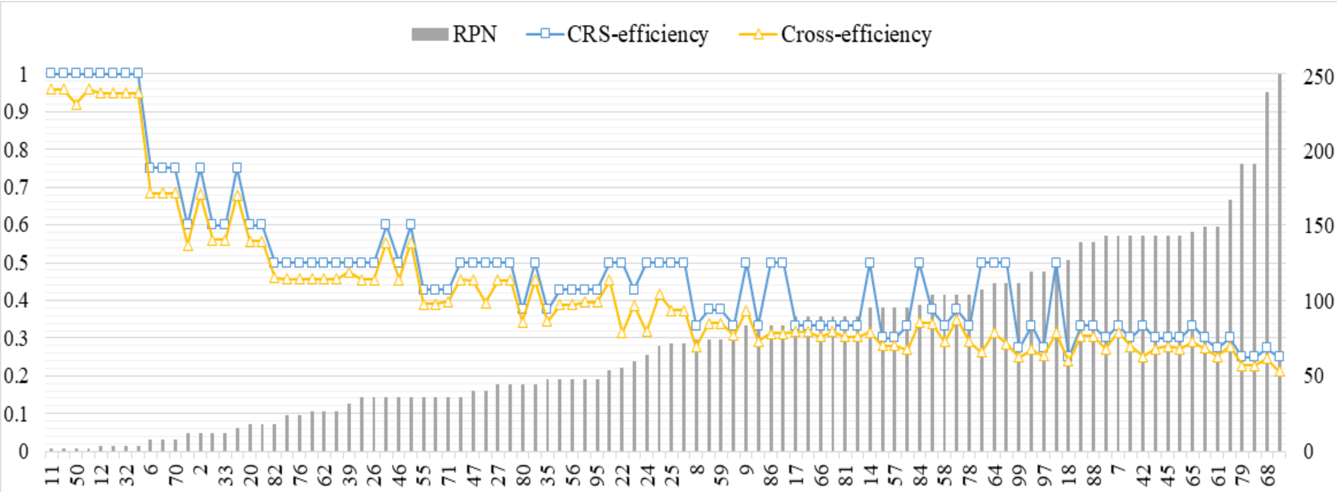

FIGURE 3. The result of traditional FMEA and DEA approach.

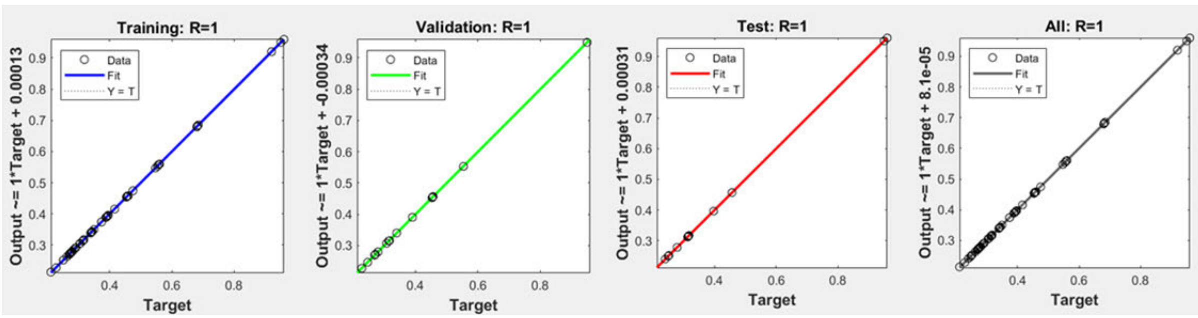

FIGURE 4. The performance of ML approach.

phenomenon, it shows that the DEA result does not adhere to the mathematical formula for computing the RPN, which is questionable. When we prioritize the average value of efficiency scores (Table 3) with respect to the source of renewable energy, biomass yields an average efficiency score of 0.3253, which is at the highest risk level. It is followed by geothermal, wind, solar, and hydropower, with the average efficiency scores of 0.3629, 0.45, 0.4587, and 0.5108, respectively.

As shown in Fig. 2, the ML approach is used to predict the level of risk based on an improvement or risk treatment scenario. ML is widely used for prediction or estimation tasks [17]. In this study, the ANN network includes four layers: the input layer, two hidden layers, and the output layer. All three variables of the risk factors (O-S-D) are mapped to the input layer. The output layer comprises the efficiency scores in which the DEA cross-efficiency is obtained. Both hidden layers consist of four neurons. The learning process is undertaken based on the data set of input and target (output) according to the training algorithm in the Neural network toolbox of MATLAB 2020b. The data samples are randomly divided into two sets: a training set (70%) and a test set (30%). The ML performance is shown in Fig. 4. Based on the results from multiple training epochs, the regression coefficient (R) between the target and output reaches one, indicating the high performance of the ML method. The comparison of cross-efficiency scores (target) and efficiency scores of the ML approach (output) is shown in Table 4 and Fig. 5. Moreover, we evaluate the ML performance using the root mean square error (RMSE), as shown in Model (7) [17].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(target_i - output_i)^2} \tag{7}$$

where target indicates the experimental or DEA cross-efficiency results and output indicates the estimated or ML results, n is the number of DMUs. Using Model (7), the RMSE obtained is 0.0005, which indicate a high performance. Therefore, the designed ANN model is useful for prediction purposes.

The leading goal of this study is to the development of methods for predicting the altered risk values when risk mitigation strategies are implemented. As such, we establish an ideal improvement scenario of risk mitigation in this illustration. The scenario is consistent with the results of the DEA cross-efficiency approach focusing on low-efficiency DMUs with respect to the two energy sources with the low-

TABLE 4. The comparison of target and output of ML approach.

Hydropower			Wind			Solar			Geothermal			Biomass		
DMU	Cross-eff. (target)	ML-eff. (output)	DMU	Cross-eff. (target)	ML-eff. (output)	DMU	Cross-eff. (target)	ML-eff. (output)	DMU	Cross-eff. (target)	ML-eff. (output)	DMU	Cross-eff. (target)	ML-eff. (output)
1	0.5473	0.5472	21	0.2787	0.2787	41	0.3173	0.3175	61	0.2512	0.2519	81	0.304	0.3042
2	0.6817	0.6819	22	0.3145	0.3148	42	0.2518	0.2523	62	0.4567	0.4568	82	0.46	0.4582
3	0.272	0.2724	23	0.339	0.3384	43	0.272	0.2724	63	0.2114	0.2133	83	0.2283	0.2275
4	0.3145	0.3145	24	0.317	0.3159	44	0.2692	0.2693	64	0.3149	0.3149	84	0.341	0.3412
5	0.3055	0.3054	25	0.3742	0.3742	45	0.2787	0.2787	65	0.2896	0.2899	85	0.2782	0.2781
6	0.685	0.6852	26	0.455	0.4555	46	0.455	0.4555	66	0.304	0.3042	86	0.3129	0.3122
7	0.3158	0.3159	27	0.454	0.4542	47	0.454	0.4536	67	0.3497	0.3499	87	0.3878	0.3883
8	0.2767	0.2758	28	0.3077	0.3074	48	0.2733	0.2737	68	0.247	0.2465	88	0.3055	0.3054
9	0.3737	0.3737	29	0.554	0.5534	49	0.554	0.5534	69	0.416	0.4154	89	0.3742	0.3742
10	0.685	0.6852	30	0.5573	0.5584	50	0.92	0.92	70	0.685	0.6852	90	0.304	0.3042
11	0.96	0.9599	31	0.96	0.9599	51	0.96	0.9599	71	0.3971	0.3966	91	0.2629	0.2629
12	0.95	0.95	32	0.95	0.95	52	0.95	0.95	72	0.454	0.4542	92	0.2849	0.2853
13	0.95	0.95	33	0.5607	0.5601	53	0.4567	0.457	73	0.3941	0.3934	93	0.3129	0.3122
14	0.3153	0.3152	34	0.3402	0.3403	54	0.68	0.6791	74	0.4567	0.4568	94	0.454	0.4542
15	0.5607	0.5601	35	0.3442	0.3435	55	0.3905	0.3905	75	0.3955	0.3958	95	0.3955	0.3958
16	0.455	0.4555	36	0.3888	0.3894	56	0.3888	0.3894	76	0.4567	0.457	96	0.455	0.4555
17	0.3173	0.3175	37	0.2803	0.28	57	0.2803	0.28	77	0.3173	0.3175	97	0.2522	0.2526
18	0.24	0.2408	38	0.2918	0.2914	58	0.2908	0.2909	78	0.2908	0.2909	98	0.2702	0.2699
19	0.4533	0.4529	39	0.475	0.4744	59	0.3402	0.3403	79	0.2283	0.2275	99	0.2497	0.2504
20	0.5573	0.5584	40	0.4567	0.4568	60	0.4286	0.3905	80	0.3428	0.3423	100	0.272	0.2724

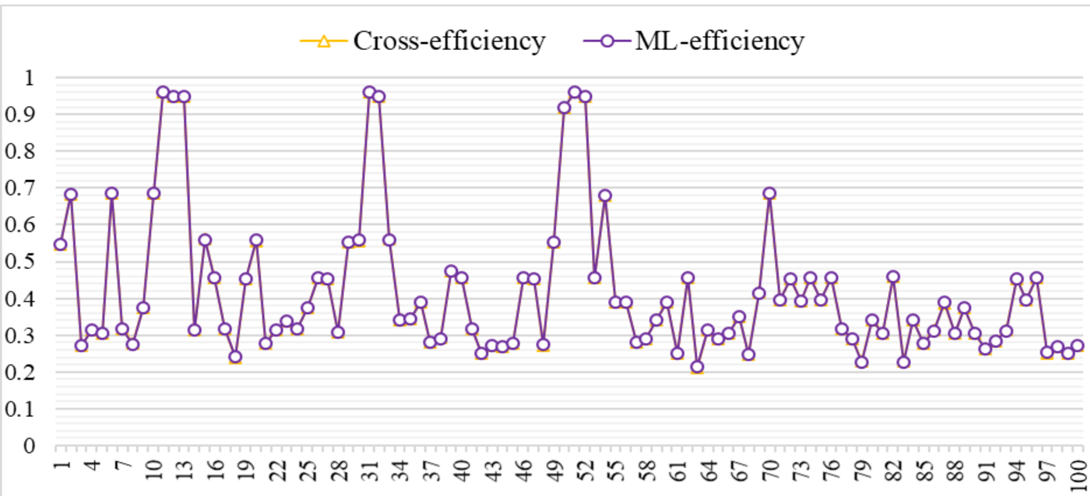

FIGURE 5. The comparison of target and output of ML approach.

est efficiency (biomass and geothermal). Table 5 presents the likelihood of improving the high level of risk factors of biomass and geothermal to match those of other renewable energy sources. The improvement scenario assumes that the risks associated with operating and investment costs, and the environmental impacts can be reduced in the future with more flexible and robust regulations. The improvement can also be induced by an increase in the development of technology, productivity, and competence of workforce. There are nine improved DMUs in the scenario (see Fig. 6).

With the simulated data set (nine DMUs with improvement and 91 DMUs without improvement of risk factors), the ML approach is used to obtain the prediction efficiency scores. The results of the prediction stage pertaining to the nine improved DMUs are analyzed and compared, are shown in Table 6 and Fig. 6. Without the integrated DEA cross-efficiency and ML approach, one can re-evaluate the improvement scenario using the DEA cross-efficiency approach. The percentages of improvement with respect to any improved DMUs and the average value is not significantly different (30.48 and 30.34). However, as can be

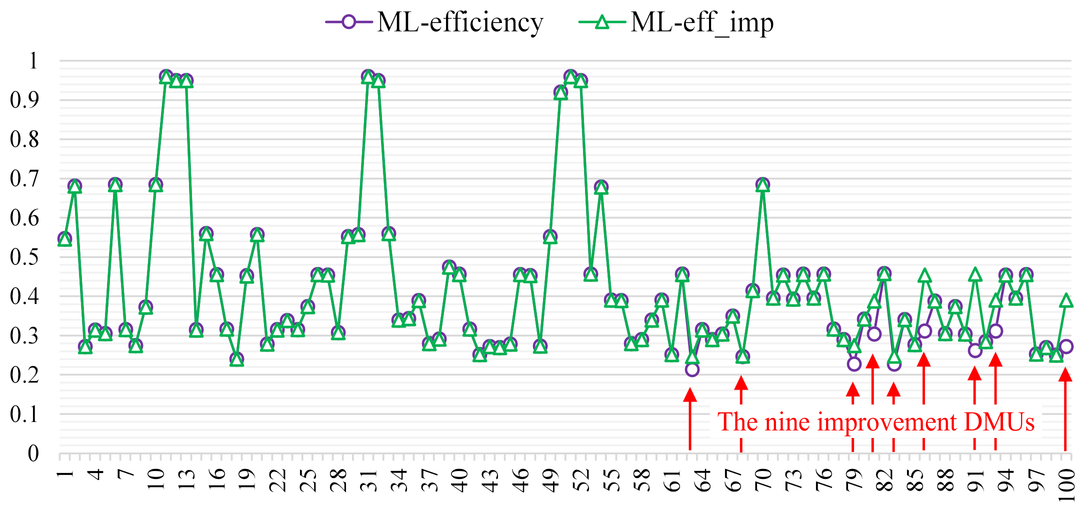

FIGURE 6. The results of ML approach of simulate data set.

TABLE 5. An ideal of improvement scenario of risk mitigation.

Risk	Base data set								Improvement scenario							
	Geothermal				Biomass				Geothermal				Biomass			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
C1-Operating	5	5	6	150	6	5	3	90	5	5	6	150	4	5	3	60
C3-Investment	9	7	4	252	8	6	4	192	7	7	4	196	7	6	4	168
P3-Change of laws and regulations	6	5	3	90	7	6	2	84	6	5	3	90	4	4	2	32
T2-Development of alternative Technologies	6	8	5	240	4	7	5	140	6	6	5	180	4	7	5	140
E2-Odor	3	3	4	36	9	6	2	108	3	3	4	36	4	3	2	24
E4-Waste	5	4	2	40	7	6	2	84	5	4	2	40	5	6	2	60
M5-Low productiveness	8	6	4	192	7	4	4	112	7	6	3	126	7	4	4	112
M6-Physical workload/ need for a qualified employee	5	3	3	45	6	6	4	144	5	3	3	45	4	3	3	36

An example of improvement: 7 to 4

= nario of improving of risk factors

TABLE 6. The results of RPN and efficiency of improvement DMUs.

DMU	RPN			Cross-efficiency			ML-efficiency		
	Current	Improve	%	Current	Improve	%	Current	Improve	%
63. GC3	252	196	22.22	0.2114	0.248	17.31	0.2133	0.2471	15.85
68. GT2	240	180	25	0.247	0.2493	0.93	0.2465	0.2483	0.73
79. GM5	192	126	34.38	0.2283	0.2742	20.11	0.2275	0.2756	21.14
81. BC1	90	60	33.33	0.304	0.3897	28.19	0.3042	0.3883	27.65
83. BC3	192	168	12.5	0.2283	0.2485	8.85	0.2275	0.2482	9.1
86. BP3	84	32	61.9	0.3129	0.455	45.41	0.3122	0.4553	45.84
91. BE2	108	24	77.78	0.2629	0.4567	73.72	0.2629	0.457	73.83
93. BE4	84	60	28.57	0.3129	0.391	24.96	0.3122	0.3906	25.11
100. BM6	144	36	75	0.272	0.3924	44.26	0.2724	0.3905	43.36
Average			36.36			30.48			30.34

seen in Table 7, the change of efficiency scores occurs in the DMUs without improvement. Specifically, the average change in efficiency score of the 91 non-improvement DMUs is 0.73 percent when DEA cross-efficiency is re-conducted. This value (DEA prediction average error) can be different when another improvement scenario is executed. Moreover, referring to DMU 68 in Fig.7, the efficiency score after improvement is lower than some DMUs without improvement, indicating the approach of ML is more robust for prediction. Finally, using the ML approach, the average prediction efficiency scores of risk with respect to biomass and geothermal change from 0.3253 to 0.3572 and

TABLE 7. The difference of average efficiency score.

Type of DMU	Number of DMU	Avg. cross-eff.	Avg. cross-eff_imp	% of changed	Avg. ML-eff	Avg. ML-eff_imp	% of changed
Improvement	9	0.2644	0.345	30.48	0.2643	0.3445	30.34
Non-improvement	91	0.4371	0.4403	0.73	0.4371	0.4371	0
All	100	0.4215	0.4317	2.42	0.4215	0.4288	1.73

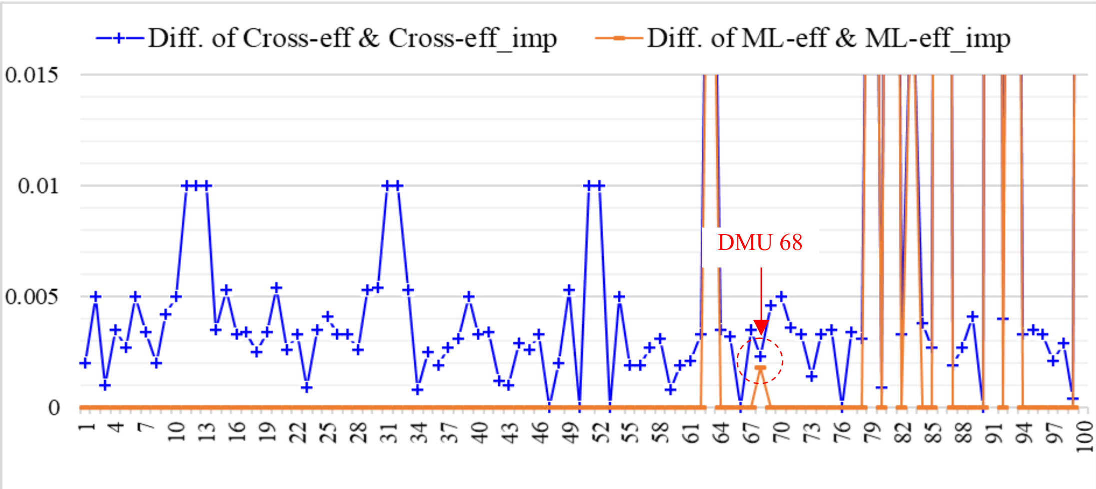

FIGURE 7. The difference of efficiency score after improvement for Cross-efficiency and ML approach.

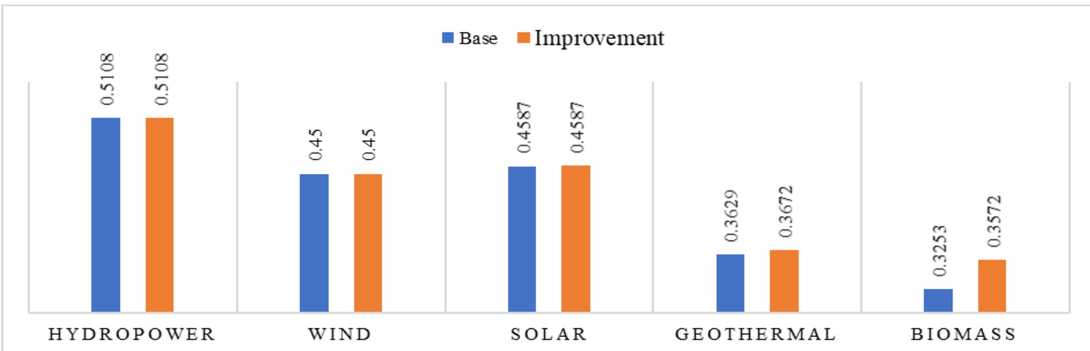

FIGURE 8. The average efficiency score for ML approach base on renewable energy sources.

0.3629 to 0.3672, respectively, when applying the abovementioned risk mitigation scenario, as shown in Fig.8.

B. CASE STUDY

To demonstrate the applicability of the FMEA-DEA cross-efficiency and ML approach for risk management, a case study on Malaysian logistics business with a group of twelve Logistics Service Provider (LSP) companies is conducted. Logistics is a critical contributor to trade and economic growth of Malaysia, which include land freight, sea freight, air freight, contract logistics (e.g., warehousing), as well as courier, express, and parcel services [61]. According to information published in 2019 [62], the Malaysian logistics sector is in its growing phase, powered by e-commerce. Indeed, the growth rate of e-commerce in Malaysia is accelerating exponentially. With expansion of the investment of government to improve the infrastructure and technology-based solutions, the logistics market is expected to further develop [63].

Unfortunately, logistics operations that are involved in the movement, storage, and flow of goods, have been directly affected by the COVID-19 pandemic, particularly the impact on transport and logistics connectivity in the landlocked areas [64]. COVID-19 has affected the global economy in three major aspects: directly influencing production and order, causing supply chain and market disruption, and creating financial impact on businesses and financial markets [65]. In the growing sector of logistics, these disruptions are impending, and risk management is required to promptly

TABLE 8. Results of risk analysis of logistic service provider (LSP) in Malaysia.

Criteria	LSP 1				LSP 2				LSP 3				LSP 4			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
A. Service price and cost	4	5	3	60	5	5	3	75	4	4	4	64	3	4	3	36
B. Service performance and customer satisfaction	4	5	3	60	5	4	3	60	2	3	4	24	3	4	4	48
C. Strategies and tactics and competitiveness	4	5	1	20	5	4	1	20	1	1	3	3	3	3	2	18
D. Operational technology	5	5	1	25	4	4	1	16	3	2	5	30	3	3	2	18
E. Waste management	2	2	3	12	2	3	5	30	1	1	5	5	4	4	3	48
F. Coordination and collaboration	5	5	1	25	5	5	1	25	2	2	3	12	5	5	3	75
G. Safety, healthy, security, and privacy	4	4	3	48	4	5	2	40	1	1	5	5	1	1	3	3
H. Employee-related skills and workforce	3	4	3	36	5	5	1	25	1	1	3	3	4	4	3	48
Criteria	LSP 5				LSP 6				LSP 7				LSP 8			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
A. Service price and cost	4	3	4	48	3	3	3	27	4	4	3	48	1	1	4	4
B. Service performance and customer satisfaction	3	2	5	30	3	3	4	36	4	3	3	36	1	1	1	1
C. Strategies, tactics and competitiveness	2	2	5	20	2	2	3	12	1	1	3	3	1	1	5	5
D. Operational technology	1	1	5	5	1	1	4	4	4	3	5	60	1	1	1	1
E. Waste management	1	1	5	5	1	1	5	5	1	1	5	5	1	1	5	5
F. Coordination and collaboration	1	1	5	5	1	1	5	5	1	1	3	3	4	2	5	40
G. Safety, healthy, security, and privacy	1	1	4	4	1	1	3	3	1	1	5	5	1	1	5	5
H. Employee-related skills and workforce	1	1	5	5	2	2	5	20	5	5	5	125	5	3	3	45
Criteria	LSP 9				LSP 10				LSP 11				LSP 12			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
A. Service price and cost	5	3	4	60	4	3	4	48	1	1	3	3	3	3	3	27
B. Service performance and customer satisfaction	4	3	4	48	2	3	4	24	2	2	3	12	3	3	3	27
C. Strategies, tactics and competitiveness	4	3	3	36	3	4	5	60	3	2	2	12	1	1	3	3
D. Operational technology	4	2	5	40	3	2	5	30	1	1	5	5	3	3	5	45
E. Waste management	4	3	5	60	1	1	5	5	1	1	5	5	1	1	5	5
F. Coordination and collaboration	1	1	3	3	2	2	5	20	2	3	5	30	3	3	5	45
G. Safety, healthy, security, and privacy	1	1	1	1	5	3	4	60	1	1	2	2	3	3	3	27
H. Employee-related skills and workforce	4	2	2	16	3	3	4	36	3	2	2	12	3	3	2	18

adapt business operations. In addition to economic impact, the COVID-19 pandemic has also immensely affected the social and environmental sustainability of human lives [66]. A case study of LSP is selected to implement the proposed risk management method for handling sustainable operation risks in logistics businesses.

To manage the sustainable operation risk under the context of COVID-19, eight criteria of sustainable operations are selected. They are (i) service price and cost, (ii) service performance and customer satisfaction, (iii) strategies, tactics and competitiveness, (iv) operational technology, (v) waste management, (vi) coordination and collaboration, (vii) safety, healthy, security, and privacy, and (viii) employee-related skills and workforce. These criteria cover three sustainable dimensions (economic, environmental, and social). The risk analysis is executed following a 1-to-5 scale of O-S-D risk factors. The responses have been obtained using online questionnaire with participants comprising twelve experts at the managerial level of each company. The ranking of 1 to 5 offers expediency and ease of interpretation [67] which is suitable when data collection is conducted via the online platform. The RPN is calculated based on the standard FMEA method. The analysis results are shown in Table 8.

All eight criteria with twelve participants constitute the DMUs, producing a total of $8 \times 12 = 96$ DMUs. To apply the DEA cross-efficiency approach, three risk factors (O-S-D) are considered as the inputs and constant of one as the output to obtain the DEA results of efficiency scores, as shown in Table 9. The ANN contains four layers: the input layer, two hidden layers, and the output layer. The risk factors (O-S-D) go to the input layer, the output layer comprises the efficiency scores with respect to the DEA cross-efficiency, while the hidden layers contain four neurons. The results of the ML approach are shown in Table 9, along with a comparison between DEA and ML. When we prioritize the average efficiency score, the service price and cost criterion yields an average efficiency score of 0.3634, which is the highest risk level. The average efficiency scores for the remaining criteria are shown in Table 10. The RMSE of the ML approach is 0.0006.

Another highlight of this case study is the prediction with respect to modification of risk values when risk mitigation strategies are identified. The Malaysian government has appropriate policies, plans, mechanisms and regulatory measures to help sustaining the logistics service sector. Among the initiatives include the Short Term Economic Recovery Plan (Penjana) and the National Technology and Innovation Sandbox (NTIS), which focus on digitalization to spur economic recovery. We anticipate that there is improvement in risk mitigation pertaining to the Malaysian logistics domain.

TABLE 9. The results of efficiency score of DEA and ML for the case study.

DMU	Cross-eff.	ML-eff.	DMU	Cross-eff.	ML-eff.	DMU	Cross-eff.	ML-eff.
1. LSP1-A	0.2681	0.2684	33. LSP5-A	0.2604	0.2607	65. LSP9-A	0.2313	0.2313
2. LSP1-B	0.2681	0.2684	34. LSP5-B	0.3153	0.3151	66. LSP9-B	0.2604	0.2607
3. LSP1-C	0.4625	0.4623	35. LSP5-C	0.4125	0.4125	67. LSP9-C	0.2847	0.2843
4. LSP1-D	0.4333	0.4332	36. LSP5-D	0.7667	0.7667	68. LSP9-D	0.2667	0.2666
5. LSP1-E	0.4514	0.4514	37. LSP5-E	0.7667	0.7667	69. LSP9-E	0.2458	0.246
6. LSP1-F	0.4333	0.4332	38. LSP5-F	0.7667	0.7667	70. LSP9-F	0.8056	0.8056
7. LSP1-G	0.2743	0.2744	39. LSP5-G	0.7813	0.7813	71. LSP9-G	1	0.9999
8. LSP1-H	0.3229	0.3232	40. LSP5-H	0.7667	0.7667	72. LSP9-H	0.3542	0.3543
9. LSP2-A	0.2389	0.2389	41. LSP6-A	0.3333	0.3333	73. LSP10-A	0.2604	0.2607
10. LSP2-B	0.2451	0.2446	42. LSP6-B	0.309	0.3091	74. LSP10-B	0.4063	0.4065
11. LSP2-C	0.4396	0.4395	43. LSP6-C	0.4514	0.4514	75. LSP10-C	0.284	0.2838
12. LSP2-D	0.4688	0.4688	44. LSP6-D	0.7813	0.7813	76. LSP10-D	0.3153	0.3151
13. LSP2-E	0.3917	0.3917	45. LSP6-E	0.7667	0.7667	77. LSP10-E	0.7667	0.7667
14. LSP2-F	0.4333	0.4332	46. LSP6-F	0.7667	0.7667	78. LSP10-F	0.4125	0.4125
15. LSP2-G	0.3167	0.3153	47. LSP6-G	0.8056	0.8056	79. LSP10-G	0.2313	0.2313
16. LSP2-H	0.4333	0.4332	48. LSP6-H	0.4125	0.4125	80. LSP10-H	0.309	0.3091
17. LSP3-A	0.25	0.2495	49. LSP7-A	0.2743	0.2744	81. LSP11-A	0.8056	0.8056
18. LSP3-B	0.4063	0.4065	50. LSP7-B	0.2847	0.2843	82. LSP11-B	0.4514	0.4514
19. LSP3-C	0.8056	0.8056	51. LSP7-C	0.8056	0.8056	83. LSP11-C	0.4028	0.4019
20. LSP3-D	0.3153	0.3151	52. LSP7-D	0.2458	0.246	84. LSP11-D	0.7667	0.7667
21. LSP3-E	0.7667	0.7667	53. LSP7-E	0.7667	0.7667	85. LSP11-E	0.7667	0.7667
22. LSP3-F	0.4514	0.4514	54. LSP7-F	0.8056	0.8056	86. LSP11-F	0.3917	0.3917
23. LSP3-G	0.7667	0.7667	55. LSP7-G	0.7667	0.7667	87. LSP11-G	0.8542	0.8542
24. LSP3-H	0.8056	0.8056	56. LSP7-H	0.2	0.2001	88. LSP11-H	0.4028	0.4019
25. LSP4-A	0.3229	0.3232	57. LSP8-A	0.7813	0.7813	89. LSP12-A	0.3333	0.3333
26. LSP4-B	0.2986	0.2984	58. LSP8-B	1	0.9999	90. LSP12-B	0.3333	0.3333
27. LSP4-C	0.3819	0.3818	59. LSP8-C	0.7667	0.7667	91. LSP12-C	0.8056	0.8056
28. LSP4-D	0.3819	0.3818	60. LSP8-D	1	0.9999	92. LSP12-D	0.2944	0.2946
29. LSP4-E	0.2743	0.2744	61. LSP8-E	0.7667	0.7667	93. LSP12-E	0.7667	0.7667
30. LSP4-F	0.2389	0.2389	62. LSP8-F	0.2667	0.2666	94. LSP12-F	0.2944	0.2946
31. LSP4-G	0.8056	0.8056	63. LSP8-G	0.7667	0.7667	95. LSP12-G	0.3333	0.3333
32. LSP4-H	0.2743	0.2744	64. LSP8-H	0.2556	0.2505	96. LSP12-H	0.3819	0.3818

TABLE 10. The average efficiency scores based on the criteria.

Criteria	Average cross-efficiency	Average ML-efficiency	RMSE (7)
A. Service price and cost	0.3633	0.3634	0.0002
B. Service performance and customer satisfaction	0.3815	0.3815	0.0003
C. Strategies, tactics and competitiveness	0.5252	0.5251	0.0003
D. Operational technology	0.5030	0.5030	0.0001
E. Waste management	0.6247	0.6248	0.0001
F. Coordination and collaboration	0.5056	0.5056	0.0001
G. Safety, healthy, security, and privacy	0.6419	0.6418	0.0004
H. Employee-related skills and workforce	0.4099	0.4094	0.0015
All criteria	0.4944	0.4943	0.0006

This is consistent with the efficiency score that focuses on the low-efficiency DMUs. Hence two criteria, i.e., the service price and cost (A) and the service performance and customer satisfaction (B), are selected to generate the anticipated improvement. Table 11 depicts the short-term one level improvement for the high risks related to the S and D factors. We fix the O factor (the occurrence of risk events) because it usually is stable since it is more related to external conditions. The improvement is also based on the comments of participants on handling the impact of COVID-19. As an example, the companies mentioned that they strongly focus on cost reduction activities by providing flexible operations to support their customers based on the emergency plan under an abnormal situation like the COVID-19 pandemic. In summary, there are 24 improved DMUs in total.

TABLE 11. An ideal improvement scenario of risk mitigation for the case study.

Risks	LSP 1				LSP 2				LSP 3				LSP 4				LSP 5				LSP 6			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
Current																								
A	4	5	3	60	5	5	3	75	4	4	4	64	3	4	3	36	4	3	4	48	3	3	3	27
B	4	5	3	60	5	4	3	60	2	3	4	24	3	4	4	48	3	2	5	30	3	3	4	36
Improvement scenario								An example of one level of improvement																
A	4	4	2	32	5	4	2	40	4	3	3	36	3	3	2	18	4	2	3	24	3	2	2	12
B	4	4	2	32	5	3	2	30	2	2	3	12	3	3	3	27	3	1	4	12	3	2	3	18
Risks	LSP 7				LSP 8				LSP 9				LSP 10				LSP 11				LSP 12			
	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN	O	S	D	RPN
Current																								
A	4	4	3	48	1	1	4	4	5	3	4	60	4	3	4	48	1	1	3	3	3	3	3	27
B	4	3	3	36	1	1	1	1	4	3	4	48	2	3	4	24	2	2	3	12	3	3	3	27
Improvement scenario																								
A	4	3	2	24	1	1	3	3	5	2	3	30	4	2	3	24	1	1	2	2	3	2	2	12
B	4	2	2	16	1	1	1	1	4	2	3	24	2	2	3	12	2	1	2	4	3	2	2	12

= scenario of improving of risk factors

TABLE 12. The results of efficiency of improvement DMUs.

DMU	ML-eff.	ML-eff_imp.	DMU	ML-eff.	ML-eff_imp.	DMU	ML-eff.	ML-eff_imp.
1. LSP1-A	0.2684	0.3218	33. LSP5-A	0.2607	0.3045	65. LSP9-A	0.2313	0.2572
2. LSP1-B	0.2684	0.3218	34. LSP5-B	0.3151	0.3745	66. LSP9-B	0.2607	0.3045
9. LSP2-A	0.2389	0.2862	41. LSP6-A	0.3333	0.4019	73. LSP10-A	0.2607	0.3045
10. LSP2-B	0.2446	0.2907	42. LSP6-B	0.3091	0.3539	74. LSP10-B	0.4065	0.4514
17. LSP3-A	0.2495	0.2843	49. LSP7-A	0.2744	0.3325	81. LSP11-A	0.8056	0.8542
18. LSP3-B	0.4065	0.4514	50. LSP7-B	0.2843	0.3543	82. LSP11-B	0.4514	0.5401
25. LSP4-A	0.3232	0.3818	57. LSP8-A	0.7813	0.8056	89. LSP12-A	0.3333	0.4019
26. LSP4-B	0.2984	0.3333	58. LSP8-B	0.9999	0.9999	90. LSP12-B	0.3333	0.4019

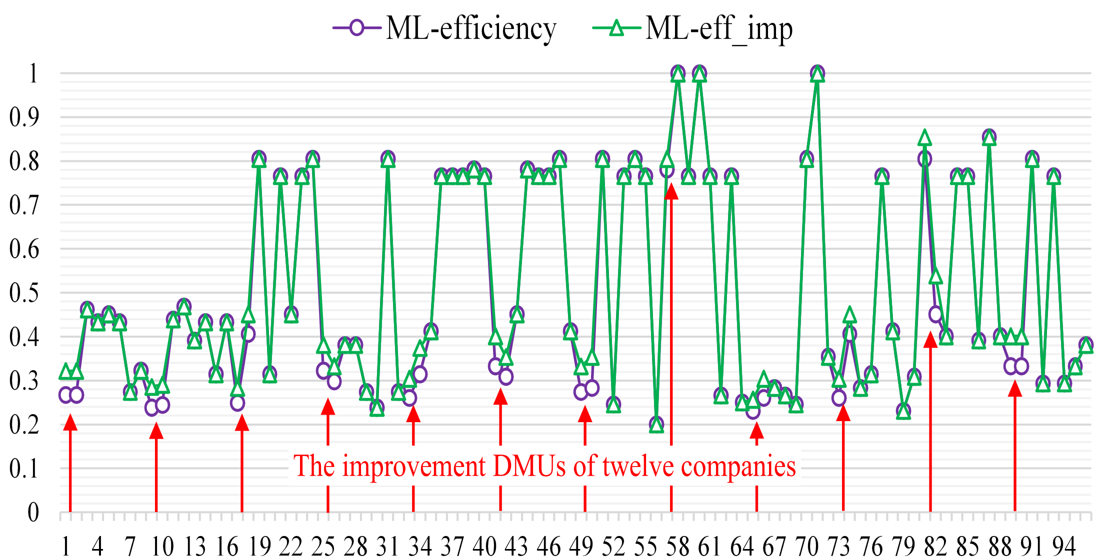

FIGURE 9. The results of ML approach based on simulated data set for the case study.

The simulated data set (24 DMUs with improvement and 72 DMUs without improvement of risk factors) is used with the ML approach to obtain the prediction efficiency scores. The results of the prediction stage of the 24 improved DMUs, along with a comparison, are shown in Table 12 and Fig. 9. With the ML approach, the average prediction efficiency

TABLE 13. An average of efficiency changed for ML and DEA Cross-efficiency approach.

Risks	Average ML-efficiency			Average DEA cross-efficiency (Rerun)		
	Base (rank*)	Improvement (rank*)	Percentage	Base (rank*)	Improvement (rank*)	Percentage
A. Service price and cost	0.3634 (8)	0.4114 (7)	13.20	0.3633 (8)	0.4183 (7)	15.12
B. Service performance and customer satisfaction	0.3815 (7)	0.4315 (6)	13.09	0.3815 (7)	0.4421 (6)	15.88
C. Strategies, tactics and competitiveness	0.5251 (3)	0.5251 (3)	-	0.5252 (3)	0.5205 (3)	-0.89
D. Operational technology	0.5030 (5)	0.5030 (5)	-	0.5030 (5)	0.5002 (4)	-0.55
E. Waste management	0.6248 (2)	0.6248 (2)	-	0.6247 (2)	0.6008 (2)	-3.82
F. Coordination and collaboration	0.5056 (4)	0.5056 (4)	-	0.5056 (4)	0.4982 (5)	-1.45
G. Safety, healthy, security, and privacy	0.6418 (1)	0.6418 (1)	-	0.6419 (1)	0.6260 (1)	-2.47
H. Employee-related skills and workforce	0.4094 (6)	0.4094 (8)	-	0.4099 (6)	0.4098 (8)	-0.02

* ranking on low to high risk level

scores of the risk of both criteria (service price and cost as well as service performance and customer satisfaction) change from 0.3634 to 0.4114 and 0.3815 to 0.4315, respectively, when applying the abovementioned risk mitigation scenario. Other non-improvement criteria remain unchanged. The results are as shown in Table 13.

To confirm the robustness of the ML approach, Table 13 presents the prediction results by re-executing the DEA cross-efficiency method for comparison. The percentage of change in the improved criteria under DEA cross-efficiency is higher than those of the ML approach. Moreover, for all non-improvement criteria, the percentage of change decreases. This implies the limitations of using the DEA cross-efficiency method for prediction purposes.

V. MANAGERIAL IMPLICATIONS AND CONCLUSION

According to the illustrations and case studies presented in Section 4, the implications pertaining to offering risk management strategies and/or policy recommendations can be deduced. Knowledge of these risks is needed by decision-makers in risk management. This study sheds light on how the proposed approach is helpful for the evaluation and prediction of efficiency based on risk information with respect to sustainable operation. There are two main findings. First, based on the FMEA-DEA cross-efficiency, the efficiency scores of DMUs of this method do not completely rely upon the RPN value. From this phenomenon, it shows that the DEA of risk assessment result does not adhere to the mathematical formula for computing the RPN, which is questionable as mentioned in the literature. Second, the efficiency scores obtained through the ML approach are comparable (in fact similar) to the results of DEA cross-efficiency method. And based on the literature which re-conducted DEA method, changes occur on all the efficiency scores even for the non-improved factors, leading to inconclusive judgement whether the strategies are effective or otherwise. In contrast, the ML approach targets only on predicting the improved ones. Nonetheless, managers adopting the methodology can encounter the following challenges.

Primarily, to obtain the complete results, the FMEA method requires tackling the O-S-D score definition. After the O-S-D information is identified, the manager can run the failure modes evaluation process using the DEA cross-efficiency method. In this phase, the risk level of DMUs can be presented by the risk-based efficiency. A DMU with a high score is deemed to have a low level of risk, while a DMU with a low score is considered as a high level of risk. The manager can then take note of the DMUs with low-efficiency score when implementing risk mitigation strategies and monitoring process establishment. However, there are various risk management strategies. Predicting the possible outcomes using ML under the strategy being considered (scenario prediction) is one of the most important processes in risk mitigation. The manager can establish the expected outcomes as a monitoring target pertaining to the risk mitigation plan.

In summary, the main research findings according to the illustration and case study indicate that the ML approach is an effective prediction method that can be applied in mitigation—monitoring stage of risk management. Combined with DEA, this DEA-ML method has been verified to yield reliable and robust results. When applying this risk management approach of integrated DEA and ML to a case study of LSP in Malaysia to manage the risks of sustainable operations under the COVID-19 pandemic, the results are noteworthy and insightful. Some managerial and high level policy recommendation are discussed, as follows.

Service price and cost, performance, and customer satisfaction are considered to have a higher degree of risk in operation than the risk of operational technology. Since technology-based solutions are in the country's logistics development plan set before the COVID-19 outbreak, the government, as well as businesses, should re-adopt the development policies that focus on cost reduction and increase the performance and flexibility in providing a logistics service to customers that must be balanced against pandemic control. Short-term and urgent solutions in service cost and performance are also necessary. Moreover, the prediction results indicate that the risk of skilled workers stands as the next priority influencing the risk mitigation policy, after the risk of service cost and performance have been focused.

In conclusion, the present study has proposed an integrated DEA and ML method for predicting and determining the risk level based on the efficiency of DMUs. The contributions of this paper are two fold. Firstly, the proposed DEA module improves the existing FMEA technique and the traditional DEA by applying the DEA cross-efficiency approach. Secondly, the ML algorithms provide better power of prediction than that of the DEA re-conducted scheme. The outcomes of this study support managers and decision-makers to assess and monitor the level of risk for handling forthcoming events in unusual conditions. It also serves as a useful knowledge repository whereby the appropriate risk treatment strategies can be planned and the associated results can be predicted, contributing towards significant robustness in sustainable business operations. However, there are certain drawbacks to this suggested technique, such as the assessment information supplied by decision makers for FMEA-DEA be given fuzziness and ambiguity while transferring language information to precise DEA input. Particularly when applied to large-scale collective decision-making. In future work for the DEA, it can be conveyed via fuzzy information in more relevant circumstances. For example, when compared to a typical DEA, the fuzzy logic related tools are helpful for describing the qualitative assessment information of decision makers. On the one hand, using the ML technique, a shallow network may be used to a small and uncertain dataset. On the other hand, a larger number of DMUs can be used to further improve the accuracy. This increases the size of the training and validation data sets, which can yield more robust results with statistical significance.

REFERENCES

[1] F. Valinejad and D. Rahmani, "Sustainability risk management in the supply chain of telecommunication companies: A case study," *J. Cleaner Prod.*, vol. 203, pp. 53–67, Dec. 2018.

[2] A. Samvedi, V. Jain, and F. T. S. Chan, "Quantifying risks in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS," *Int. J. Prod. Res.*, vol. 51, no. 8, pp. 2433–2442, Apr. 2013.

[3] R. Fattahi and M. Khalilzadeh, "Risk evaluation using a novel hybrid method based on FMEA, extended MULTIMOORA, and AHP methods under fuzzy environment," *Saf. Sci.*, vol. 102, pp. 290–300, Feb. 2018.

[4] Q. An, F. Meng, S. Ang, and X. Chen, "A new approach for fair efficiency decomposition in two-stage structure system," *Oper. Res.*, vol. 18, no. 1, pp. 257–272, Apr. 2018.

[5] L. Yan, W. Tong, D. Hui, and W. Zongzhi, "Research and application on risk assessment DEA model of crowd crushing and trampling accidents in subway stations," *Procedia Eng.*, vol. 43, pp. 494–498, Jan. 2012.

[6] I. E. Tsolas and V. Charles, "Incorporating risk into bank efficiency: A satisficing DEA approach to assess the Greek banking crisis," *Expert Syst. Appl.*, vol. 42, no. 7, pp. 3491–3500, May 2015.

[7] N. Zhu, C. Zhu, and A. Emrouznejad, "A combined machine learning algorithms and DEA method for measuring and predicting the efficiency of Chinese manufacturing listed companies," *J. Manage. Sci. Eng.*, Oct. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2096232020300469?via%3Dihub

[8] S. Almashaqbeh, J. E. Munive-Hernandez, and M. K. Khan, "A system dynamics model for risk assessment of strategic customer performance perspective in power plants," in *Proc. 3rd Eur. Int. Conf. Ind. Eng. Oper. Manage.*, 2019, pp. 1–13.

[9] H.-C. Liu, X.-Q. Chen, C.-Y. Duan, and Y.-M. Wang, "Failure mode and effect analysis using multi-criteria decision making methods: A systematic literature review," *Comput. Ind. Eng.*, vol. 135, pp. 881–897, Sep. 2019.

[10] N. Parvez, M. G. Rakib, and S. Islam, "Integrated FMEA approach for supplier selection problem: The case on steel manufacturing company," *SSRN Electron. J.*, pp. 1–20, Jan. 2016.

[11] F. Y. Meng, L. W. Fan, P. Zhou, and D. Q. Zhou, "Measuring environmental performance in China's industrial sectors with non-radial DEA," *Math. Comput. Model.*, vol. 58, nos. 5–6, pp. 1047–1056, Sep. 2013.

[12] M. Dotoli, N. Epicoco, M. Falagario, and F. Sciancalepore, "A cross-efficiency fuzzy data envelopment analysis technique for performance evaluation of decision making units under uncertainty," *Comput. Ind. Eng.*, vol. 79, pp. 103–114, Jan. 2015.

[13] Y. Fan and M. Stevenson, "A review of supply chain risk management: Definition, theory, and research agenda," *Int. J. Phys. Distrib. Logistics Manage.*, vol. 48, no. 3, pp. 205–230, Mar. 2018.

[14] R. B. Abidoye, A. P. C. Chan, F. A. Abidoye, and O. S. Oshodi, "Predicting property price index using artificial intelligence techniques," *Int. J. Housing Markets Anal.*, vol. 12, no. 6, pp. 1072–1092, Nov. 2019.

[15] T. Sun and L. J. Sales, "Predicting public procurement irregularity: An application of neural networks," *J. Emerg. Technol. Accounting*, vol. 15, no. 1, pp. 141–154, Jul. 2018.

[16] W. Zhang, X. Feng, F. Goerlandt, and Q. Liu, "Towards a convolutional neural network model for classifying regional ship collision risk levels for waterway risk analysis," *Rel. Eng. Syst. Saf.*, vol. 204, Dec. 2020, Art. no. 107127.

[17] V. Salehi, B. Veitch, and M. Musharraf, "Measuring and improving adaptive capacity in resilient systems by means of an integrated DEA-machine learning approach," *Appl. Ergonom.*, vol. 82, Jan. 2020, Art. no. 102975.

[18] F. Duhamel, V. Carbone, and V. Moatti, "The impact of internal and external collaboration on the performance of supply chain risk management," *Int. J. Logistics Syst. Manage.*, vol. 23, no. 4, pp. 534–557, 2016.

[19] J. Hallikas, I. Karvonen, U. Pulkkinen, V.-M. Virolainen, and M. Tuominen, "Risk management processes in supplier networks," *Int. J. Prod. Econ.*, vol. 90, no. 1, pp. 47–58, Jul. 2004.

[20] G. Purdy, "ISO 31000: 2009—Setting a new standard for risk management," *Risk Anal. Int. J.*, vol. 30, no. 6, pp. 881–886, 2010.

[21] B. Stosic, M. Mihic, R. Milutinovic, and S. Isljamovic, "Risk identification in product innovation projects: New perspectives and lessons learned," *Technol. Anal. Strategic Manage.*, vol. 29, no. 2, pp. 133–148, Feb. 2017.

[22] B. K. Lyon and G. Popov, "Risk treatment strategies: Harmonizing the hierarchy of controls and inherently safer design concepts," *Prof. Saf.*, vol. 64, no. 5, pp. 34–43, 2019.

[23] Z. Y. Han and W. G. Weng, "Comparison study on qualitative and quantitative risk assessment methods for urban natural gas pipeline network," *J. Hazardous Mater.*, vol. 189, nos. 1–2, pp. 509–518, May 2011.

[24] L. A. Cox, Jr., D. Babayev, and W. Huber, "Some limitations of qualitative risk rating systems," *Risk Anal.*, vol. 25, no. 3, pp. 651–662, Jun. 2005.

[25] A. T. de Almeida, M. H. Alencar, T. V. Garcez, and R. J. P. Ferreira, "A systematic literature review of multicriteria and multi-objective models applied in risk management," *IMA J. Manage. Math.*, vol. 28, no. 2, pp. 153–184, Apr. 2017.

[26] K. Kaewfak, V.-N. Huynh, V. Ammarapala, and N. Ratisoontorn, "A risk analysis based on a two-stage model of fuzzy AHP-DEA for multimodal freight transportation systems," *IEEE Access*, vol. 8, pp. 153756–153773, 2020.

[27] H.-C. Liu, L. Liu, N. Liu, and L.-X. Mao, "Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment," *Expert Syst. Appl.*, vol. 39, no. 17, pp. 12926–12934, Dec. 2012.

[28] K.-S. Chin, Y.-M. Wang, G. K. K. Poon, and J.-B. Yang, "Failure mode and effects analysis by data envelopment analysis," *Decis. Support Syst.*, vol. 48, no. 1, pp. 246–256, Dec. 2009.

[29] D. S. Chang, J. H. Chung, K. L. Sun, and F. C. Yang, "A novel approach for evaluating the risk of health care failure modes," *J. Med. Syst.*, vol. 36, no. 6, pp. 3967–3974, Dec. 2012.

[30] D. Chang and K. P. Sun, "Applying DEA to enhance assessment capability of FMEA," *Int. J. Qual. Rel. Manage.*, vol. 26, no. 6, pp. 629–643, Jun. 2009.

[31] H.-C. Liu, J.-X. You, Q.-L. Lin, and H. Li, ''Risk assessment in system FMEA combining fuzzy weighted average with fuzzy decision-making trial and evaluation laboratory,'' *Int. J. Comput. Integr. Manuf.*, vol. 28, no. 7, pp. 701–714, Jul. 2015.

[32] Y.-M. Wang, K.-S. Chin, G. K. K. Poon, and J.-B. Yang, ''Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean,'' *Expert Syst. Appl.*, vol. 36, no. 2, pp. 1195–1207, Mar. 2009.

[33] B. Vahdani, M. Salimi, and M. Charkhchian, ''A new FMEA method by integrating fuzzy belief structure and TOPSIS to improve risk evaluation process,'' *Int. J. Adv. Manuf. Technol.*, vol. 77, nos. 1–4, pp. 357–368, Mar. 2015.

[34] M. J. Rezaee, S. Yousefi, M. Eshkevari, M. Valipour, and M. Saberi, ''Risk analysis of health, safety and environment in chemical industry integrating linguistic FMEA, fuzzy inference system and fuzzy DEA,'' *Stochastic Environ. Res. Risk Assessment*, vol. 34, no. 1, pp. 201–218, Jan. 2020.

[35] M. Norman and B. Stoker, *Data Envelopment Analysis: The Assessment of Performance*. Hoboken, NJ, USA: Wiley, 1991.

[36] J. Wu, J. Chu, J. Sun, and Q. Zhu, ''DEA cross-efficiency evaluation based on Pareto improvement,'' *Eur. J. Oper. Res.*, vol. 248, no. 2, pp. 571–579, Jan. 2016.

[37] T. R. Sexton, R. H. Silkman, and A. J. Hogan, ''Data envelopment analysis: Critique and extensions,'' *New Directions Program Eval.*, vol. 1986, no. 32, pp. 73–105, 1986.

[38] A. Hatami-Marbini, P. J. Agrell, M. Tavana, and P. Khoshnevis, ''A flexible cross-efficiency fuzzy data envelopment analysis model for sustainable sourcing,'' *J. Cleaner Prod.*, vol. 142, pp. 2761–2779, Jan. 2017.

[39] A. Ray and A. K. Chaudhuri, ''Smart healthcare disease diagnosis and patient management: Innovation, improvement and skill development,'' *Mach. Learn. Appl.*, vol. 3, Mar. 2021, Art. no. 100011.

[40] M. Leo, S. Sharma, and K. Maddulety, ''Machine learning in banking risk management: A literature review,'' *Risks*, vol. 7, no. 1, p. 29, Mar. 2019.

[41] J. Zhang, Z. Li, Z. Pu, and C. Xu, ''Comparing prediction performance for crash injury severity among various machine learning and statistical methods,'' *IEEE Access*, vol. 6, pp. 60079–60087, 2018.

[42] S. K. Chandrinos, G. Sakkas, and N. D. Lagaros, ''AIRMS: A risk management tool using machine learning,'' *Expert Syst. Appl.*, vol. 105, pp. 34–48, Sep. 2018.

[43] N. Paltrinieri, L. Comfort, and G. Reniers, ''Learning about risk: Machine learning for risk assessment,'' *Saf. Sci.*, vol. 118, pp. 475–486, Oct. 2019.

[44] A. Gondia, A. Siam, W. El-Dakhakhni, and A. H. Nassar, ''Machine learning algorithms for construction projects delay risk prediction,'' *J. Construct. Eng. Manage.*, vol. 146, no. 1, Jan. 2020, Art. no. 04019085.

[45] A. Charnes, W. W. Cooper, and E. Rhodes, ''Measuring the efficiency of decision making units,'' *Eur. J. Oper. Res.*, vol. 2, no. 6, pp. 429–444, Nov. 1978.

[46] J. Zhu, *Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis With Spreadsheets*. Cham, Switzerland: Springer, 2009.

[47] Y. Gong, J. Liu, and J. Zhu, ''When to increase firms' sustainable operations for efficiency? A data envelopment analysis in the retailing industry,'' *Eur. J. Oper. Res.*, vol. 277, no. 3, pp. 1010–1026, Sep. 2019.

[48] H. F. Lewis and T. R. Sexton, ''Network DEA: Efficiency analysis of organizations with complex internal structure,'' *Comput. Oper. Res.*, vol. 31, no. 9, pp. 1365–1410, Aug. 2004.

[49] D. T. Barnum, M. Johnson, and J. M. Gleason, ''Importance of statistical evidence in estimating valid DEA scores,'' *J. Med. Syst.*, vol. 40, no. 3, p. 47, Mar. 2016.

[50] P. A. D. A. Garcia, I. C. L. Junior, and M. A. Oliveira, ''A weight restricted DEA model for FMEA risk prioritization,'' *Production*, vol. 23, no. 3, pp. 500–507, Nov. 2012.

[51] H.-H. Liu, Y.-Y. Song, and G.-L. Yang, ''Cross-efficiency evaluation in data envelopment analysis based on prospect theory,'' *Eur. J. Oper. Res.*, vol. 273, no. 1, pp. 364–375, Feb. 2019.

[52] M. Falagario, F. Sciancalepore, N. Costantino, and R. Pietroforte, ''Using a DEA-cross efficiency approach in public procurement tenders,'' *Eur. J. Oper. Res.*, vol. 218, no. 2, pp. 523–529, Apr. 2012.

[53] F. R. Lima-Junior and L. C. R. Carpinetti, ''Predicting supply chain performance based on SCOR metrics and multilayer perceptron neural networks,'' *Int. J. Prod. Econ.*, vol. 212, pp. 19–38, Jun. 2019.

[54] A. Hashemi Fath, F. Madanifar, and M. Abbasi, ''Implementation of multilayer perceptron (MLP) and radial basis function (RBF) neural networks to predict solution gas-oil ratio of crude oil systems,'' *Petroleum*, vol. 6, no. 1, pp. 80–91, Mar. 2020.

[55] A. Aguinaga, X. Luo, V. Hidalgo, E. Cando, and F. Llulluna, ''A feed-forward backpropagation neural network method for remaining useful life prediction of Francis turbines,'' in *Proc. 3rd World Congr. Mech., Chem., Mater. Eng.*, Jun. 2017, pp. 8–10.

[56] S. U. Amin, K. Agarwal, and R. Beg, ''Genetic neural network based data mining in prediction of heart disease using risk factors,'' in *Proc. IEEE Conf. Inf. Commun. Technol.*, Apr. 2013, pp. 1227–1231.

[57] D. Baruah, D. C. Baruah, and M. K. Hazarika, ''Artificial neural network based modeling of biomass gasification in fixed bed downdraft gasifiers,'' *Biomass Bioenergy*, vol. 98, pp. 264–271, Mar. 2017.

[58] H. Moayedi and A. Rezaei, ''An artificial neural network approach for under-reamed piles subjected to uplift forces in dry sand,'' *Neural Comput. Appl.*, vol. 31, no. 2, pp. 327–336, Feb. 2019.

[59] M. Narvekar, P. Fargose, and D. Mukhopadhyay, ''Weather forecasting using ann with error backpropagation algorithm,'' in *Proc. Int. Conf. Data Eng. Commun. Technol.* Singapore: Springer, 2017, pp. 629–639.

[60] B. Karatop, B. Taşkan, E. Adar, and C. Kubat, ''Decision analysis related to the renewable energy investments in turkey based on a fuzzy AHP-EDAS-Fuzzy FMEA approach,'' *Comput. Ind. Eng.*, vol. 151, Jan. 2021, Art. no. 106958.

[61] Ken Research. (2019). *Malaysia Logistics and Warehousing Market is Expected to Reach Over MYR 200 Billion in Terms of Revenues by the Year 2023*. [Online]. Available: https://www.prnewswire.com/news-releases/malaysia-logistics-and-warehousing-market-is-expected-to-reach-over-myr-200-billion-in-terms-of-revenues-by-the-year-2023-ken-research-300919627.html

[62] Swiss Business Hub ASEAN. (2019). *Digital and E-Commerce Industry in Malaysia: Gateway to the Fastest Growing Region in the World*. [Online]. Available: https://www.s-ge.com/en/article/global-opportunities/20184-c6-malaysia-digital-industry

[63] ReportLinker. (2020). *Malaysia Freight and Logistics Market—Growth, Trends, and Forecast (2019–2024)*. [Online]. Available: https://www.reportlinker.com/p05778408/?utm_source=GNW

[64] United Nations. (2020). *Impact of COVID-19 on Transport and Logistics Connectivity in the Caribbean*. [Online]. Available: https://www.cepal.org/en/publications/46507-impact-covid-19-transport-and-logistics-connectivity-caribbean

[65] 360marketupdates. (2020). *Malaysia Freight and Logistics Market 2020 Impact of COVID 19 on Peak Countries Data, Industry Size, Future Trends, Growth Key Factors, Demand, Business Share, Sales & Income, Manufacture Players, Application, Scope, and Opportunities*. [Online]. Available: https://www.wicz.com/story/42768880/malaysia-freight-and-logistics-market-2020-impact-of-covid-19-on-peak-countries-data-industry-size-future-trends-growth-key-factors-demand-business

[66] M. Ranjbari, Z. Shams Esfandabadi, M. C. Zanetti, S. D. Scagnelli, P.-O. Siebers, M. Aghbashlo, W. Peng, F. Quatraro, and M. Tabatabaei, ''Three pillars of sustainability in the wake of COVID-19: A systematic review and future research agenda for sustainable development,'' *J. Cleaner Prod.*, vol. 297, May 2021, Art. no. 126660.

[67] D. H. Stamatis, *Failure Mode and Effect Analysis: FMEA From Theory to Execution*. Meerut, India: Quality Press, 2003.