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A Dynamic Type-1 Fuzzy Logic System for the Development of a New Warehouse Assessment Scheme

WAFA' H. ALALAWEEN[1], ABDALLAH H. ALALAWIN[2], MAHDI MAHFOUF[3], AND OMAR H. ABDALLAH[4]

[1]Department of Industrial Engineering, The University of Jordan, Amman 11942, Jordan
[2]Department of Industrial Engineering, The Hashemite University, Zarqa 13133, Jordan
[3]Department of Automatic Control and Systems Engineering, The University of Sheffield, Sheffield S10 2TN, U.K.
[4]Dnata, Amman 11180, Jordan

Corresponding author: Wafa' H. Alalaween (w.alaween@ju.edu.jo)

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ABSTRACT A new dynamic assessment algorithm based on the Type-1 Fuzzy Logic System (T1FLS) is proposed in this research work to develop a dynamic warehouse assessment scheme. First, the criteria and the sub-criteria that affect a warehouse performance are identified and, then, classified into a number of clusters. Second, the warehouse performance score is determined by employing the T1FLS that is developed by using expert knowledge and/or digital data. The data for the new assessed warehouses are then evaluated to ensure that the new data are not redundant and, thus, can lead to meaningful information. Finally, such new data are utilized to dynamically update the T1FLS. The algorithm has been validated on a series of actual warehouses in Jordan, and it has been shown that the presented scheme can successfully assess the warehouses with respect to the identified criteria. In addition to being dynamic, the newly proposed assessment framework can take into consideration uncertainties naturally, this being due to fuzzy logic which has the ability to model them intrinsically via the concept of vagueness.

INDEX TERMS Audit checklist, dynamic Type-1 fuzzy logic system, NICE classification, warehouse assessment scheme.

I. INTRODUCTION

In this new era of rapid globalization and high cost pressure, logistics and supply chain management have attracted a lot of interests, this being due to their essential role in various businesses. In order to focus on their core businesses, enterprises often tend to outsource their logistics activities to third-party logistics providers (3PLPs) [1]. In general, logistics outsourcing has potential advantages in terms of costs, efficiency, reputation, and supply chain quality and flexibility [2]. With the significant increase in the number of the 3PLPs, assessing the various 3PLPs available is an indispensable process for these enterprises, where eliciting the best 3PLP allows these enterprises to use its core competencies, as a competitive advantage, to perform their logistics activities in the best possible way [3]. However, assessing various 3PLPs and selecting the best one can prove to be 'tricky', this is due to the huge number of criteria and sub-criteria, and their different importance levels that need to be considered [4].

A considerable body of research has hitherto focused on the process of assessing and selecting the best 3PLPs [3]–[5]. Since such a multi-criteria decision-making (MCDM) process usually starts with defining the relevant standard definitions, some of the research work has been devoted to identifying the critical criteria required to evaluate various 3PLPs such as quality, cost, flexibility and service innovation [4]. Furthermore, several research studies have focused on the various MCDM approaches that can be used to evaluate 3PLPs [6]–[8]. These approaches are, in general, based on either qualitative experience or quantitative analysis [3]. For instance, linear weighting approaches have been performed to weight defined criteria and then, assess the performance of 3PLPs based on the weighted criteria. Such a step is, commonly, followed by estimating the overall performance [5].

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The Analytic Hierarchy Process (AHP) approach, as a linear weighting approach, has also been utilized to evaluate the 3PLPs service quality taking into consideration various criteria (e.g. reliability and assurance) [9]–[11]. In addition, the Analytical Network Process (ANP) technique, as a general form of the AHP approach, has already been investigated in the related literature to consider the interrelationships among the considered criteria [12], [13]. For example, the ANP technique was implemented to rank various 3PLPs by classifying the defined criteria into three levels: (i) strategic criteria called determinants (e.g. cost and compatibility), (ii) dimensions that support the accomplishment of the determinants (e.g. operational performance and risk management), and (iii) enablers that support the respective dimensions [12]. The AHP and the ANP paradigms have been successfully employed in this area. However, the relative weights in these algorithms are determined based on a relatively large number of pairwise comparison questions (i.e. the number of pairwise comparison questions for 10 criteria is 44). Mathematical programming paradigms have been also utilized to assess 3PLPs [14]–[16]. For instance, Data Envelopment Analysis (DEA), as a linear programming approach, has been utilized to estimate the efficiency of a number of 3PLPs and elicit the best one [15], [16]. Artificial Intelligence (AI) paradigms have been extensively and successfully utilized in many research areas such as industrial, pharmaceutical and medical applications [17]–[19]. Therefore, some of the AI paradigms (e.g. case-based reasoning) have been implemented to incorporate human expertise in the evaluation paradigms that are based on the Fuzzy Logic to assess 3PLPs [20]–[23]. For example, the Artificial Neural Network (ANN) was developed and trained using the data that resulted from the ANP approach to select an enterprise resource planning software [24].

In general, all proposed MCDM approaches have their own limitations as well as strengths [25]–[27]. Therefore, approaches that integrate two or more of the evaluation paradigms have been proposed in the related literature in order to circumvent the limitations of applying one approach [10], [25]. For example, a framework that integrated case-based reasoning, rule-based reasoning and compromise programming models in a fuzzy environment was proposed to assess 3PLPs effectively [28]. In addition, a framework that integrated ANNs and Fuzzy Logic was proposed to select the best 3PLP in the reverse logistics [10]. The concept of fuzzy sets has also been embedded in various MCDM paradigms to deal with the uncertainties in the subjective information that are usually provided. For instance, the fuzzy sets were embedded in the ANP, AHP and DEA paradigms [29], [30]. For example, 3PLPs were assessed by integrating a fuzzy AHP approach with TOPSIS [31]. The integration of more than one algorithm has indeed circumvented the limitations of employing one algorithm. However, to the best of our knowledge, none of the presented MCDM algorithms has considered the dynamic nature of the majority of the MCDM cases (e.g. the dynamic nature of the business environment).

The majority of the presented research papers have assessed the services provided by 3PLPs, but none of them has hitherto been devoted to developing a comprehensive assessment of warehouse logistics and facilities which is based on an assessment algorithm that can consider the dynamic nature of such a case, in addition to considering the various criteria and the highly uncertain environment. Since warehouse logistics and facilities are considered to be the main resources that can determine the performance of a 3PLP, and a significant ratio of the total costs is expended on them [26], a comprehensive and rigorous warehouse assessment scheme that is based on a new assessment scheme is proposed in this research. Such an assessment algorithm is based on the dynamic Type-1 Fuzzy Logic System (T1FLS). Such a new assessment algorithm can (i) deal with the various criteria with no need for a relatively large number of pairwise comparisons and the determination of the relative weights, (ii) handle the uncertainties in the provided information and the assessment process naturally, and (iii) consider the dynamic nature of such a case. The remainder of this research paper is organized as follows: the assessment criteria and the corresponding sub-criteria that can determine the performance of a warehouse and its logistics activities are discussed in Section II. The new assessment algorithm that is based on the dynamic T1FLS is presented in Section III. The warehouse assessment scheme is presented and validated in Section IV. Finally, the concluding remarks with some future pointers to the research are presented in Section V.

II. WAREHOUSE ASSESSMENT CRITERIA

In this research work, the ten criteria and the corresponding sub-criteria that can determine the performance of a warehouse were carefully defined. Some of these criteria were identified from the related literature (i.e. research papers and books), whereas the remaining ones were identified by employing experts' knowledge via structured meetings and distributing an online survey. The defined criteria are presented in Figure 1 and briefly described next.

A. FACILITIES

Facilities play a significant role in the supply chain networks and directly affect a warehouse performance. To illustrate, the number of warehouses and their locations can determine their efficiency in terms of cost, market penetration and customer support [32], [33]. The various sub-criteria that relate to the facilities are (i) the location (e.g. the accessibility to local and global transport network); (ii) the number of locations (e.g. the optimal number of warehouses); (iii) the layout (e.g. efficient warehouse flow); (iv) work conditions and the workplace environment (e.g. monitoring temperature and humidity); and (v) security (e.g. the use of alarms and surveillance).

B. MATERIAL HANDLING EQUIPMENT

Material handling equipment (MHE) is mechanical equipment used for the storage, control, handling, protection

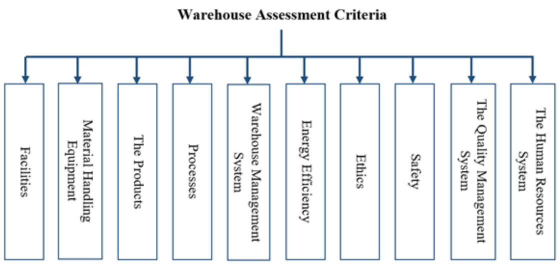

FIGURE 1. Warehouse assessment criteria.

TABLE 1. The warehouse processes and the related sub-sub-criteria.

Processes	Sub-sub-criteria
Pre-advice	• An agreement contains the related details • Schedule for arrivals, • Shipment details.
Receiving	• Adequate receiving protocol, • Documenting the related information, • Health and safety issues, • Procedures and forms to deal with non-conforming items.
Checking	• Checklists for the received items, • Frequent checking.
Put-away	• A system to managing the related practices, • Utilizing the appropriate techniques (e.g. First-In First-Out).
Cross-docking	• Manage the related activities (e.g. staff required), • Area for this process and its requirements.
Storing	• Documenting the stored items information, • Preventive actions to prevent damage and waste.
Replenishment	• An efficient replenishment system (e.g. plan and time).
Picking	• A system to control the picking process, • Defined key performance indicators, • Picking instructions.
Packing	• Packing system (e.g. pallets), • The use of suitable materials (i.e. recycled and lightweight).
Dispatching	• A proper system (e.g. departure time and load optimization), • The optimal utilization of the space and equipment.
Value-added service	• Warehouse services that go above and beyond customer needs.

and movement of products throughout many processes [34]. Although the MHE does not add a value to products, it adds to the costs, where it has been found that handling accounts for approximately 20% to 25% of the total costs [35]. Therefore, the MHE is of paramount importance when it comes to evaluating the efficiency of the 3PLP warehouses and the related operations. This is because it (i) helps to minimize accidents, where handling materials accounts for approximately 21% and more than 25% of permanent and temporary disabilities, respectively [35]; (ii) it improves the efficiency; and (iii) it improves warehouse layout (i.e. well-organized space). The MHE can be carefully assessed by considering the best MHE and its periodical test, safety training and the related information signage and instructions.

C. PRODUCTS

The major roles of any warehouse are to store and assemble products, add-value to orders, and organize delivery activities and orders to companies and/or customers. The vast majority, if not all, warehouse operations are all about products. Therefore, product-related activities need to be carefully assessed. For the various product classes, a labeling system, product traceability and waste management protocol should be assessed.

D. PROCESSES

Warehouses may vary in terms of functions and management; however, their processes remain almost the same. Understanding and evaluating such processes are essential in order to improve them and, consequently, improve the efficiency of warehouses [36]. The warehouse key processes, as sub-criteria, and the corresponding sub-sub-criteria, that need to be considered in the development of a warehouse assessment scheme are presented in Table 1.

E. WAREHOUSE MANAGEMENT SYSTEM

A warehouse management system (WMS), as a software that organizes the daily plans and the required available resources, is one of the main criteria that are commonly used in evaluating a warehouse performance [37]. In order to be an efficient one, the WMS should (i) contain all the key operations and their importance; (ii) have the ability to interface with other systems; and (iii) be accessible and protected.

F. ENERGY EFFICIENCY

In general, warehouses can considerably minimize costs by targeting energy efficiency. Such a reduction in the costs can be of thousands to hundreds of thousands of dollars a year depending on the warehouse size [38]. Energy efficiency without a considerable capital investment can thus improve the performance of a warehouse. Therefore, the implementation of an energy management system and the use of solar panels, wind turbines and/or biomass boilers are important aspects that need to be considered in the evaluation of warehouses.

G. ETHICS

Codes of ethics and conduct are commonly considered to be key issues in today's business, as they can considerably influence the world economic system. In addition, they can also affect global transactions and human rights [39]. The ethical duties are to (i) employees (e.g. compensation and work conditions); (ii) clients (e.g. confidential information); (iii) companies in the same industry (e.g. avoiding monopolistic practices); and (iv) the nation (e.g. interest in public welfare and social responsibility) [40].

H. SAFETY

Accidents, injuries and hazards may occur quite frequently in warehouses compared to other facilities and businesses, where the number of factors that can affect the number of injuries and accidents is relatively large [41]. Therefore, occupational safety and health administrative rules and regulations should be strictly followed to ensure that employees work in a safe and healthful environment. Assessing the safety of a warehouse environment includes evaluating aspects related, for instance, to the use of hazard codes, number of exit and fire doors, contingency plan (i.e. emergency plan for system downtime, labor and supplier issues, etc.) and health and safety training.

I. QUALITY MANAGEMENT SYSTEM

The impact of the implementation of a quality management system on warehouse processes and supply chain has been well-recognized in practice but not in the related literature [42]. The majority of the 3PLPs are recently aware of the importance of the integration between quality management and logistics in order to improve the various logistics operations and processes and raise the standards of logistics services [42], [43]. Therefore, the quality management system is considered to be one of the criteria that need to be utilized in evaluating warehouses. Such a criterion can be assessed by various aspects related to system documentation, control of documents and records, management review, internal auditing, corrective and preventive actions, and SMART performance measurements.

J. HUMAN RESOURCES SYSTEM

Human resources are considered to be important assets for a warehouse of a 3PLP, where the success of a 3PLP significantly depends on the skills, experience and the positive and creative contribution of its staff [44]. In addition, an effective human resources system is a key to achieve a competitive advantage. Such a system can be evaluated by taking into account a system for training and development, and daily and weekly human resource planning.

III. THE DYNAMIC TYPE-1 FUZZY LOGIC SYSTEM ALGORITHM

Decision-making is considered to be one of the basic concepts of the cognitive process. In other words, decision-making is the process of identifying the best alternatives when various criteria (perhaps conflicting ones) are taken into account. Therefore, the MCDM process is commonly implemented to evaluate multiple judgments and handle imprecise information [30], [45]. In the MCDM, there is, more often than not, a need for systematic paradigms, this being due to the number of the criteria involved and uncertainties that should be carefully handled [46, 47]. In addition, the dynamic nature of the majority of the cases investigated (e.g. business and health care) needs to be taken into consideration. Therefore, in this research paper, a dynamic assessment algorithm based on the T1FLS is proposed to tackle such difficulties. In general, Fuzzy Logic, proposed a few decades ago by Zadeh, is a process of reasoning that imitates human reasoning (i.e. the process of decision making in humans) [48], [49]. Because of the uncertain environment for the majority of the engineering applications and because of its ability to effectively deal with such uncertainties, Fuzzy Logic has found its way to many areas including, but not limited to, pharmaceutical, marine, manufacturing and medical ones [29], [45], [48].

Figure 2 presents the main steps of the proposed algorithm that is based on the dynamic T1FLS. Following the identification of the case investigated and the main aim, the associated criteria are defined. The criteria can be identified by surveying the related literature and/or utilizing expert knowledge. Sub-criteria can also be defined when more levels of details are required. It is worth mentioning that an audit checklist can be prepared at this stage for a systematic assessment. The alternatives (i.e. warehouses) can then be assessed based on

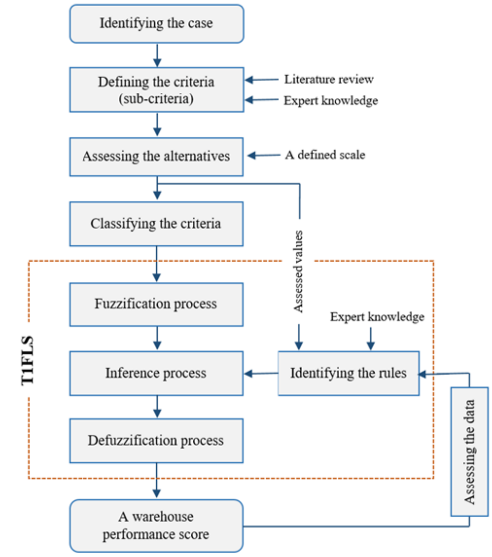

FIGURE 2. The flowchart of the dynamic assessment algorithm based on the T1FLS.

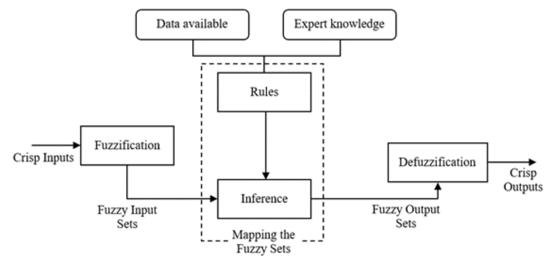

FIGURE 3. The T1FLS structure.

the criteria using a defined scale. Such a scale can be numeric (e.g. a scale of 1 to 10) or linguistic (e.g. poor, satisfactory and good). The identified criteria are then classified into a number of clusters based on the assessed values that are given to the criteria. Based on the data available (i.e. categorical or numerical data), expert knowledge and/or clustering algorithms (e.g. K-means clustering and Gaussian Mixture Model) can be employed in the classification process. Such a step is followed by developing the T1FLS.

In general, the T1FLS consists of four processes, as shown in Figure 3. The fuzzification process usually converts the crisp inputs $(x_1, x_2 \ldots x_n)$ to fuzzy sets (F_j^i) with the corresponding membership function, where (F_j^i) represents the i^{th} fuzzy set for the j^{th} variable. Various types of membership functions can be employed such as triangular, trapezoidal and Gaussian functions. Because of the continuity and smoothness properties of the Gaussian function which allow the system to be a universal approximator, such a function is employed in this research work. The membership degree of the Gaussian function $(\mu_j^i(x_i))$ can be written as follows [48]:

$$\mu_{10}^{4}(x_{10}) = \exp\left[-\frac{1}{2}\left(\frac{x_j - M^i}{\sigma^i}\right)^2\right] \tag{1}$$

where M^i and σ^i represent the i^{th} set mean and the standard deviation, respectively. The fuzzy inference process can then map the fuzzy inputs to the fuzzy outputs by utilizing the linguistic rules. Rules can be, in general, provided as expert knowledge and/or extracted from collected data related to the case under investigation. Such a mapping process can be represented mathematically by the fuzzy basis function ($\varphi_i(\mathbf{x})$) that can be commonly expressed as follows [48]:

$$\varphi_i(x) = \frac{\prod_{j=1}^{n} \mu_j^i(x_j)}{\sum_{i=1}^{R} \prod_{j=1}^{n} \mu_j^i(x_j)} \tag{2}$$

where $\mathbf{x}$ represents the input vector and the rest of the parameters are as defined previously. The linguistic representation of the fuzzy logic rules is as follows [48]:

Rule$^{\mathbf{i}}$: IF x_1 is F_1^i …and x_n is F_n^i, **THEN** y_i is P^i.

where F_j^i and P^i are the j^{th} antecedent and consequent membership function of the i^{th} rule, respectively. In this research work, the P^i is presented as a fuzzy set with a membership function. Fuzzy output sets are the output of the inference process. Such a fuzzy output is finally defuzzified to determine the crisp output. For this purpose, the centroid defuzzifier can be utilized. Such a defuzzifier can be written as follows [48]:

$$y(x) = \frac{\sum_{i=1}^{R} y_i \mu_p(y_i)}{\sum_{i=1}^{R} \mu_p(y_i)} \tag{3}$$

In the context of developing an assessment algorithm, the crisp inputs and the crisp output of the T1FLS are obtained from the previously assessed warehouses. To illustrate, the performance values of warehouses with respect to the identified criteria and the warehouse overall performance score are considered as the crisp inputs and the crisp output of the T1FLS, respectively. It is worth mentioning at this stage that there is no need for the fuzzification process when a suitable linguistic scale is used. The rules of the developed T1FLS can be provided by experts in this area or can be extracted from a number of warehouse assessments called a data set. Therefore, a new assessment can be obtained for a new warehouse.

The dynamic nature of the majority of the MCDM cases, in particular, those related to business, needs to be considered in order to develop a reliable assessment algorithm. In this research paper, a dynamic T1FLS can, therefore, be developed in a way that the provided/extracted fuzzy rules and, consequently, the inference process can be updated over time. The update can be performed by adding the new assessment data to the current data set that is used to extract the fuzzy rules. In addition, experts can also amend the defined rules whenever there is a need to. In order to ensure that the new assessment data are not redundant and, thus, can lead to extracting meaningful and informative rules, the new data need to be evaluated before being added to the data set and utilized to update the T1FLS. Such a process can be implemented every specific period of time. Once the new data are added and the T1FLS is updated, the performance score of warehouses can be re-evaluated.

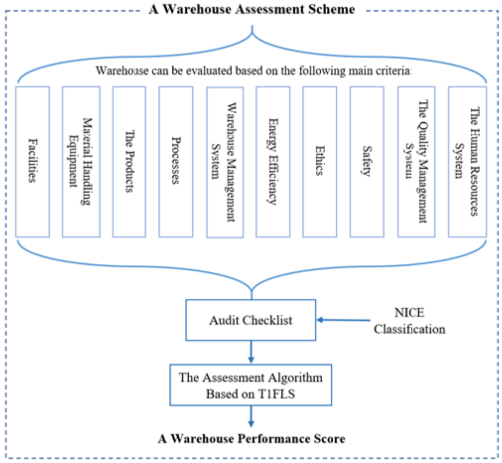

FIGURE 4. An overview of the developed warehouse assessment scheme.

IV. THE WAREHOUSE ASSESSMENT SCHEME

A. WAREHOUSES ASSESSMENT

A warehouse assessment scheme was developed by employing the proposed dynamic T1FLS assessment algorithm. An overview of such an assessment scheme is presented in Figure 4. In order to assess warehouses successfully, the criteria and the sub-criteria that determine the performance of a warehouse were firstly identified using the related literature and experts' knowledge, as briefly described in Section II. An audit checklist was then prepared. Such a checklist was developed for the first time to state all the corresponding questions that can be used to assess a warehouse. For instance, a question that is related to the location, as a sub-criterion of the facilities, is "Has the organization considered the accessibility to local and global transport network for labor?" In a similar manner, all the questions that correspond to the criteria and the sub-criteria were listed in the audit checklist.

A warehouse can be assessed by answering all the questions stated in the audit checklist by assigning a value in the range of 0 to 10 to each question and for each warehouse. Approximately 45 various warehouses in Jordan were assessed using the developed checklist. It is worth mentioning that the assessment of the criteria significantly depends on the products that warehouses deal with. To elucidate further, controlling the temperature, as a sub-sub-criterion of the "Facilities" criterion, can have a considerable effect on a warehouse performance value when a warehouse deals with pharmaceuticals and medical products, however, it can have a negligible effect on it when a warehouse deals with metal products. Therefore, products that warehouses deal with should be classified to develop a reliable warehouse assessment scheme. Various product classification strategies have hitherto been presented in the related literature to serve different purposes such as trade and customs [50]. In this research paper, NICE classification, which is a classification prepared by the United International Bureaux for the Protection of

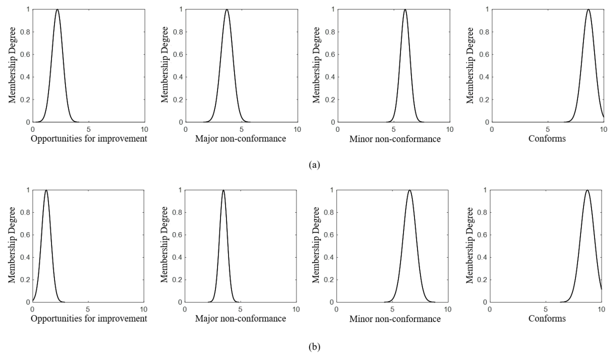

FIGURE 5. Examples of the four clusters for (a) Class 7: Machines, machine tools, power-operated tools; motors and engines, except for land vehicles; machine coupling and transmission components, except for land vehicles; agricultural implements, other than hand-operated hand tools; incubators for eggs; automatic vending machines; and (b) Class 25: Clothing, footwear, headwear (The class names are from WIPO, 2020 [50]).

Intellectual Property (BIRPI), was employed. Such a classification consists of a list of 34 product classes, each one contains a list of goods that are ordered alphabetically [50].

B. DYNAMIC T1FLS: IMPLEMENTATION AND RESULTS

Once various warehouses were assessed, the proposed dynamic T1FLS assessment algorithm can be applied. Based on the NICE classification and the assessment of warehouses with respect to the defined criteria and sub-criteria, as mentioned above, the ten criteria were classified into four clusters, namely, ''Opportunities for improvements'', ''Major non-conformance'', ''Minor non-conformance'' and ''Conforms''. It is worth emphasizing at this stage that the K-means clustering algorithm, as an unsupervised one, was utilized to classify the ten criteria into the four clusters. The parameters (i.e. mean and standard deviation) for these clusters were also determined. Figure 5 shows such clusters with their parameters for Class 7 and Class 25, as examples. It is noticeable that the two classes have different values of the parameters for these clusters.

The T1FLS was then developed to determine the performance score of a warehouse. The inputs of the T1FLS were the performance values of the ten criteria, whereas the output is the overall performance scores of the warehouses. Since the T1FLS is, in general, a supervised paradigm, such performance values were initially obtained from assessed warehouses using an assessment algorithm that integrated the Genetic Algorithm and the Analytic Network Process. Due to the curse of dimensionality (i.e. analyzing high dimensional spaces), the performance values of the sub-criteria were implicitly considered in the performance values of the corresponding criteria. The value of each input was fuzzified by estimating the membership degrees of the input to the four clusters defined above by using the parameters calculated in the previous step. For example, the performance value of the ''Human Resources System'' criterion, as an input, for a warehouse that deals with machine tools and related products (i.e. Class 7) was 8 out of 10. The membership degree of such a criterion to the ''Conforms'' cluster was then calculated as follows:

$$\mu_{10}^{4}\left(x_{10}\right)=\exp\left[-\frac{1}{2}\left(\frac{8-8.63}{0.55}\right)^{2}\right]=0.52 \tag{4}$$

where 8.63 and 0.55 are the mean and the standard deviation values for the ''Conforms'' cluster as determined by the K-means clustering algorithm. In a similar manner, the calculations of the fuzzification process were performed.

The rules for such a fuzzy system were initialized by utilizing experts' knowledge in both academia and industry via structured meetings and extracting informative rules from 45 warehouses, which were assessed previously using an assessment algorithm that integrated the Genetic Algorithm and the Analytic Network Process. Since the T1FLS is, in general, considered to be a powerful interpolator, some rules were identified using expert knowledge in order to cover all the areas in the space investigated. To illustrate, the following rule was included in the rules base by experts:

> **IF** *the "Facilities" criterion is "Opportunities for improvements" and the "Material Handling Equipment" criterion is "Opportunities for improvements" and the "Products" criterion is "Opportunities for improvements" and the "Processes" criterion is "Opportunities for improvements" and the "Warehouse Management System" criterion is "Opportunities for improvements" and the "Energy Efficiency" criterion is "Opportunities for improvements" and the "Ethics" criterion is "Opportunities for improvements" and the "Safety" criterion is "Opportunities for improvements" and the "Quality Management System" criterion is "Opportunities for improvements" and the "Human Resources" criterion is "Opportunities for improvements",* **THEN** *the "Warehouse Performance" is "Unsatisfactory".*

Such a rule is simple and expected but since none of the warehouses assessed defined such a rule, it was necessary to define it. Then, the fuzzy inference engine or simply the inference combined the defined fuzzy logic rules to map the fuzzified input sets to the output fuzzy sets, as presented in Equation (2). In this research work, Mamdani implication, by which the fuzzy inputs were connected by the product t-norm, was utilized. It is worth emphasizing at this stage that the defined rules and their parameters were optimized by employing the steepest descent algorithm with the well-known adaptive back-propagation network [48]. The output of the fuzzy inference engine was fuzzy outputs. Such fuzzy outputs were defuzzified leading to a crisp output using the centroid defuzzifier presented in Equation (3). Such a crisp output is the warehouse performance score. Figure 6 presents an optimized fuzzy rule, as an example, for Class 7. Such a rule can be read as follows:

> ***Rule:*** **IF** *the "Facilities" criterion is "Minor non-conformance" and the "Material Handling Equipment" criterion is "Conforms" and the*

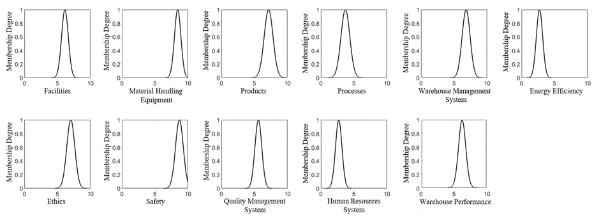

FIGURE 6. An example of one of the rules for Class 7.

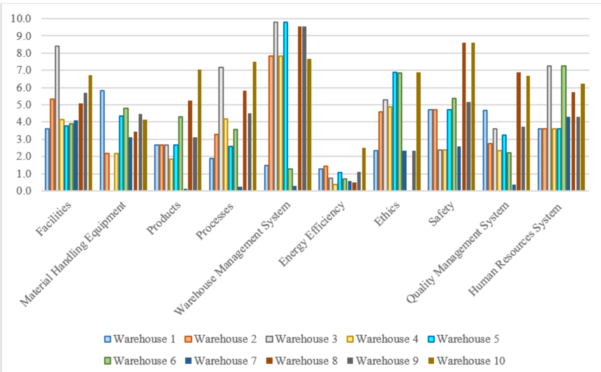

FIGURE 7. An example of a warehouse performance using the proposed warehouse assessment scheme.

"Products" criterion is "Minor non-conformance" and the "Processes" criterion is "Major non-conformance" and the "Warehouse Management System" criterion is "Minor non-conformance" and the "Energy Efficiency" criterion is "Major non-conformance" and the "Ethics" criterion is "Minor non-conformance" and the "Safety" criterion is "Conforms" and the "Quality Management System" criterion is "Minor non-conformance" and the "Human Resources" criterion is "Major non-conformance", **THEN** *the "Warehouse Performance" is "Satisfactory".*

Once the T1FLS was developed, it can now be utilized to determine the performance score of new warehouses. Once a number of new warehouses is assessed in a specific time period (e.g. six months or a year), such a T1FLS can be directly updated based on them. Updating the T1FLS based on new assessed warehouses gives the T1FLS the dynamic nature, as it is called in this research a dynamic T1FLS. In order to validate such a dynamic step, 10 new warehouses were assessed using the developed T1FLS and as described above. The detailed performance (i.e. the performance values of the ten criteria) for the 10 warehouses is presented in Figure 7. It is noticeable that the performance values of the main criteria vary for the warehouses. For instance, the performance values of the "Warehouse Management System" vary considerably among the warehouses, where some performance values are more than seven and the rest are less than two. Furthermore, the performance value of the "Energy Efficiency" criterion was small for the majority of the warehouses, this being due to the fact that enterprises in Jordan are still investing in the concept of "Green Warehouse". Based on the performance values of the 10 criteria, the overall performance values of each warehouse was determined by the T1FLS. Such scores were in the range of 1.8, for Warehouse 7, to 6.8, for Warehouse 10. The data of these warehouses were, then, added to the data set that was initially utilized to develop the T1FLS by extracting some of the meaningful rules. It was noted that such new data updated the parameters (i.e. mean and standard deviation) of some of the rules' fuzzy sets. To illustrate, the parameters of the rule presented in Figure 6 were slightly changed as shown in Figure 8. It is apparent that the mean values for the "Facilities", "Material Handling Equipment", "Products", "Processes", "Safety" and "Human Resources System" criteria were changed by 0.87 (to the right), 0.15 (to the left), 0.35 (to the right), 0.91 (to the right), 0.78 (to the left) and 0.89 (to the right), respectively. In addition, the mean value for the "Warehouse Performance" was also changed by 0.23 (to the right). It is worth mentioning that these changes did not change the linguistic form of such a rule. Furthermore, such data did not add a new rule to the rules base. However, a new rule can be added or deleted when more data are considered to update the T1FLS. Such data are usually available in the majority of real life cases when a specific period of time is considered.

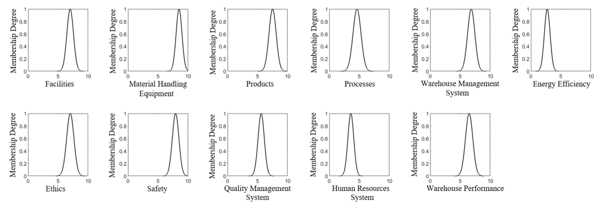

FIGURE 8. The modified example for one of the rules for Class 7.

C. COMPARATIVE STUDIES

Various assessment algorithms were employed in this research work for comparison purposes. Because of their proven efficiencies in various application, fuzzy AHP (FAHP), fuzzy ANP (FANP) and fuzzy DEA, as common algorithms, and interval rough number-weighted aggregated sum product assessment (IRN-WASPAS) [51] and criteria importance through inter criteria correlation-weighted aggregated sum product assessment (CRITIC-WASPAS) with interval type-2 fuzzy sets [26], as newly proposed algorithms, were used to assess warehouses. As examples, the results for three warehouses performing differently (i.e. unsatisfactory, satisfactory and well) are shown in Figure 9. It was noticeable that the warehouse performance values determined by FAHP and FANP were relatively close, this being due to the fact that the ANP is the general form of the AHP. In addition, it was found that the FDEA underestimated the performance of those warehouses which perform in an unsatisfactory way and overestimated the performance of those warehouses which perform well. This can be attributed to the fact the DEA relies on observing the most efficient decision-making units (DMUs) (i.e. warehouses) to establish the production frontier

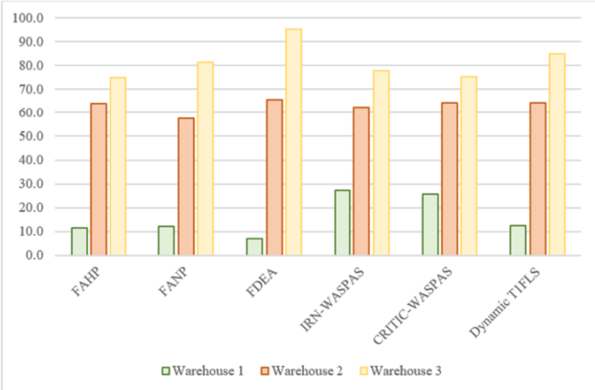

FIGURE 9. **Warehouses assessment using various algorithms.**

(i.e. best practice) against which all DMUs are compared. Furthermore, it was apparent that both IRN-WASPAS and CRITIC-WASPAS slightly overestimated the performance of those warehouses which perform in an unsatisfactory way. In addition, none of the presented algorithms considered the dynamic nature of the business environment. Therefore, for every specific time period, there will be a need to recalculate the parameters of the algorithms. For the FAHP and FANP, as examples, the relative weights and the pairwise comparison (i.e. conducting a survey) need to be recalculated which are considered to be computationally expensive. However, the proposed dynamic T1FLS was able to evaluate the performance of the warehouses in a way that mimics the human way, in addition to its ability to utilize new assessed warehouses to update its parameters without the need to redo the calculations.

V. CONCLUSION

In this research work, a new warehouse assessment scheme based on the dynamic Type-1 Fuzzy Logic System (T1FLS) was successfully developed for the first time to assess warehouses in enterprises, in particular, third-party logistics providers (3PLPs) whose warehouses and the related logistics activities can determine their performance. The development of such a scheme consisted of several stages. First, the main criteria and the related sub-criteria that determine a warehouse performance were defined and, then, classified into four clusters. Second, the warehouse overall performance score was determined using the T1FLS that was developed using expert knowledge and collected data. Finally and in order to develop a dynamic T1FLS, the data for ten new assessed warehouses were evaluated and employed to update the T1FLS. Validated on various warehouses, it was found that the assessment scheme that was based on the proposed dynamic T1FLS algorithm was able to (i) deal with the associated criteria systematically; (ii) handle uncertainties, by uncertainties one means the linguistic uncertainty and the uncertainty that can result from the assessment process; and (iii) consider the dynamic nature of some cases. Furthermore, the proposed assessment scheme can lead to a significant impact not only on warehouses and 3PLPs, but also on the multi-criteria decision-making area where equally challenging dynamic cases can be evaluated.

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WAFA' H. ALALAWEEN received the Ph.D. degree from The University of Sheffield, U.K., in 2018. Since 2018, she has been teaching various courses related to artificial intelligence and deterministic and stochastic optimization. During the Ph.D. studies, she was involved in teaching different courses for undergraduate and postgraduate engineering students. She is currently an Assistant Professor with The University of Jordan. She has been recently working on various funded projects. She has published various research articles in reputable journals and conferences. Her research interests include artificial intelligence, biologically inspired computing and optimization, and fuzzy and neural fuzzy systems.

ABDALLAH H. ALALAWIN received the Ph.D. degree from the University of Salento, Lecce, Italy, in 2012. He is currently working as an Assistant Professor with the Department of Industrial Engineering, The Hashemite University. He is a Technical Expert for product certification and inspection systems with more than 14 years of experience. His research interests include supply chain management and intelligent systems.

MAHDI MAHFOUF received the M.Phil. and Ph.D. degrees in systems and control engineering from The University of Sheffield, Sheffield, U.K., in 1987 and 1991, respectively. He has been a Personal Chair in intelligent systems engineering with The University of Sheffield, since 2005. He has authored more than 300 articles, more than 110 of these being journal articles, and authored or coauthored one book and five book chapters. He has been working in the areas of intelligent systems modeling, optimization and control in biomedicine, and industrial systems for more than 30 years.

OMAR H. ABDALLAH received the B.Sc. degree in industrial engineering from Mutah University, Jordan, in 2015. He is currently working at Dnata, Amman, Jordan. His research interests include supply chain management and artificial intelligence.