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AlAlawin, A.H., AlAlaween, W.H., Salem, M.A. et al. (3 more authors) (2022) A fuzzy logic based assessment algorithm for developing a warehouse assessment scheme. Computers & Industrial Engineering, 168. 108088. ISSN 0360-8352

https://doi.org/10.1016/j.cie.2022.108088

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https://doi.org/10.1016/j.cie.2022.108088

A Fuzzy Logic Based Assessment Algorithm for Developing a Warehouse Assessment Scheme

Abdallah H. AlAlawin a,* , Wafa' H. AlAlaween b,* , Mujahed A. Salem b , Mahdi Mahfouf c , Nibal T. Albashabsheh b , Changjiang He c a Department of Industrial Engineering, Faculty of Engineering, The Hashemite University, B.O box 330127, Zarqa 13133, Jordan b Department of Industrial Engineering, The University of Jordan, Amman, Jordan c Automatic Control and Systems Engineering Department, The University of Sheffield, Sheffield, UK

ARTICLE INFO

Article history:
Received 00 December 00
Received in revised form 00 January 00
Accepted 00 February 00

Keywords:
Data Envelopment Analysis,
Grey Relational Analysis, Interval Type-2 Fuzzy Logic System,
Warehouse Assessment Scheme

ABSTRACT

A new integrated assessment algorithm is proposed for a warehouse assessment scheme. This new algorithm integrates three paradigms, namely, Grey Relational Analysis (GRA), Data Envelopment Analysis (DEA), and an Interval Type-2 Fuzzy Logic System (IT2FLS). Based on the defined criteria and the various warehouses assessed according to these criteria, the GRA is employed to determine the grey relational grade. The DEA is, then, utilized to estimate the warehouse efficiency scores. Finally, the IT2FLS is developed to map the efficiency scores of the warehouses to the assessed values of the defined criteria. The developed IT2FLS can be used to assess new warehouses without re-performing the calculations of the GRA and the DEA. Validated on several warehouses, the integrated assessment algorithm can assess warehouses successfully, and can tackle the uncertainties during the assessment process. In addition to comparing the warehouses with the best practice, it can also provide managers with a linguistic understanding of the effect of the defined criteria on the warehouse performance.

1. Introduction

Enterprises these days tend to outsource all or some of the logistics activities to third-party logistics providers (3PLPs). Because of the several advantages of outsourcing in terms of quality, flexibility, cost and efficiency, the number of enterprises that outsource their logistics activities has considerably increased. For instance, 77% of United State manufacturers outsourced their logistics activities to 3PLPs, such a number was doubled in less than a decade. Therefore, the number of 3PLPs has also increased (Asian et al., 2019). With such a considerable increase in their number, selecting the best 3PLP that can perform the logistics activities in the optimal way becomes a non-trivial task (Marasco, 2008). This can be attributed to the conflicting criteria that should be considered in addition to their importance levels.

* *Corresponding author.* Tel.: xxxx
E-mail address: xxxx
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Several studies have investigated the assessment of 3PLPs which is considered to be a multi-criteria decision-making (MCDM) process, in order to elicit the best one (AlAlaween, AlAlawin, Mahfouf, & Abdallah, 2021). Many researchers have focused on investigating the criteria and the sub-criteria of such an MCDM process (Jovčić et al., 2019). For instance, cost, service quality, corporate image and flexibility were identified as examples of some criteria that affect a 3PLP performance (Mardani et al., 2016). Other researchers investigated the implementation and development of various MCDM (Goepel & Performance, 2019). Linear weighting algorithms such as the Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) has been employed to evaluate 3PLPs (Yadav et al., 2020). Although the AHP and the ANP have been successfully utilized, determining the relative weights of the defined criteria in these algorithms is considered to be computationally expensive, this being due to the fact that a considerable number of pairwise comparison questions is required (AlAlaween, AlAlawin, Mahfouf, & Abdallah, 2021). Mathematical programming (e.g. Data Envelopment Analysis (DEA)) has also been developed to assess 3PLPs and select the best one (Soheilirad et al., 2018). The DEA was, for instance, deployed to determine the relative efficiency of 3PLPs and then to select the one with the maximum efficiency value (Bajec & Tuljak-Suban, 2019). As the artificial intelligence models have been extensively used in various academic and industrial areas (e.g. manufacturing and pharmaceutical) (AlAlaween et al., 2021), they have recently been employed in the logistics and supply chain area to mimic the human way of thinking by incorporating experts' knowledge (AlAlaween, AlAlawin, Mahfouf, & Abdallah, 2021). A Feedforward Artificial Neural Network (ANN), as a powerful interpolator, was developed based on the output of the ANP algorithm to choose a resource planning software for an enterprise (Yazgan et al., 2009). Likewise, an MCDM algorithm based on Fuzzy Logic was utilized to develop a dynamic MCDM algorithm to evaluate various warehouses as the main resources of 3PLPs (AlAlaween, AlAlawin, Mahfouf, & Abdallah, 2021).

In addition to the single MCDM algorithms presented, paradigms that integrate two or more MCDM algorithms have been also proposed. For instance, an algorithm that integrated Interval Rough Number (IRN) based on the Best-Worst Method (BWM) and the Weighted Aggregated Sum Product Assessment (WASPAS) method was proposed to evaluate 3PLPs (Pamucar et al., 2019). With the recent development in the computing power, fuzzy systems have been commonly utilized and embedded with other algorithms to consider uncertainties (Alalaween et al., 2018). Therefore, fuzzy logic was incorporated with the AHP, ANP and DEA to tackle the uncertainties that may be embedded in the subjective information provided (Bouzon et al., 2016; Chen et al., 2018). For example, the Fuzzy AHP (FAHP) was integrated with TOPSIS in order to evaluate 3PLPs (Singh et al., 2012). Likewise, an algorithm that integrated Criteria Importance Through Inter-criteria Correlation, WASPAS and Interval Type-2 Fuzzy Sets was proposed to realistically weight the defined criteria and, thus, evaluate 3PLPs (Keshavarz Ghorabaee et al., 2017). The frameworks that integrated two or more of the MCDM algorithms have indeed circumvented the potential limitations of using one algorithm, as it has been shown in the provided literature (Pamucar et al., 2019).

In the related literature, warehouses and their logistics have been evaluated as a part of the 3PLPs assessment. Since they can considerably affect the performance of a 3PLP and its cost (Keshavarz Ghorabaee et al., 2017), evaluating warehouses and their logistics can provide better insights into 3PLPs performance and, thus, allow managers to elicit the best one reliably. Therefore, a warehouse assessment scheme is presented in this research paper. Such an assessment scheme is based on a new MCDM algorithm that is proposed by integrating the Grey System Theory, Linear Optimization and Type-2 Fuzzy Logic. The proposed MCDM algorithm can (i) assess warehouses (i.e. alternatives) according to various criteria, sub-criteria and sub-sub-criteria without the pairwise comparisons used usually to estimate the relative weights of the defined criteria; (ii) tackle the uncertainties in the information provided and/or during the assessment process; (iii) compare the warehouses with the best practice; and (iv) provide a linguistic understanding of the effect of the defined criteria on the warehouse performance. This research paper is organized as follows: the development of the integrated assessment algorithm is discussed in Section 2. The warehouse data that include the criteria and their sub-criteria, and the warehouses assessed are briefly discussed in Section 3. The implementation of the integrated assessment algorithm and the results obtained are discussed in Section 4, whereas the conclusions and some future works are presented in Section 5.

2. Development of the Integrated Algorithm

The MCDM process, as a sub-discipline of the operations research, is considered to be a complex cognitive process where one needs to identify the best course of actions or alternatives while considering a number of conflicting criteria (Bouzon et al., 2016). In addition to the conflicting criteria, the majority, if not all, of the MCDM cases are usually surrounded by uncertainties that may make the process of eliciting the best alternative even more complex (AlAlaween et al., 2020). Therefore, in this research work, an integrated MCDM algorithm that integrates the Grey System Theory, Linear Optimization and Fuzzy Logic is presented. Figure 1 shows the schematic diagram of the integrated paradigm. The criteria that are used to assess various alternatives are identified. Such a step, as a common step for all MCDM algorithms, is followed by assessing the alternatives based on the identified criteria and by using a predefined scale. The GRA is, then, utilized in order to determine the grey relational grade. It is worth emphasizing that the GRA calculations are based on the classification of the criteria into Larger-The-Better (LTB), Nominal-The-Best (NTB) (i.e. close to a desired value) and Smaller-The-Better (STB). The estimated grey relational grade, as an output, and the assessed values of the defined criteria, as inputs, are used to develop the DEA to estimate the efficiency score of the alternatives. In order to develop the DEA paradigm successfully and maximize the efficiency, the inputs need to be minimized. Therefore, one needs to consider the nature of the inputs (i.e. the assessed value of the defined criteria). To illustrate, for the values of the LTB and NTB criteria, one needs to take the difference from the maximum and the desired values, respectively, before considering such criteria as inputs, whereas the values of the STB criteria can directly be considered as inputs. Once the efficiency scores of the alternatives are determined using the DEA, the IT2FLS is developed to map the efficiency score of the alternatives to the assessed values of the defined criteria to determine the warehouse performance. Although it is computationally expensive when compared to type-1 fuzzy logic system (T1FLS), IT2FLS was utilized in this research work because of its ability to handle uncertainties more efficiently and intrinsically when compared to T1FLS. Such a model can also be used to assess new alternatives without re-performing the calculations of the GRA and the DEA. In addition, the derived linguistic understanding in the form of the If-Then rules can be utilized to understand the relationships between the defined criteria and the warehouse performance. The mathematics behind these three algorithms are presented in this section to help the reader to get grips with the key developments. For further reading about these algorithms, readers can refer to several references (AlAlaween et al., 2017; Charnes et al., 1978; Hu, 2020; Huang et al., 2019; Kaffash et al., 2020; Karnik & Mendel, 2001; Mendel, 2017; Zhou et al., 2018).

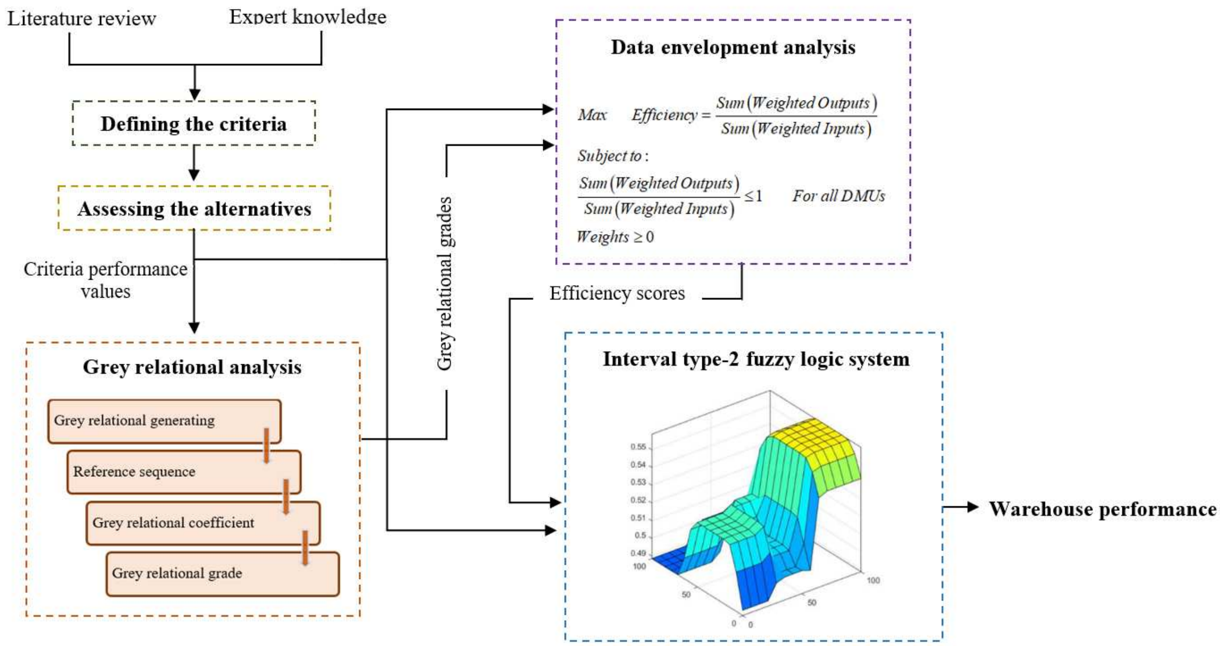


Figure 1- Schematic diagram of the integrated assessment algorithm.

2.1. Grey Relational Analysis

The GRA, as a sub-discipline of the Grey System Theory, is commonly used to determine a correlation between a specific sequence, the so-called reference sequence, and comparability sequences. Based on such a correlation, the sequences can be ranked (Huang et al., 2019). In general, the GRA starts with the grey relational generating step, in which the performance values of the alternatives considered are transformed into comparability sequences, in order to normalize the performance measures. The comparability sequence (x_{ij}) of the i^{th} alternative and the j^{th} attribute can be expressed as follows (Huang et al., 2019):

$$x_{ij} = \begin{cases} \dfrac{y_{ij}-Min\left(y_{ij}^{i}\right)}{Max\left(y_{ij}^{i}\right)-Min\left(y_{ij}^{i}\right)} & For\ LTB \\ \dfrac{Max\left(y_{ij}^{i}\right)-y_{ij}}{Max\left(y_{ij}^{i}\right)-Min\left(y_{ij}^{i}\right)} & For\ STB \\ 1-\dfrac{\left|y_{ij}-y_j^*\right|}{Max\left\{Max\left(y_{ij}^{i}\right)-y_j^*, y_j^*-Min\left(y_{ij}^{i}\right)\right\}} & For\ NTB \end{cases} \tag{1}$$

where y_{ij} stands for the performance value of the i^{th} alternative and the j^{th} attribute, and y_j^* stands for the desired value for the NTB criteria. The superscript i is used to indicate that the minimum and maximum operations are determined over the alternatives. The calculated x_{ij} is in the range of 0 to 1, where a value of 1, or closer to 1, means that the performance value of the i^{th} alternative is the best for the j^{th} attribute. Therefore, the alternative whose performance values are higher (i.e. equal to 1) is considered to be the best choice. However, such an alternative does not usually exist. Therefore, a reference sequence definition step is often required to define the reference sequence (x_{0j}). Such a step is followed by the grey relational coefficient calculation step. The grey relational coefficient is written as follows (Hu, 2020):

$$\lambda\left(x_{0j}, x_{ij}\right)=\frac{\Delta_{min}+\xi\Delta_{max}}{\Delta_{ij}+\xi\Delta_{max}} \tag{2}$$

where Δ_{ij} is the absolute value of the difference between x_{0j} and x_{ij}. The parameters Δ_{min} and Δ_{max} stand for the minimum and maximum values of Δ_{ij}, respectively, and ξ stands for the distinguishing coefficient that is usually in the range of 0 to 1. Once the grey relational coefficients are calculated, the grey relational grade (γ_i) for the i^{th} alternative can be evaluated by calculating the weighted average of the grey relational coefficients for the corresponding alternative. It is worth mentioning that decision-makers usually define the weights that must sum to unity.

2.2. Data Envelopment Analysis

The DEA that was introduced more than four decades ago is a non-parametric mathematical and linear optimization paradigm (Charnes et al., 1978; Kaffash et al., 2020). It estimates the relative efficiency of comparable units that are commonly called decision-making units (DMUs) by using their inputs and outputs (Kaffash et al., 2020). The DEA has been successfully employed in various areas including, but not limited to, manufacturing, industrial, financial and environmental areas (Mardani et al., 2018). Among the various DEA models that have been presented, the CCR model is the most common one (Zhou et al., 2018). Such a model that is based on linear programming maximizes the relative efficiency (θ) that represents the ratio of the sum of the weighted outputs to the sum of the weighted inputs of defined DMUs (Charnes et al., 1978). Therefore, the efficiency of DMU_o whose *s* inputs and *q* outputs are (η_{1o}, η_{2o}, … η_{so}) and (γ_{1o}, γ_{2o}, …, γ_{qo}), respectively, can be estimated using the linear optimization model as follows (Charnes et al., 1978):

$$\begin{gathered} Max\theta = \upsilon_1\gamma_{1o} + \cdots + \upsilon_q\gamma_{qo} \\ Subject\ to: \\ \tau_1\eta_{1o} + \cdots + \tau_s\eta_{so} = 1 \\ \upsilon_1\gamma_{1r} + \cdots + \upsilon_q\gamma_{qr} \le \tau_1\eta_{1r} + \cdots + \tau_s\eta_{sr} \quad \forall r \\ \tau_1, \dots, \tau_s \ge 0 \\ \upsilon_1, \dots, \upsilon_q \ge 0 \end{gathered} \tag{3}$$

where υ and τ stand for the weights for the outputs and the inputs, respectively. The objective of such a model is to maximize the relative efficiency of the DMU_o by maximizing the sum of its weighted outputs while the sum of its weighted inputs must equal one, as presented in the first constraint of the model. In addition, the second constraint implies that the efficiency of the r^{th} DMU does not exceed one. The weights for the outputs and the inputs must be greater than or equal to zero.

2.3. Interval Type-2 Fuzzy Logic System

The IT2FLS, as a data-driven model, has been recently employed in many applications such as pharmaceutics (Mendel, 2017; Peng et al., 2020). In addition to the advancement in computing power, this can be attributed to its ability to (i) represent complex processes whose physical models cannot be developed or, perhaps, does not exist, (ii) deal with uncertainties, and (iii) provide a linguistic understanding of the process under examination (AlAlaween et al., 2017). In general, the IT2FLS is analysed by using fuzzy sets that are represented by membership functions. An interval type-2 fuzzy set is commonly expressed as follows (Mendel, 2017):

$$\tilde{F} = \int_{z\in Z}\int_{J_z\subseteq[0,1]} 1/(z, v) \tag{4}$$

where z stands for the primary variable whose measurement domain is represented by Z. The parameter J_z represents the primary membership degree, and v represents the secondary variable that belongs to J_z.

Figure 2- The IT2FLS structure.

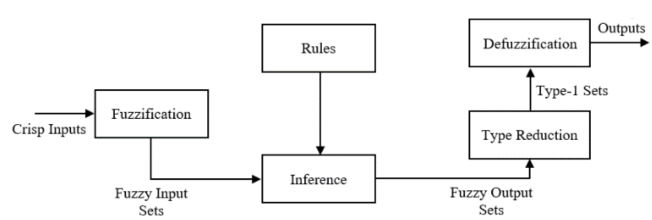


Figure 2 presents the structure of the IT2FLS that is embedded in the proposed algorithm. The crisp inputs (z_1, z_2 …z_n) are commonly fuzzified to calculate the upper and lower membership functions $\left[\underline{\mu}_{\tilde{F}_k^l}, \overline{\mu}_{\tilde{F}_k^l}\right]$ for the l^{th} fuzzy set and the k^{th} variable using the interval type-2 fuzzy sets ($\tilde{F}_k^l$). Different types of membership functions (e.g. sigmoid and trapezoidal) can be utilized. Because of its ability to work as a universal approximator, the Gaussian membership function is employed in this research work. It can be written as follows (Mendel, 2017):

$$\mu_k^l(z_k) = exp\left[-\frac{1}{2}\left(\frac{z_k-m_k^l}{\sigma_k^l}\right)\right],\ m_k^l \in \left[m_{k1}^l, m_{k2}^l\right] \tag{5}$$

where the parameters of the fuzzy set are represented by the mean (m_k^l) and the standard deviation (σ_k^l). The footprint of uncertainty is represented by the union of the membership functions bounded between the lower and the upper functions. Once the input fuzzy sets are determined, they are mapped to the output fuzzy sets by employing the If-Then rules. Such a process is called inference. The rules can be represented as follows (AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021) :

Rule l: IF z_1 is $\tilde{F}_1^l$ … and z_m is$\tilde{F}_m^l$, THEN w is$\tilde{G}^l$.

where w and $\widetilde{G}^l$ represent the output and its l^{th} fuzzy set using a Mamdani IT2FLS. Once the output type-2 fuzzy set is obtained, type reduction, by which the type-2 fuzzy set is reduced into a type-1 fuzzy set, takes place. It is worth mentioning that the majority of the IT2FLS computational effort is incurred by the type reduction step, where the lower and upper points of the interval are determined by utilizing the well-known Karnik-Mendel (KM) algorithm (Karnik & Mendel, 2001). Finally, the type-1 fuzzy set is defuzzified to determine the crisp output. The defuzzification process is implemented by determining the average value (Mendel, 2017).

3. Warehouses Data

3.1. Assessment Criteria

In order to assess warehouses, the criteria that can affect the warehouse performance need to be identified. In this research paper, ten criteria were defined by (i) interviewing experts; (ii) distributing an online survey; and (iii) reviewing the related literature (AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021). The identified criteria and their sub-criteria are presented in Table 1 and summarized as follows:

- **Facilities:** Warehouse facilities play a considerable role in its performance. The corresponding five sub-criteria are "Location", "Number of locations", "Layout", "Work conditions and workplace environment" and "Security". Various sub-sub-criteria can be defined for each sub-criterion. To elucidate, the "Number of locations" sub-criterion consists of three sub-sub-criteria, namely, defining the optimal number of warehouses based on a conducted study, inbound and outbound transportation, and existing protocol to respond to urgent orders.
- **Material Handling Equipment:** Although it does not directly add value to the products stored (Venkataraman & Pinto, 2016), material handling equipment can improve a warehouse performance. Such a criterion consists of three sub-criteria as listed in Table 1 and many sub-sub-criteria. For instance, "Optimal material handling system" consists of various sub-sub-criteria, namely, the design of the material handling system, the order of products handled, the handling tasks, and walkways.
- **Products:** Since the main aim of a warehouse is to store products, their related activities can determine its performance. Therefore, the products related activities are considered to be the sub-criteria of such a criterion, as summarized in Table 1. A set of sub-sub-criteria are related to the products' sub-criteria. For example, "Labelling system" comprises of four sub-sub-criteria, namely, identification of products, identification of movable containers, ease of use, and the labels' attributes.
- **Processes:** Ten warehouse processes can, in general, be identified, as listed in Table 1. Each process, as a sub-criterion, comprises of several measures, as sub-sub-criteria, that need to be assessed (Kłodawski et al., 2017). For example, the "Receiving process" has four sub-sub-criterion, namely, adequate receiving protocol, documenting the information, procedures and forms to deal with non-conforming items and returns, and health and safety instructions.
- **Warehouse Management System:** An effective warehouse management system can support and control the related warehouse activities and resources. Such a system can be evaluated by its three main sub-criteria, which can be evaluated by several sub-sub-criteria. For instance, "ability to interface" has several sub-sub-criteria including its ability to interact with the enterprise resource planning system.
- **Energy Efficiency:** Since efficient use of energy can significantly reduce warehouse cost, it can determine the warehouse performance (Kozyrakis, 2013). Its effect on the performance can be determined by the two main sub-criteria mentioned in Table 1. The "Use of an efficient energy system" has, for example, a variety of sub-sub-criteria that include energy-saving equipment such as movement sensors and timers, and the levels of heating and air conditioning.
- **Ethics:** In general, code of ethics and conduct affect a warehouse performance, enterprises as well as the world economy (Murphy & Poist, 2002). Such codes towards employees, enterprises, customers and the nation need to be defined and evaluated in the warehouses assessment scheme.
- **Safety:** It has been proven that the number of accidents in warehouses is more than that for any other facilities (de Koster et al., 2011) . This is the main reason behind the stringent health and safety rules in warehouses as they can affect their performance. Safety, as a criterion, consists of three sub-criteria, as mentioned in Table 1, where each one comprises of several sub-sub-criteria. For example, "Hazard codes" criterion includes chemical hazards (e.g. chemical materials) and physical hazards (e.g. flammable products).
- **Quality Management System:** Although it has not been well cited in the literature (Lee et al., 2013), a quality management system has been utilized to improve warehouses related activities and logistics. Such a system is assessed by four sub-criteria, each of them is assessed by several sub-sub-criteria. For instance, "Internal audit" can be evaluated by its frequency and performance measures used.
- **Human Resources System:** Effective human resources that include staff experience and knowledge can significantly affect a warehouse performance. Therefore, human resources planning and the staff training can, in general, be used as sub-criteria to assess it. For instance, staff training can include training plan, records of the training and suggested improvements.

Table 1 -The defined criteria and their sub-criteria.

Criteria	Sub-criteria
Facilities	• Location • Number of locations • Layout • Work conditions and workplace environment • Security
Material handling equipment	• Optimal material handling system • Periodical tests and preventive maintenance • Risk assessment and safety training and instructions
Products	• Labelling system • Product traceability • Waste management system
Processes	• Pre-advice • Receiving • Checking • Put-away • Cross-docking • Storing • Replenishment • Picking and packing • Dispatching • Value-added services
Warehouse management system	• All operations • Ability to interface • Being accessible and protected
Energy efficiency	• Use of an efficient energy system • Use of solar panels, biomass and wind turbines
Ethics	• Code of ethics • Code of conduct
Safety	• Safe environment • Hazard codes • Contingency plan
Quality management system	• System documentation and control • Internal audit • Management review • Preventive and corrective actions
Human resources system	• Training and development • Resources planning

3.2. Warehouses Assessment

A warehouse can be assessed by assigning a value that represents the performance for each question mentioned in the audit checklist. The value assigned depends on the scale used. In this research work, a scale of 0 to 100 was employed. By using the audit checklist, 45 warehouses dealing with various types of products were assessed. The performance values of the defined criteria for these warehouses are provided in Appendix A. Since the products that a warehouse deals with significantly affect the assessment of the criteria, the product types were considered in the implementation of the proposed integrated assessment algorithm. Therefore, products should be classified into a number of classes that need to be taken into account during the implementation of the assessment algorithm. In this research paper, NICE classification that contains 34 classes, each class consists of a list of goods ordered alphabetically is used (WIPO, 2020).

The criterion performance values for five warehouses, as examples, are shown in Figure 3. It is apparent that such values (e.g. the values of the "Quality Management System" and "Products" criteria) vary significantly among the warehouses assessed. In addition, it is shown that the values of the "Energy Efficiency" criterion were lower for most warehouses when compared to other criteria. This can be attributed to the fact that green warehouse strategies are in the development stage.

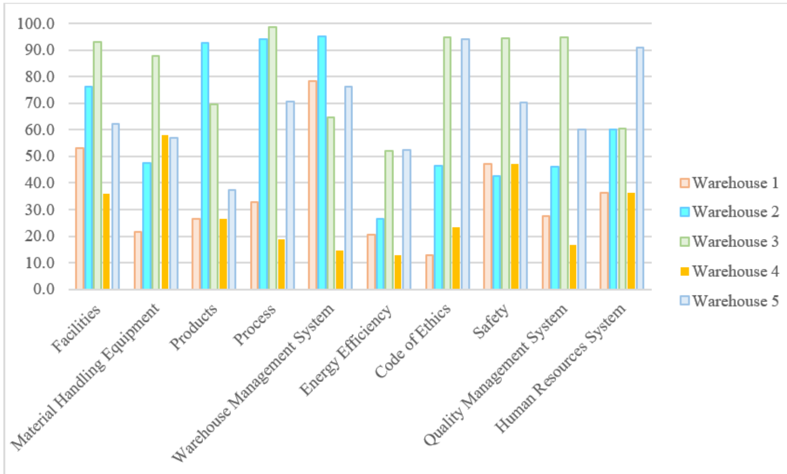


Figure 3- Examples of the warehouses assessed.

4. Results and Discussion

4.1. Implementation and Results

To determine the performance score of the warehouses assessed, the proposed integrated assessment algorithm is implemented. Figure 4 shows the flowchart of the warehouse assessment using the integrated algorithm. Once the criteria, sub-criteria were defined and the warehouses were evaluated, as discussed in Section 3, the criterion performance values for the warehouses assessed were transformed into comparability sequences by the grey relational step. Since the performance values of the criteria are preferred to be as large as possible, the LTB equation presented in (1) was utilized. For instance, the comparability sequence of the "Facilities" criterion for Warehouse 1 presented in Figure 3, as an example, was calculated as follows:

$$x_{11} = \frac{53.1 - 6.2}{100 - 6.2} = 0.5$$

where 6.2 and 100 are the minimum and maximum performance values for the "Facilities" criterion, and 53.1 is the performance value of such a criterion for Warehouse 1. In a similar manner, the comparability sequences of the defined criteria were determined as presented in Table 2. It is noticeable that the comparability sequence of the "Warehouse Management System" criterion was the highest. Since none of the 45 warehouses has comparability sequences of 1, a reference sequence whose comparability sequences of the 10 criteria are 1 was defined. It is worth mentioning that such a reference, which is used only for comparison purposes, represents an ideal warehouse (i.e. best practice) that may not exist in real life. The grey relational coefficients were then calculated. For instance, the grey relational coefficient of the "Facilities" criterion for Warehouse 1 presented above in Figure 3 was determined as follows:

$$\begin{cases} \Delta_{ij} = |1 - 0.5| = 0.5 \\ \lambda(x_{01}, x_{11}) = \dfrac{0 + 0.5 \times 1}{0.5 + 0.5 \times 1} = 0.5 \end{cases}$$

where Δ_{min} and Δ_{max} are 0 and 1, respectively. In this research work, the distinguishing coefficient was selected to be 0.5. In a similar manner, the grey relational coefficients for the defined criteria were determined as presented in Table 2. The grey relational grades for the 45 warehouses were then estimated. It is worth mentioning that NICE classification was utilized at this stage so that the various product classes can have different weights for the defined criteria.

The weight values of the criteria for each product class were optimized by employing the DEA paradigm. The CCR model, as the most common one, was utilized in this research work where each warehouse was considered as a DMU. The DEA paradigm aimed at maximizing the relative efficiency (θ) of a DMU by maximizing its outputs and minimizing its inputs. Therefore, the difference values between the maximum value of the scale selected (i.e. a value of 100) and the criterion performance values were considered as inputs, whereas the grey relational grade was considered as an output. Thus, the DEA optimization model that was used to determine the performance of DMU_1 representing Warehouse 1 is as follows:

$$\mathrm{Max}\theta = 0.45\upsilon_1$$
$$\text{Subject to:}$$
$$46.9\tau_1 + 78.2\tau_2 \ldots + 63.8\tau_s = 1$$
$$\upsilon_1\gamma_{1r} \le \tau_1\eta_{1r} + \cdots + \tau_s\eta_{sr} \quad r = 1, \ldots, 45$$
$$\tau_1, \ldots, \tau_s \ge 0$$
$$\upsilon_1, \ldots, \upsilon_q \ge 0$$

where the parameters are as defined above. The DEA mathematical model was solved using the optimization toolbox on MATLAB (R2018b). The overall performance score of Warehouse 1 is 0.4. In a similar manner, the overall scores of the 45 warehouses were also calculated. It is worth mentioning that the overall performance scores were in the range of 0.22 to 0.81.

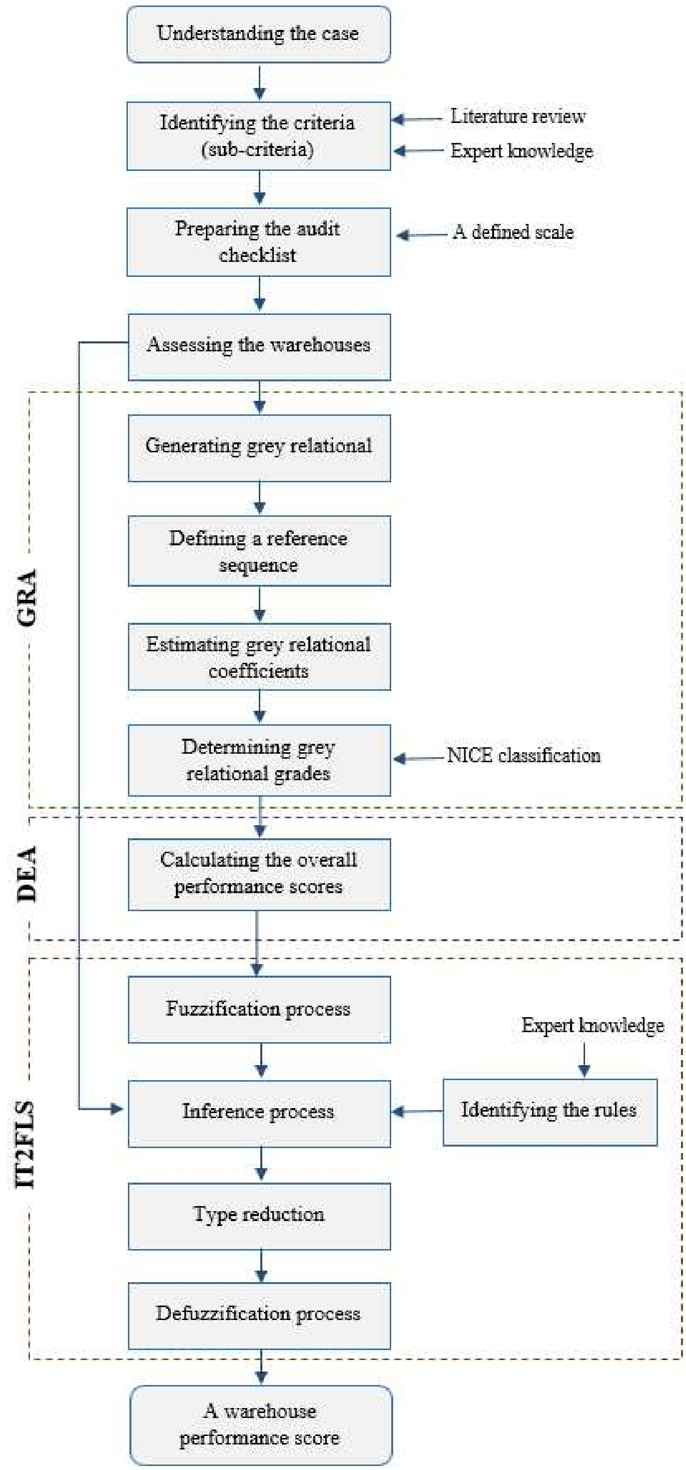


Figure 4- The flowchart of the warehouse assessment scheme based on the integrated algorithm.

Table 2- The performance values and the GRA values for Warehouse 1.

	Facilities	Material Handling Equipment	Products	Process	Warehouse Management System	Energy Efficiency	Code of Ethics	Safety	Quality Management System	Human Resources System
Performance value	53.1	21.8	26.5	32.8	78.3	20.7	13.0	47.2	27.5	36.3
Comparability sequence	0.50	0.22	0.26	0.32	0.78	0.26	0.07	0.46	0.25	0.26
Reference sequence	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Δ_{1j}	0.50	0.78	0.74	0.68	0.22	0.74	0.93	0.54	0.75	0.74
Grey relational coefficient	0.50	0.39	0.40	0.42	0.69	0.40	0.35	0.48	0.40	0.40
DEA inputs	46.9	78.2	73.5	67.2	21.7	79.3	87.0	52.8	72.5	63.8

The IT2FLS paradigm was then developed to map the criterion performance values to the overall performance score. Therefore, the data set of the 45 warehouses were divided into two sets, namely, the training set that contains the data for 36 warehouses and the testing set that contains the data for 9 warehouses. The former was utilized to allow the IT2FLS to learn the relationships between the performance values of the defined criteria, as inputs, and the overall performance score. Such relationships are usually presented as informative rules (i.e. fuzzy If-Then rules). The latter was used to test the IT2FLS generalization capabilities. It is worth mentioning that various numbers of rules in the range of 1 to 20 were tested, the one that was finally chosen was the one that resulted in the minimum error. For a specific number of rules, the IT2FLS parameters (i.e. the means and the standard deviation of each set) were initialized using a clustering algorithm. In this research work, the interval type-2 fuzzy clustering algorithm proposed in (Rubio & Castillo, 2013) was employed. Once the IT2FLS parameters were initialized, they were optimized using the steepest descent algorithm with the well-known back-propagation network.

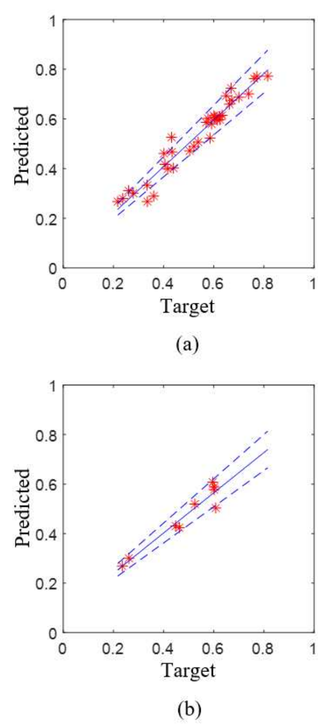
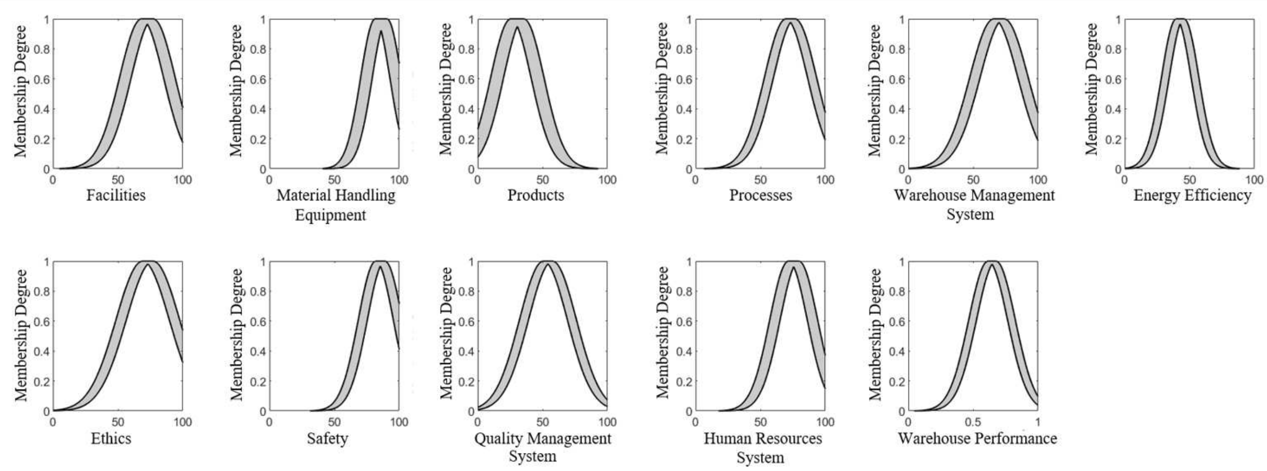


Figure 5- The performance of the IT2FLS for (a) Training and (b) Testing sets.

The performance of the IT2FLS by using 10 rules is shown in Figure 5. The error values measured via the RMSE for the training and testing sets are 0.037 and 0.040, respectively. The coefficient of determination (R^2) for the training and testing sets are 0.94 and 0.93, respectively. It is noticeable that the majority of the predicted points lay within a 90% confidence interval. It is worth emphasizing that the rules for the IT2FLS were initialized by initializing their parameters (i.e. mean and standard deviation for each input) using the clustering algorithm based on the data of the 45 warehouses provided in Appendix A. The parameters of such rules were then optimized using the steepest descent algorithm leading to the optimized rules that were then represented linguistically. A rule, as an example, out of a total of 10 is presented in Figure 6. The shaded area in such a figure presents the footprint of uncertainty. In order to represent the linguistic form of the defined rules, a criteria linguistic scale that consists of four levels: “Opportunities for improvements”, “Major non-conformance", "Minor non-conformance" and "Conforms", was utilized in this research paper. Because it is a common scale used in various standardization schemes, such a linguistic scale was employed in the development of the proposed warehouse assessment scheme. Thus, the linguistic form of the rule is also presented in Figure 6.

Figure 7 presents two examples of response surfaces of the warehouse performance using two criteria at a time. It is apparent that the warehouse performance, as a function of the defined criteria such as "Code of Ethics", "Human Resources System" and "Processes", is a highly non-linear function. Furthermore, the warehouse performance reached a saturation level with a value of 0.56 when the "Human Resources System" reached the maximum values of the scale. In addition, it is apparent that the increase in such a criterion can increase the warehouse performance by approximately 6%. Likewise, when the "Human Resources System" and "Processes" performance values were in the range of 0 to 50, the warehouse performance was better than it when the "Human Resources System" and "Processes" performance values were in the ranges of 0 to 50 and 50 to 100, respectively. Such a decrease in the warehouse performance value, which is less than 1%, can be attributed to the interaction among all the defined criteria which cannot be represented in a three-dimensional plot. Such a behaviour was also noticeable when the performance value of the "Code of Ethics" was in the range of 70 to 100.

Figure 6 - An example of a rule for the overall warehouse performance.



Rule 1: IF the "Facilities" criterion is "Minor non-conformance" and the "Material Handling Equipment" criterion is "Conforms" and the "Products" criterion is "Major non-conformance" and the "Processes" criterion is "Minor 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 "Major non-conformance" and the "Safety" criterion is "Conforms" and the "Quality Management System" criterion is "Major non-conformance" and the "Human Resources System" criterion is "Minor non-conformance", **THEN** the "Warehouse Performance" is "Satisfactory".

Figure 7 - The response surface of the warehouse performance with two criteria: (a) Code of Ethics and Human Resources System, and (b) Processes and Human Resources System.

4.2. Comparative Studies

For comparison purposes, various MCDM paradigms were implemented. In addition to the fuzzy AHP (FAHP), fuzzy ANP (FANP) and fuzzy DEA (FDEA), as commonly used paradigms, IRN-WASPAS (Pamucar et al., 2019) and CRITIC-WASPAS with interval type-2 fuzzy sets (Keshavarz Ghorabaee et al., 2017), as recently presented algorithms, were employed to estimate the performance values for ten newly warehouses. Table 3 shows examples of the results obtained for three warehouses that performed differently. It is apparent that the performance values of the three warehouses estimated using the FAHP and the FANP were very close. This can be attributed to that the ANP algorithm is considered to be the general form of the AHP algorithm. Such algorithms depend on the calculation of the relative weights that rely on a considerable number of pairwise comparisons. To illustrate, the number of pairwise comparisons that were required to estimate the relative weight values of the main criteria is 44 ones. It is also noticeable in Table 3 that the performance values of the warehouses performing well and unsatisfactory were overestimated and underestimated, respectively, when the FDEA was used, this being due to that the FDEA determines the relative efficiencies of the warehouses with respect to the most efficient one. Likewise, overestimation of the performance values of the warehouses performing unsatisfactorily when the IRN-WASPAS and CRITIC-WASPAS were also noticeable. In addition, when new warehouses need to be assessed by such algorithms, one needs to recalculate all the parameters of these algorithms, such a step is considered to be computationally expensive. For instance, a more efficient warehouse needs to be considered in the FDEA and a survey needs to be re-conducted to determine the relative weight values in the FAHP and FANP every time period. However, the integrated paradigm was able to estimate the performance of new warehouses using the developed IT2FLS without the need to recalculate the algorithm parameters. In addition, the presented algorithm provided a linguistic understanding of the relationships between the warehouse performance and the defined criteria. Such an understanding was represented in the form of the If-Then rules. Since the IT2FLS, as a computationally expensive algorithm, and T1FLS can both deal with uncertainties at different levels, this raises the question of whether the performance of proposed integrated algorithm can be obtained when the T1FLS is used instead of the IT2FLS. Therefore, the T1FLS was integrated with the GRA and the DEA to develop an MCDM algorithm. Thus, the T1FLS was utilized to map the criterion performance values to the overall performance score obtained by the DEA as summarized in Figure 4 and explained in Section 4.1. In order to develop the T1FLS, the data set of the 45 warehouses were divided into two sets, namely, the training set (36 warehouses) and the testing set (9 warehouses). Various numbers of rules in the range of 1 to 20 were tested, the one that was finally chosen was the one that resulted in the minimum error. For 12 rules, the performance values of the T1FLS measured via the RMSE for the training and testing sets were 0.042 and 0.045, respectively. In addition, the values of the R^2 for the training and testing sets were 0.89 and 0.88, respectively. It is noticeable that the performance values of the IT2FLS (i.e. RMSE (training, testing) = [0.037, 0.040] and R^2 (training, testing) = [0.94, 0.93]) were better than that of the T1FLS. This can be attributed the ability of the IT2FLS in handling the uncertainties more efficiently when compared to it is counterpart T1FLS.

Table 3- Examples of three warehouses assessed using various algorithms.

Warehouses	Performance score					
	FAHP	FANP	FDEA	IRN-WASPAS	CRITIC-WASPAS	Integrated Algorithm
Warehouse 1	0.1	0.123	0.069	0.274	0.256	0.156
Warehouse 2	0.6	0.577	0.655	0.623	0.643	0.623
Warehouse 3	0.7	0.813	0.952	0.779	0.752	0.831

5. Conclusion

A new integrated assessment algorithm was proposed to develop a warehouse assessment scheme. Such an integrated algorithm integrated three paradigms, namely, Grey Relational Analysis (GRA), Data Envelopment Analysis (DEA) and the Interval Type-2 Fuzzy Logic System (IT2FLS). Once the criteria were defined and warehouses were assessed according to these criteria, the GRA was utilized to estimate the grey relational grade. The DEA was, then, employed to estimate the efficiency scores. Such a step was followed by mapping the assessed values of the criteria to the efficiency score using the IT2FLS. New warehouses can then be assessed without re-performing the calculations of the GRA and the DEA. Validated on 45 warehouses, the proposed integrated algorithm was able to (i) successfully evaluate warehouses using the defined criteria; (ii) handle the uncertainties during the assessment process; (iii) compare the warehouses with the best practice; and (iv) provide users with a linguistic understanding of the effect of the defined criteria on the warehouse performance. In addition, the integrated assessment algorithm is considered to be a promising development not only for warehouses and third-party logistics providers, but also for those areas where decisions need to be made when conflicting criteria need to be considered. In the future, it is worth considering the dynamic nature of the business environment by incorporating a dynamic IT2FLS in the proposed integrated algorithm. In addition, it is advantageous to consider different interrelationship values between the identified criteria.

Acknowledgements

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Table A.1 – The performance values of the criteria for 45 warehouses.

Warehouses	Facilities	Material Handling Equipment	Products	Process	Warehouse Management System	Energy Efficiency	Code of Ethics	Safety	Quality Management System	Human Resources System
Warehouse 1	53.1	21.8	26.5	32.8	78.3	20.7	13.0	47.2	27.5	36.3
Warehouse 2	76.3	47.5	92.7	93.9	95.1	26.7	46.5	42.8	46.1	60.0
Warehouse 3	93.0	87.8	69.6	98.5	64.7	52.1	94.7	94.4	94.8	60.4
Warehouse 4	36.0	58.0	26.5	18.7	14.7	12.8	23.3	47.2	16.8	36.3
Warehouse 5	62.2	56.8	37.3	70.7	76.1	52.5	93.9	70.2	60.0	90.8
Warehouse 6	83.8	0.0	26.5	71.6	97.8	3.3	11.9	23.6	16.1	72.5
Warehouse 7	41.5	21.8	18.6	41.6	78.3	40.6	6.9	23.6	13.4	36.3
Warehouse 8	37.6	43.5	26.5	25.9	97.8	32.7	23.3	47.2	32.5	36.3
Warehouse 9	75.8	31.0	70.5	52.8	95.6	23.6	23.3	86.2	73.3	28.8
Warehouse 10	75.1	20.7	70.5	51.5	95.6	18.5	23.3	86.2	71.8	14.4
Warehouse 11	56.5	17.8	74.8	76.8	95.1	52.5	77.6	21.4	18.7	15.0
Warehouse 12	41.2	31.0	1.1	2.4	4.9	12.6	23.3	25.9	3.7	43.1
Warehouse 13	50.6	34.4	52.4	58.2	95.6	19.3	17.6	86.2	68.9	57.5
Warehouse 14	20.0	27.8	81.3	28.0	3.3	13.8	23.3	18.8	7.7	93.3
Warehouse 15	53.8	40.9	50.4	59.6	40.8	12.9	14.9	75.5	30.8	28.8
Warehouse 16	38.8	30.8	35.2	40.9	76.1	23.0	77.6	21.4	12.4	30.0
Warehouse 17	18.1	23.1	18.8	41.2	2.7	3.8	15.5	18.8	4.6	17.5
Warehouse 18	73.4	81.8	15.0	9.2	15.9	15.0	24.5	45.3	10.2	28.8
Warehouse 19	57.4	17.1	55.1	36.3	20.1	32.9	28.2	21.7	7.7	14.3
Warehouse 20	37.4	17.1	49.4	72.0	100.0	23.5	28.2	72.3	68.1	73.8
Warehouse 21	14.2	11.5	18.8	12.8	23.4	14.9	6.9	10.9	12.9	17.5
Warehouse 22	39.0	47.8	43.1	35.8	12.7	3.0	40.4	53.6	22.2	72.5
Warehouse 23	56.9	44.8	31.3	45.1	95.6	10.9	23.3	51.7	37.4	43.1
Warehouse 24	63.3	27.7	39.9	16.3	12.5	20.9	28.8	24.9	7.3	69.4
Warehouse 25	94.4	56.4	85.6	89.0	95.1	13.3	77.6	71.3	71.9	45.0
Warehouse 26	99.7	65.4	61.4	90.0	95.6	38.9	46.5	86.2	84.2	76.7
Warehouse 27	32.7	20.4	18.6	33.0	6.2	5.7	33.1	18.9	15.0	44.1
Warehouse 28	56.1	100.0	33.8	62.6	80.4	26.7	95.9	28.4	23.2	50.0
Warehouse 29	86.7	35.6	100.0	64.9	76.1	26.7	46.5	71.3	66.6	50.0
Warehouse 30	67.0	41.3	70.5	45.1	76.5	14.5	6.3	86.2	66.9	62.3
Warehouse 31	36.3	20.1	32.9	28.2	4.9	12.6	23.4	14.9	6.9	86.2
Warehouse 32	72.0	100.0	100.0	28.2	95.6	19.3	12.7	3.0	40.4	26.7
Warehouse 33	12.8	23.4	14.9	6.9	6.2	9.2	32.7	20.4	18.6	33.0
Warehouse 34	35.8	12.7	3.0	40.4	95.1	36.3	76.3	47.5	100.0	100.0
Warehouse 35	45.1	95.6	10.9	23.3	80.4	72.0	56.1	100.0	33.8	62.6
Warehouse 36	6.2	33.8	62.6	80.4	5.7	12.8	86.7	35.6	100.0	64.9
Warehouse 37	95.1	100.0	36.8	76.1	26.7	35.8	80.4	90.0	95.6	23.3
Warehouse 38	80.4	70.5	45.1	76.5	26.7	45.1	80.4	33.0	76.5	61.1
Warehouse 39	70.5	6.2	64.9	25.9	97.8	32.7	76.5	100.0	14.5	42.0
Warehouse 40	32.1	95.1	33.1	52.8	95.6	23.6	87.8	62.6	80.4	56.3
Warehouse 41	32.9	69.6	46.5	51.5	95.6	18.5	20.1	72.0	95.6	25.9
Warehouse 42	52.8	62.6	95.9	76.8	95.1	52.5	76.1	24.5	6.2	52.8
Warehouse 43	52.5	33.1	45.1	2.4	4.9	12.6	12.8	56.9	95.1	56.8
Warehouse 44	32.8	28.2	65.1	64.9	25.9	27.4	26.7	49.3	80.4	83.8
Warehouse 45	100.0	87.8	69.6	98.5	64.7	54.1	100.0	100.0	100.0	60.4