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A Grey-Relational-Based Type-1 Fuzzy Logic Analysis for the Development of a Warehouse Assessment Scheme

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Abstract.

In this work, the integration between the type-1 fuzzy logic system (T1FLS) and the grey relational analysis (GRA) is investigated to present a warehouse assessment scheme. First, numerous warehouses are assessed based on a defined set of criteria by assigning a warehouse score to each criterion. Second, the GRA is utilized to estimate the grey relational grade, as an overall warehouse performance measure. At this stage, the NICE classification is employed to assign weights for the criteria according to the products that warehouses deal with. The T1FLS is, then, implemented to map the warehouses' scores of the criteria to the overall warehouse performance indicator. Once the T1FLS is established, it can be employed to directly evaluate new warehouses. Furthermore, this transparent scheme is able to provide a linguistic explanation of the relationships between the given criteria and the warehouse performance. The overall root mean square value for the T1FLS is 0.033.

Keywords: Grey Relational Analysis, Type-1 Fuzzy Logic System, Warehouse Assessment Scheme

1. Introduction

These days, enterprises mostly aim to outsource logistics and warehouse activities to a third-party. This has positively affected such enterprises in terms of performance, cost, flexibility and reputation (Guarnieri et al., 2015). With the increasing number of enterprises that use to outsource their activities and the number of third-party logistic providers (3PLPs), there is a strong need to evaluate the performance of the various 3PLPs in order to select the best one that can perform the enterprise activities (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021). However, such a multi-criteria decision making (MCDM) task is not as easy as it may seem at the first glance, this being due to the number of the criteria and their level of details that need to be taken into account and to their different importance levels (Mardani et al., 2016).

The evaluation of 3PLPs and various MCDM methods for selecting the best 3PLP have been the subject of numerous research articles (Goepel & Performance, 2019; Mardani et al., 2016). Some papers have discussed the criteria that need to be used in evaluating 3PLPs. Such criteria include, for example, reputation, cost, quality as well as delivery time (Mardani et al., 2016). In addition, some papers have been devoted to the development of both qualitative as well as quantitative MCDM approaches (Goepel & Performance, 2019; Roy et al., 2019). For instance, the analytic hierarchy process (AHP) has been utilized to assign weights to the given criteria and, then, evaluate 3PLPs accordingly (Evangelista et al., 2018). Likewise, the analytic network process (ANP) that generalized the AHP has been used to assess 3PLPs in the same way AHP does but by taking into consideration the interrelationships among the given criteria (Tjader et al., 2014). Furthermore, data envelopment analysis, as a linear optimization algorithm, has also been employed to elicit the optimal 3PLP that has the maximum efficiency (Bajec & Tuljak-Suban, 2019). Due to the improvement in the computing capacities these days, artificial intelligence paradigms such as artificial neural network and fuzzy logic have been developed to assess 3PLPs (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021). For instance, a dynamic T1FLS was presented to assess various warehouses in different 3PLPs (AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021).

In general, the presented MCDM approaches have their own strengths and limitations. Therefore, the integration of two or more MCDM approaches has hitherto been investigated before (Keshavarz Ghorabaee et al., 2017). For instance, the fuzzy logic was embedded with the AHP, ANP and DEA in order to deal with uncertainties. In this context, uncertainties imply not only uncertainties in the subjective information but these also uncertainties in the estimation of the overall performance (AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021). In addition, the genetic algorithm was embedded with the ANP in order to circumvent the pairwise comparison computations and to linguistically and numerically represent the strength of the interrelationships (AlAlaween, AlAlawin, Al-Durgham, et al., 2021). Likewise, the weighted aggregated sum product assessment approach was integrated with the interval type-2 fuzzy to weight a set of given criteria that were used to assess 3PLPs (Keshavarz Ghorabaee et al., 2017). It was shown that the integration of two or more of the MCDM approaches was able to circumvent the limitations of a single approach. It is worth mentioning that the majority of these papers assessed warehouses and their related activities as a part of the 3PLPs. Since warehouses and their related activities account for most of the cost (Keshavarz Ghorabaee et al., 2017), there is, therefore, a strong need to assess them effectively and systematically in order to offer clearer insights to decision-makers. In this research work, an MCDM algorithm that integrates the type-1 fuzzy logic system (T1FLS) and the grey relational analysis (GRA) is proposed to present a warehouse assessment scheme based on the criteria that affect its performance and its related activities. Such an algorithm can assess warehouses according to the defined criteria and can deal with uncertainties. The rest of the paper is organized as follows: the criteria that affect the warehouse performance are summarized in Section 2. The MCDM algorithm that integrates the T1FLS and the GRA is presented in Section 3, where the results obtained by implementing the algorithm are discussed in Section 4. The conclusions and some future work are, finally, summarized in Section 5.

2. Criteria

The set of criteria that influences a warehouse performance was identified by reviewing the literature and expert knowledge via interviews and online survey (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021; AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021). The set of the ten criteria is shown in Table 1. In addition, the sub-criteria for each criterion were also defined and shown in Table 1.

For each sub-criterion defined in Table 1, a set of sub-sub-criteria were identified to account for different levels of details. For example, “Layout”, as a sub-criterion, has several sub-sub-criteria related to (i) the space of workstations and activities; (ii) space requirements for activities; (iii) support area (e.g. locker room and food services); (iv) warehouse flow and system operations; (v) ergonomic layout requirements (e.g. human-machine interface); (vi) flexibility of a layout design; and (vii) comprehensive signage in multiple language. To systematically evaluate warehouses, a checklist that contains several questions related to each sub-sub-criterion was developed. For instance, various question can be used to assess the sub-sub-criteria related to the layout. An examples of such questions is “Has the organization determined the space of workstations and activities according to a conducted study or standards?”

Table I The criteria and the sub-criteria (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021; AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021).

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. The proposed algorithm

In general, a MCDM process, where the optimal set of scenarios or alternatives need to be identified, can be a complex process in particular when a number of conflicting criteria need to be taken into account (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021). Likewise, most of the MCDM problems are surrounded by uncertainties that can determine the fate of the MCDM process (Wafa'H et al., 2021). Thus, an MCDM algorithm that integrates T1FLS and the GRA is presented to develop a warehouse assessment scheme based on the criteria listed in Section 2. The schematic diagram of the proposed MCDM algorithm is depicted in Figure 1. As presented in such a figure, the set of the criteria is utilized in evaluating the warehouses, or generally the alternatives. In such a step, a checklist can be utilized to facilitate the process of evaluating the warehouses/alternatives based on a predefined scale. The GRA is, then, employed to estimate the grey relational grade, as a performance indicator of the warehouses. The T1FLS is, then, utilized to map the performance indicator of the warehouses to the performance indicators of the criteria for the warehouses. Once the T1FLS is successfully established, it can be directly used to calculate the performance indicators for new warehouses without the need to re-implement the GRA algorithm. Furthermore, the T1FLS can provide a linguistic understanding of the relationships between the warehouse performance and the defined criteria in the form of fuzzy If-Then rules. To get grips with the mathematics behind the GRA and the T1FLS, the key developments of such algorithms are summarized in the following sub-sections. For further details, readers can refer to various references (AlAlaween, Alalawin, Mahfouf, & Abdallah, 2021; Hu, 2020; Huang et al., 2019; Mendel, 2017).

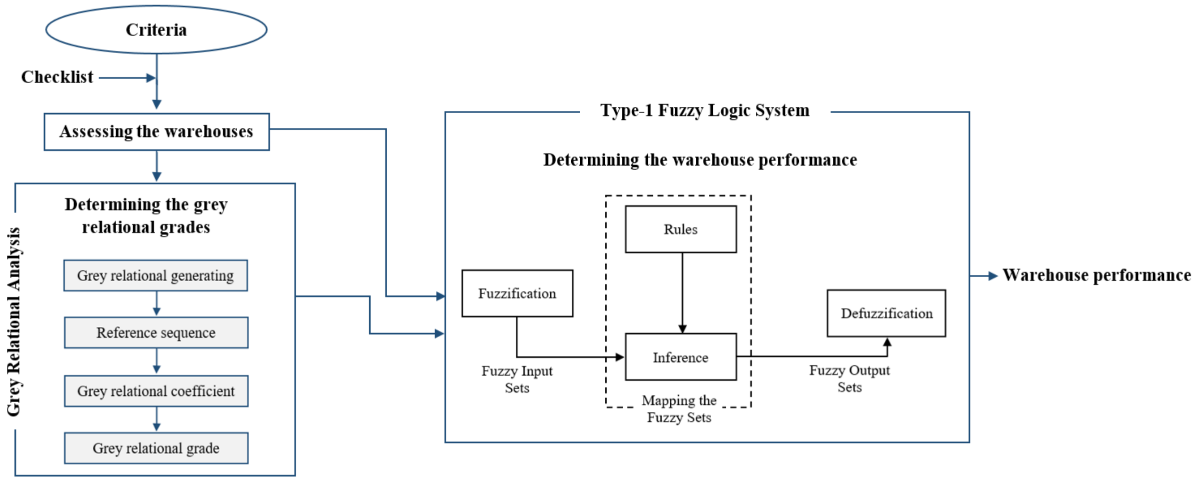

Figure 1 The schematic diagram of the new proposed algorithm for the warehouse assessment scheme development.

3.1 Grey Relational Analysis

In general, the GRA is employed to estimate the correlation between a reference sequence and comparability sequences, where such a correlation is, then, utilized to rank the sequences (Huang et al., 2019). As shown in Figure 1, the first step of the GRA is the grey relational generating step. It is worth mentioning that the calculations in such a step depend on classifying the criteria into Larger-The-Better (LTB), Nominal-The-Best (NTB) (i.e. close to a desired value (p_j^*) and Smaller-The-Better (STB). In this step, the comparability sequences (x_{ij}) of the i^{th} alternative and the j^{th} attribute are determined using the performance values (p_{ij}) as follows (Huang et al., 2019):

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

where the superscript i is used to indicate that the minimum/maximum operations are estimated over the alternatives. It is worth noting that x_{ij} is in the range of 0 to 1, where a value that is close to 1 implies that the performance value is better for the j^{th} attribute (Hu, 2020). Thus, the alternative with high x_{ij} values (i.e. a value of 1 or close) is deemed to represent the best one. Since such an alternative does not commonly exist, a reference sequence (x_{0j}) is often defined. Based on x_{0j}, the grey relational coefficient (η) is then estimated as follows (Hu, 2020):

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

where Δ_{ij} represents the absolute value of ($x_{0j} - x_{ij}$), and the parameters $\Delta_{\min}$ and $\Delta_{\max}$ represent their minimum and maximum values, respectively. The parameter λ represents the distinguishing coefficient, which is in the range of 0 to 1. Finally, the i^{th} grey relational grade (θ_i) can be estimated by determining the weighted average of the coefficients for the i^{th} alternative (Huang et al., 2019).

3.2Type-1 Fuzzy Logic System

The T1FLS has been utilized in many areas (e.g. pharmaceuticals and manufacturing) (AlAlaween, AlAlawin, Al-Durgham, et al., 2021). In addition to its ability to extract linguistic understanding, this can be attributed to its ability to represent complex input-output relationships and to deal with uncertainties (AlAlaween, AlAlawin, Mahfouf, Abdallah, et al., 2021). The T1FLS consists of four stages, as presented in Figure 1. In general, the fuzzification process transforms the crisp input (z) into the fuzzy input vector and defines its membership functions. Many types of the membership functions (e.g. trapezoidal and triangular) can be utilized. Because of its continuity and smoothness attributes, the Gaussian membership function is employed in this research paper. The fuzzy inputs are, then, mapped to the fuzzy outputs in the inference operation that uses the linguistic rules, which are usually provided by experts in the area under investigation or extracted from a provided data set. The inference stage can be expressed by the fuzzy basis function ($\varphi_l(\mathbf{z})$) as follows (Karnik & Mendel, 2001):

$$\varphi_l(\mathbf{z}) = \frac{\prod_{s=1}^{n} \mu_s^l(z_s)}{\sum_{l=1}^{R} \prod_{s=1}^{n} \mu_s^l(z_s)} \qquad (3)$$

where ($\mu_s^l(z_s)$) represents the l^{th} membership degree of the Gaussian function. The If-Then linguistic fuzzy rules can be expressed as follows:

Rule^{l}: IF z_1 is F_1^l … and z_n is F_n^l, **THEN** y_l is B^l.

where F_s^l and B^l represent the membership function of the s^{th} antecedent and consequent of the l^{th} rule, respectively. Since the fuzzy outputs result from the inference operation, the defuzzification process is required to estimate a crisp output. In this research work, the centroid defuzzifier is employed (Karnik & Mendel, 2001).

4. Warehouses Assessment Scheme

In order to develop the warehouse assessment scheme, 45 warehouses were assessed by giving a performance indicator in the range of 0 to 100 for each question in the checklist prepared. It is worth mentioning that the warehouses deal with different types of products. This significantly affects the evaluation process and, thus, it needs to be considered during the development of the scheme. To explain further, monitoring and measuring the humidity, as a sub-sub-criterion, is important for the warehouses that deal with pharmaceuticals and powder but it is negligible for the warehouses that deal with metals. Therefore, in this research work, NICE classification was used to consider the different products that warehouses deal with (WIPO, 2020). Figure 2 shows the performance of the given criteria for three warehouses as illustrative examples. It is shown that such performance indicators differ among the warehouses.

Based on these values, the performance value was estimated based on the presented algorithm. First, the comparability sequences were estimated using performance indicators of the criteria by the grey relational step. In such a step, the equation corresponds to the LTB attribute was utilized. A reference sequence with comparability sequences of 1 (i.e. an ideal warehouse) was identified. Such a step was followed by estimating the grey relational coefficients as presented in Equation 2 and by using a value of 0.5 for the distinguishing coefficient. The grey relational grades were then calculated. In such a step, the NICE classification was employed so various values of the weights of the criteria were considered for the different products that warehouses deal with. Table 2 shows the GRA calculation for Warehouse 2.

The T1FLS was then established to map the performance of the criteria to the grey relational grades of the warehouses which represent the overall performance. In order to train and test such a model, the data for the 45 warehouses were classified into two sets: training and testing sets, which contain 36 and 9 warehouses, respectively. Different numbers of rules in the range of 1 to 20 were employed and the number of rules led to the minimum error was finally used. The parameters of T1FLS were initialized using k-means clustering and then optimized using the steepest descent algorithm (Mendel, 2017). The performance of the developed T1FLS for the training and the testing sets using 7 rules was as expected, where the root mean square error values for the training and testing sets were 0.032 and 0.036, respectively. In addition, the coefficient of determination (R^2) is R^2 (Train, Test) = [0.91, 0.92]. Therefore, such a model can now be used to estimate the performance indicators for new warehouses without the need to re-perform the GRA calculation.

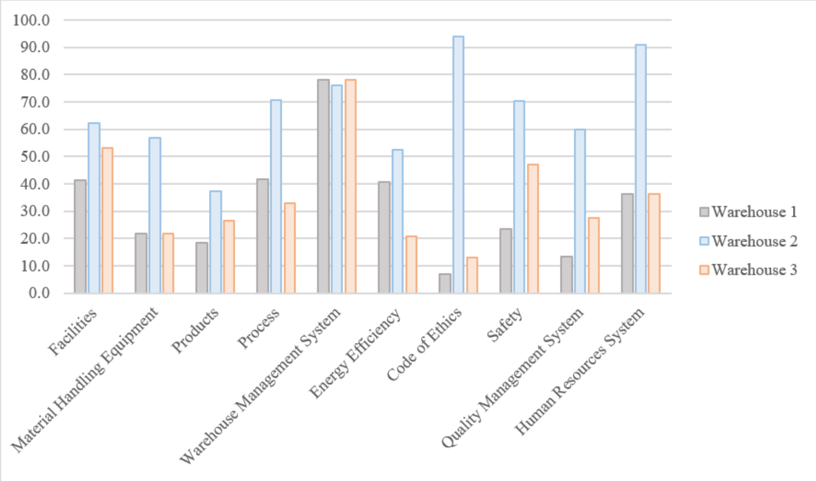

Figure 2 Examples of the evaluated warehouses.

Table II The calculation of the grey relational analysis for Warehouse 2.

	Facilities	Material Handling Equipment	Products	Process	Warehouse Management System	Energy Efficiency	Code of Ethics	Safety	Quality Management System	Human Resources System
Warehouse 2	62.2	56.8	37.3	70.7	76.1	52.5	93.9	70.2	60.0	90.8
Grey relational generating	0.60	0.57	0.37	0.71	0.75	0.72	0.93	0.69	0.58	0.89
Grey relational coefficient	0.55	0.54	0.44	0.63	0.67	0.64	0.88	0.62	0.55	0.82
Weights	0.15	0.09	0.14	0.11	0.18	0.05	0.04	0.08	0.11	0.05
Grey Relational Grade	0.61									

5. CONCLUSIONS

In this research work, a new paradigm that integrated the grey relational analysis (GRA) and the type-1 fuzzy logic system (T1FLS) was introduced to present a warehouse assessment scheme. Ten criteria that mostly affected warehouses dealing with various products were defined. Such a step was followed by evaluating 45 warehouses. The GRA was then employed to calculate the grey relational grades, as performance indicators. Such a performance was then mapped to the performance of the criteria by using T1FLS. The T1FLS can then be used to evaluate the performance for new warehouses without re-performing the GRA calculation. The algorithm introduced in this work was able to evaluate warehouses successfully. In addition, such an algorithm can be advantageous in the multi-criteria decision-making area.

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