FUZZY LOGIC IN A RESHORING DECISION-MAKING CONTEXT

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ABSTRACT

This paper investigates the feasibility of using fuzzy logic for reshoring decision-making. To achieve this a fuzzy logic system for reshoring decision-making was implemented. The system was configured in two different ways to cover the two main fuzzy logic modeling approaches and sixteen fuzzy inference settings were used in each configuration. The research shows that fuzzy logic is a feasible method for reshoring decision-making. The reduced rule base configuration was more accurate than the complete rule base configuration. However, the reduced rule base also generated more conflicts in particular settings. Among all the fuzzy inference settings used in this research, one of the settings outperformed the others. With regard to the particular inference methods, the research show that maximum is the preferred aggregation method while middle of maximum is the preferred defuzzification method.

Keywords: Reshoring, Fuzzy logic, decision-making, decision-support, Manufacturing location decision.

1. INTRODUCTION

Reshoring decisions are complex in both structure and handling as the number of decision factors could grow rapidly and make it difficult, or even impossible, to manually identify an optimal solution that is resilient over time (Gray et al, 2017). The more prominent groups of factors to consider in a reshoring decision include quality related factors (Arlbjørn & Mikkelsen, 2014), cost related factors (Engström et al, 2018), market related factors (Tate et al, 2014) and strategy related factors (Baraldi et al, 2018). The complexity is not only related to the vast number of factors that must be considered in the decision but also with regard to trade-offs and paradoxes between the factors that must be balanced (Eriksson et al, 2018) and to lack of sufficient data on the factors or uncertainties in available data (Pelissari et al, 2018). Lack of institutional experience further adds to the complexity in reshoring decision-making (Bals et al, 2016).

The high level of complexity and uncertainty in strategic reshoring decision-making requires more advanced and sophisticated decision support systems to help firm to make more appropriate reshoring decisions that are resilient over time (Barbieri et al, 2018). It has been concluded that there is a general lack of decision support in the reshoring domain (Kinkel, 2012). Some manually handled decision-making frameworks have been proposed in the literature for the handling of complex reshoring decisions in a formal and structured manner (e.g., Gylling et al, 2015). These frameworks, nevertheless, are predominantly theoretical exercises that lack both digital and automated decision support capabilities. Thus, there is a great demand for more advanced and sophisticated decision support systems in the reshoring domain (Hilletofth et al, 2019).

The need for such advanced and sophisticated decision support systems can be addressed in many ways. A basic requirement for such decision support systems is that they must be efficient and effective, as well as provide pertinent, accurate, reliable and interpretable information in order for the decision-maker to make a qualified decision. For a complex decision like reshoring this is very challenging. A branch of mathematics, called fuzzy logic (Zadeh, 1965), recently has been explored in strategic reshoring decision-making to handle complexity and uncertainty in a formal and structured manner (Hilletofth et al, 2019). The aim of this study is to investigate the feasibility of using fuzzy logic for reshoring decision-making. To achieve this a fuzzy logic system for reshoring decision-making was conceived and implemented. The system was configured in two different ways to cover the two main fuzzy logic modeling approaches and sixteen fuzzy inference settings were used in each configuration. The input for each of the configurations were twenty input (or decision) scenarios that consisted of six decision criteria. The decision scenarios provided the necessary test data to evaluate the feasibility of the develop fuzzy logic system for reshoring decision-making.

2. RELATED LITERATURE

The key goal of the fuzzy logic (or inference) system is decision-making and the system include four functional parts: Fuzzification interface, Knowledge base, decision-making unit and defuzzification interface.

The fuzzification interface transforms the crisp inputs into linguistic variables. A linguistic variable is a variable whose values are not expressed in numbers but words (i.e., linguistic terms). The most common way to define linguistic labels is to use absolute labels such as low-medium-high (Pei and Zheng, 2017). An alternative is to use relative labels such as positive-neutral-negative (Phong et al, 2011). Absolute linguistic labels are bound to a common and agreed upon definition consensus among the system users. In practice, it is not easy to implement absolute linguistic labels as they give rise to some common issues. One issue is that an absolute label, such as medium, may have a different meaning for different people (Wang et al, 2018). One way to capture these different interpretations is to establish weight for criteria or importance from every system user (Wu and Mendel, 2007). Another issue is that an absolute label, such as high, could have both a positive and negative meaning depending of the particular variable considered. For example, high quality is something considered to be positive while high cost is something considered to be negative. This double significance can cause confusion and loss of information among the system users. Relative labels circumvent these issues and also eliminates the need to create unique and specific linguistic labels for each variable (Hilletofth et al, 2019). The inherent meaning of a relative label is also the same to any system user. However, relative linguistic labels are only applicable under conditions where absolute labels are not required (Pei and Zheng, 2017). For instance, when several alternatives should be ranked absolute labels are usually preferable (Hilletofth et al, 2019).

The knowledge base includes a database with the membership functions and a database with the fuzzy inference (or if-then) rules (i.e., rule base). A membership function defines a fuzzy set that represents a linguistic label (Gegov et al, 2017). Each element of the set of the linguistic label is mapped to a value between 0 and 1. This value determines the degree of truth in the evaluation (Barnabas, 2013). The selection of the type and shape of the membership function for a linguistic label is generally based on the decision-makers previous knowledge of the linguistic variable and trial and error learning processes (Sambariya & Prasad, 2017). The membership function that is the most appropriate for the given problem should be chosen (Sadjadi et al, 2018) and the choice affects the accuracy of the fuzzy system (Muzaffar & Ahmed, 2010). The membership function should be normalized (i.e., has a maximum value of 1), convex (i.e., has only one maxima) and distinct (i.e., has a restricted overlapping between other functions) (Zimmermann, 1991).

The design of the fuzzy rules is the cornerstone in the development of a fuzzy logic system (Mendel, 2017). It is common to involve domain experts in the design since they have a more indepth knowledge of the domain (Liao, 2005). Thus, the domain experts must be aware of the rule structure. The design of the rules can be realized in different ways (Duţu et al, 2018). The most common approach is to create all possible combinations based on the available linguistic variables and labels (i.e. a complete set of fuzzy rules). An alternative is to develop a reduced set of fuzzy rules (Xiong & Litz, 2002). This means that only the rules that are relevant to the problem at hand and that are more intuitive to a domain expert are created. A third option is to extract fuzzy rules from training data (Coelho et al, 2016). One major drawback of the approach of extracting fuzzy rules from training data is the need of a reasonable amount of training data to work on (Raja and Ramaiah, 2017).

A complete set of fuzzy rules eliminates the risk of inconsistencies between the fuzzy rules but decreases the interpretability of the fuzzy rules (Cordón, 2011). However, this approach soon become unmanageable with an increasing number of required rules (Gacto et al, 2011). The required number of rules increase exponentially with the number of linguistic variables and labels. It is challenge to domain experts, to be aware of the difference between numerous of fuzzy rules and how these differences should be demonstrated in the output (Chen et al, 2018). Several constraints to fuzzy rules, such as rule size, have been identified in order to increase interpretable of fuzzy rules (Mencar and Fanelli, 2008). A reduced set of fuzzy rules, on the other hand, increases the interpretability of the rules but comes with a risk of inconsistencies between them (Gegov et al, 2017). Inconsistencies between the fuzzy rules must be dealt with by changing rule structure in order to generate accurate results (Cordón and Herrera, 2000). The issue of inconsistencies between fuzzy rules can also be mitigated by using fuzzy rule weighs (Lughofer, 2013).

The approach of using domain experts to assign the consequent to the fuzzy rules is much easier when a reduced set of fuzzy rules have been designed compared to a complete set of fuzzy rules (Cpałka, 2017). However, with an increasing number of fuzzy rules most domain experts find it complex and time consuming to assign the consequent to each rule (Gacto et al, 2011). An alternative is to assign the consequent automatically. One way to achieve this is to use linguistic variable weights (Cheng et al, 1999). The weight, or value, assigned to a linguistic variable indicate its relative importance in relation to other linguistic variables (Leung and Cao, 2000). After assigning the weights, the consequent is computed by adding or subtracting the linguistic variable weights for each of the rules (Hilletofth et al, 2019). A positive consequent indicates that the decision suggestion should be further evaluated while a negative consequent indicates that the decision suggestion should not be further evaluated. The higher the value, the stronger the decision suggestion is.

The decision-making unit performs the inference operations on the rules from the fuzzy rule base to determine a fuzzy output (Jang, 1993). The most common fuzzy logic operations, also known as standard operations, are union (i.e., 'or'), intersection (i.e., 'and') and complement (i.e., 'not') (Berenji, 1992). The inference operations on fuzzy sets are operations by which several fuzzy sets (the antecedents) are combined in a desirable way to produce a single fuzzy set (the consequent). This is done through a t-norm operator, that performs either multiplication or minimum operation on the input fuzzy sets (the antecedents). The resulting fuzzy set (the consequent) is either crisp or fuzzy depending on the weights of the fuzzy rules (Jang, 1993).

The defuzzification interface transforms the fuzzy result into a crisp output. This involves the process of rounding off the fuzzy result to a crisp, single scalar equivalent. There exist a vast number of defuzzification method such as center of gravity method, weighted average method, mean of maxima method, basic defuzzification distribution method, semi-linear defuzzification method, center of sums method, center of the largest area method, and maxima method (Van Leekwijck & Kerre, 1999). The choice of defuzzification method is critical in mapping the fuzzy result to a crisp output. Also, if one of the methods seem unsatisfactory for a given application, it is possible to choose another one and modify the parameters until a satisfactory method is found (Esogbue & Song, 2003). This is a trial and error method leading to the selection of appropriate defuzzification method. The selection of a suitable defuzzification method is based on the given application (Barnabas, 2013) and the choice affects the accuracy of the fuzzy inference system (Muzaffar & Ahmed, 2010). The center of gravity and maxima methods, however, seem to provide the best results for a large number of applications (Van Leekwijck & Kerre, 1999).

3. FUZZY INFERENCE SYSTEM

A fuzzy logic system for reshoring decision-making was conceived and implemented. The system was configured in two different ways to cover the two main fuzzy logic modeling approaches (i.e., precise and linguistic). The system was created using the fuzzy logic toolbox found in MATLAB® and was based on knowledge acquired from experts in the reshoring domain. The implementation process consisted of four steps.

In the first implementation step, the linguistic variables are defined. In this paper, a linguistic variable is a reshoring criterion. Reshoring criteria could be regarded as the factors influencing the reshoring decisions and could be found in the drivers, enablers and barriers of reshoring (Wiesmann et al, 2017)). We have chosen to use six high-level reshoring criteria that correspond to common competitive priorities within the operations strategy field. The reason for choosing common competitive priorities as the main evaluation criteria for the reshoring decision, is that they provide a holistic view on how to create competitiveness, which is the main goal of any manufacturing relocation decision.

The six criteria are: cost, quality, time, flexibility, innovation and sustainability. The criteria comprise several sub-criteria, however, the fuzzy logic system used in this paper only considers the criteria level. The choice to make use of only the criteria level could be considered a limitation. Still, there is a tradeoff between complexity and implementability and the chosen approach is considered appropriate for the evaluation of the applicability of fuzzy logic for reshoring decision-making. The six criteria serve as input to the fuzzy logic system. Apart from the six input criteria, there exists one output criterion. The output criterion indicates whether a specific combination of input criteria values, called an input scenario further on, is sufficient to recommend a reshoring evaluation or not).

The different linguistic variables (or criteria) are grouped based on their level of importance. The level of importance could of course differ between different decision-makers and countries. The importance of each criterion is assigned according to the involved reshoring experts. Group A include the most important criteria from a reshoring point-of-view, Group B include indicates lesser important criteria and Group C include indicates the least important criterion. The six criteria are thus grouped into three sets, each signaling a level of importance. Cost and quality are assigned the highest importance. This means that if cost or quality should be negative (i.e., if cost increases or if quality decreases), this would have a high impact on the final decision. Time, flexibility, and innovation are assigned medium importance and sustainability is assigned the lowest importance.

In the second implementation step, the linguistic labels are defined. In this paper, relative linguistic labels were applied in the fuzzy logic system. The relative labels positive-neutral-negative are used in both the configurations. One advantage of relative labels is that the same labels can be used for all the linguistic variables in a specific application without a need to create unique and specific labels for each variable. Another advantage is that the inherent meaning of a relative label is the same to any user of the fuzzy logic system. For example, in a reshoring context, a positive impact on quality (referring to the fact that the quality of a product or process will improve) is an accepted and commonly understood term by all managers. A third advantage of relative labels is that they eliminate the need of having absolute or concrete values, therefore keeping the number of labels down to only the meaningful ones. Thus, relative labels help to increase the interpretability of the fuzzy rules and to reduce the complexity when designing fuzzy rules.

In the third implementation step, the membership functions are defined. The domain experts were used to specify the type of membership function that suited the application. The choice of the membership function affects the performance of the fuzzy inference system and the smoothness of the input-output surface. Thus, smooth gaussian functions are used as input and output membership functions in the both of the configurations. The six input linguistic variables are represented by three gaussian membership functions in both of the configurations while the output linguistic variable is represented by two gaussian membership functions in both of the configurations. The shape of the membership functions is the same for all the linguistic variables in each of the two configurations. The gaussian membership function depends only on two parameters, the standard deviation (σ) and center of the peak (c). It is essential to set appropriate values of the membership function parameters and this was done using trial-and-error method in collaboration with the domain experts.

In the fourth implementation step, the fuzzy rules are defined. The system was configured in two different ways in order to cover the two main fuzzy logic modeling approaches. The first configuration applied precise fuzzy modeling while the second configuration applied linguistic fuzzy modeling. The first configuration reduces the interpretability by considering all possible fuzzy rules but improves the situation through a simple scheme that creates fuzzy rules that are interpretable and consistent. The second configuration increases the interpretability of the fuzzy rules by keeping the number of rules to a minimum. This comes with a risk of inconsistencies between the rules, which must be dealt with to generate accurate results.

In the first configuration a complete set of fuzzy rules was created. These fuzzy rules were created through a semi-automatic approach and the consequents were automatically assigned using linguistic variable weights. The advantage of this approach is that the consequent for each fuzzy rule in a complete set rapidly and automatically can be assigned without human interference. This eliminates the arduous task of assigning the consequent to all of the fuzzy rules. Thus, linguistic variable weights help reduce the complexity when designing fuzzy rules. A three-step procedure was used. First a weight was assigned to each linguistic variable (step 1). After that, the complete set of fuzzy rules was created based on the variable weights (step 2). With six linguistic variables (criteria) that have an impact on the decision and three linguistic labels for each variable the total number of fuzzy rules is 36 = 729. Finally, the consequent part of each fuzzy rule was computed by adding or subtracting the linguistic variable weights in the rule. The reshoring experts were only involved in assigning the linguistic variable weights (step 1).

In the second configuration a reduced set of fuzzy rules was created. This was accomplished by using high-level rules. The idea behind high-level rules is to ease the task of the reshoring experts so that they do not have to directly involved in the design of low-level fuzzy rules. One advantage of high-level rules is increased interpretability by keeping the number of rules to a minimum. Another advantage is reduced complexity when designing fuzzy rules by only considering the rules that are most relevant to the problem. Thus, high-level rules help to increase the interpretability of the fuzzy rules and to reduce the complexity when designing fuzzy rules. A three-step procedure was used. First a weight was assigned to each linguistic variable (step 1). After that, high-level rules were created based on the variable weights (step 2). In total, 42 high-level rules were created. Finally, the high-level rules were translated into fuzzy rules (step 3). For instance, it was sufficient with one fuzzy rule to translate the first high-level rule while three fuzzy rules had to be created to fully translate the third high-level rule. In total, the 42 high-level rules were translated into 156 fuzzy rules. The reshoring experts were only involved in creating the high-level rules (step 1 to 2).

Sixteen fuzzy inference settings were used in the configurations (Table 1). Minimum (Min) and Product (Prod) were used for AND methods while maximum (Max) was used for OR method. The OR method does not impact the system since there are no OR operations in the fuzzy rules. Minimum (Min) and Product (Prod) were used as implication methods while maximum (Max) and Sum of rule outputs (Sum) were used as aggregation methods. Finally, middle of maximum (Mom) and center of gravity (centroid) were used as defuzzification methods. The fuzzy logic toolbox provides more setting alternatives for each parameter but only the most relevant setting for each parameter was considered based on the existing literature.

Table 1. The fuzzy inference settings

Setting	AND method	OR method	Implication method	Aggregati on method	Defuzzificat ion method
1	Min	Max	Min	Max	Centroid
2	Min	Max	Min	Max	Mom
3	Min	Max	Min	Sum	Centroid
4	Min	Max	Min	Sum	Mom
5	Min	Max	Prod	Max	Centroid
6	Min	Max	Prod	Max	Mom
7	Min	Max	Prod	Sum	Centroid
8	Min	Max	Prod	Sum	Mom
9	Prod	Max	Min	Max	Centroid
10	Prod	Max	Min	Max	Mom
11	Prod	Max	Min	Sum	Centroid
12	Prod	Max	Min	Sum	Mom
13	Prod	Max	Prod	Max	Centroid
14	Prod	Max	Prod	Max	Mom
15	Prod	Max	Prod	Sum	Centroid
16	Prod	Max	Prod	Sum	Mom

4. RESULTS

The goal of the fuzzy logic system is to provide an output that consists of a decision recommendation that is as close as possible to that of reshoring experts. If there exists a major discrepancy, the system needs to be tuned. To be able to perform this tuning, some valid input data is required. The input for each of the two configurations were 20 input (or decision) scenarios that consisted of six decision criteria (Table 2). Half of the input scenarios (1-10) were created by academic experts from the reshoring domain while the other half (11-20) were created by fuzzy logic experts to further test the system. The scenarios created by the fuzzy logic experts are of a more problematic nature (e.g., completely neutral, weakly positive or weakly negative).

The decision scenarios provided the necessary test data to evaluate if the fuzzy logic system provided accurate results. A scenario consists of a 6-tuple made up of input values of the 6 criteria that range from -5 to +5. -5 indicates that the criterion would be affected in an extremely negative way if reshoring would take place while +5 indicates that the criterion would be affected in an extremely positive way. The output value ranges from -5.00 to +5.00 where values between -5.00 to 0.00 indicate 'don't evaluate' while 0.01 to +5.00 indicate 'evaluate'. A higher (or lower) value gives a stronger indication whether to evaluate (or not evaluate) reshoring.

Table 2. The input scenarios

Scenario	Criteria					
	Cost	Quality	Time	Flexibility	Innovation	Sustainability
1	-5	-1	-3	-2	-3	3
2	2	5	-1	3	4	1
3	-3	-4	-3	0	4	-1
4	3	-4	0	-3	-5	-3
5	-4	-2	5	-1	0	5
6	4	2	-4	2	2	-5
7	-4	2	1	0	2	5
8	2	-1	3	0	1	5
9	3	5	5	2	5	-3
10	-3	-5	3	-2	5	-2
11	0	0	0	0	0	0
12	3	-4	2	-2	-2	2
13	-5	0	3	5	5	4
14	-5	4	2	-1	-4	3
15	-2	-5	-5	-2	-5	5
16	-3	5	5	3	5	-3
17	1	-5	1	1	1	-5
18	-5	1	-5	-5	-5	1
19	5	-1	5	5	5	-1
20	-1	5	-1	-1	-1	5

The results from the first configuration (precise fuzzy modeling) are shown in Table 3 while the results from the second configuration (linguistic fuzzy modeling) are shown in Table 4. The Expert opinion shows the reshoring experts evaluation of the decision scenarios while the System output shows the result from the fuzzy logic system. The conflict column indicates whether there is a difference in the evaluation between the expert and the system.

The results from the first configuration indicate that there is alignment between expert opinion and system output. For most of the settings (1, 2, 4, 5, 6, 9, 10, 11, 12, 13 and 14) there is no conflict in any of the scenarios, while for the other settings (3, 7, 8, 15, and 16) there are conflicts in three of the scenarios. However, in total there were only 8 conflict out of 320 system outputs (2,5%). The three scenarios where conflicts occur belong to the group created by the fuzzy logic expert to further test the system. The mean absolute error (MAE) is calculated for each setting across all the scenarios. A smaller MAE value indicates a higher alignment between the expert and the system. The minimum MAE was 0.63 and was obtained with Setting 2.

The results from the second configuration indicate that there is alignment between expert opinion and system outputs. In Setting 1, 2, 5, 6 there are no conflicts for any of the scenarios, while in the remaining settings (3, 4, and 7 to 16) three are conflicts in three of the scenarios (same scenarios as in the first configuration). Still, in total there were only 24 conflict out of 320 system outputs (7,5%). The minimum MAE was 0.48 and was obtained with Setting 2.

Table 3. Expert and system recommendations in the first configuration

Scenario	Expert opinion	System output															
		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16
1	-5	-2,27	-3,00	-1,21	-2,00	-2,95	-5,00	-2,45	-5,00	-1,49	-2,00	-1,22	-2,00	-3,04	-5,00	-3,04	-5,00
2	4	2,27	3,00	1,41	2,00	2,95	5,00	2,69	5,00	1,19	1,65	0,83	1,65	3,04	5,00	3,04	5,00
3	-4	-2,27	-3,00	-1,37	-2,00	-2,95	-5,00	-2,42	-5,00	-1,89	-2,50	-1,45	-2,50	-3,04	-5,00	-3,03	-5,00
4	-4	-2,85	-4,00	-1,96	-3,00	-3,01	-5,00	-2,84	-5,00	-2,44	-3,20	-2,08	-3,00	-3,04	-5,00	-3,03	-5,00
5	-4	-2,12	-3,00	-1,32	-1,50	-2,71	-5,00	-2,13	-5,00	-1,84	-2,50	-1,38	-1,55	-2,86	-5,00	-2,81	-5,00
6	4	2,50	3,50	1,31	2,00	2,86	5,00	1,91	5,00	1,73	2,35	1,52	1,50	2,86	5,00	2,80	5,00
7	3	1,70	3,00	0,68	1,00	2,11	5,00	1,03	5,00	1,53	2,05	1,06	1,35	2,86	5,00	2,63	5,00
8	3	0,89	3,00	0,95	1,00	1,11	5,00	1,66	5,00	1,04	1,65	0,64	0,65	2,11	5,00	2,37	5,00
9	5	2,63	3,50	2,08	3,50	3,04	5,00	2,85	5,00	2,26	2,95	2,12	2,95	3,04	5,00	3,04	5,00
10	-4	-2,60	-3,50	-1,73	-2,50	-2,99	-5,00	-2,62	-5,00	-1,89	-2,50	-1,71	-2,50	-3,04	-5,00	-3,03	-5,00
11	-3	-2,17	-5,00	-0,14	0,00	-2,40	-5,00	-0,22	-5,00	-2,17	-5,00	-0,40	0,00	-2,40	-5,00	-0,82	-5,00
12	-3	-2,50	-3,50	-1,06	-2,00	-2,86	-5,00	-1,98	-5,00	-1,33	-1,80	-1,08	-1,30	-2,86	-5,00	-2,60	-5,00
13	3	1,94	4,00	1,61	3,00	2,17	5,00	2,07	5,00	2,18	3,90	1,91	2,80	2,40	5,00	2,35	5,00
14	-3	-0,89	-3,00	-0,44	-1,00	-1,11	-5,00	-0,91	-5,00	-0,79	-2,25	-0,39	-0,40	-1,11	-5,00	-0,67	-5,00
15	-5	-2,63	-3,50	-2,00	-3,50	-3,04	-5,00	-2,81	-5,00	-2,22	-2,90	-2,05	-2,90	-3,04	-5,00	-3,04	-5,00
16	4	2,87	4,00	2,47	4,00	3,04	5,00	2,95	5,00	2,49	3,30	2,39	3,30	3,04	5,00	3,04	5,00
17	3	0,89	3,00	-1,24[a]	0,00	1,11	5,00	-2,30[a]	-5,00[a]	0,42	1,05	0,05	0,25	1,11	5,00	-1,20[a]	-5,00[a]
18	-3	-2,30	-3,00	-1,75	-3,00	-3,04	-5,00	-2,90	-5,00	-1,66	-2,20	-1,30	-2,20	-3,04	-5,00	-3,04	-5,00
19	3	2,30	3,00	1,75	3,00	3,04	5,00	2,89	5,00	1,66	2,20	1,30	2,20	3,04	5,00	3,03	5,00
20	-3	-0,89	-3,00	0,83[a]	0,00	-1,11	-5,00	1,58[a]	5,00[a]	-0,59	-1,05	-0,17	-0,50	-1,96	-5,00	-0,15	-5,00
	MAE	1.58	0.63	2.49	1.65	1.78	1.35	1.88	1.95	2.09	1.49	2.40	1.88	1.01	1.35	1.34	1.65

Table 4. Expert and system recommendations in the second configuration

Scenario	Expert opinion	System output															
		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16
1	-5	-2,27	-3,00	-1,81	-2,00	-2,95	-5,00	-2,84	-5,00	-2,30	-3,00	-1,87	-3,00	-3,04	-5,00	-3,04	-5,00
2	4	2,60	3,50	2,06	2,50	2,99	5,00	2,81	5,00	2,63	3,50	2,52	3,50	3,04	5,00	3,04	5,00
3	-4	-2,85	-4,00	-2,22	-3,00	-3,01	-5,00	-2,66	-5,00	-2,82	-3,90	-2,78	-3,90	-3,04	-5,00	-3,03	-5,00
4	-4	-2,85	-4,00	-2,36	-3,00	-3,01	-5,00	-2,96	-5,00	-2,63	-3,50	-2,27	-3,10	-3,03	-5,00	-3,03	-5,00
5	-4	-2,50	-3,50	-1,38	-2,00	-2,86	-5,00	-1,78	-5,00	-2,56	-3,45	-2,42	-2,50	-3,00	-5,00	-2,88	-5,00
6	4	2,50	3,50	1,64	2,00	2,86	5,00	2,07	5,00	2,57	3,45	2,51	2,60	3,01	5,00	2,97	5,00
7	3	1,70	3,00	1,43	1,00	2,11	5,00	2,27	5,00	1,09	2,05	0,95	0,55	1,71	5,00	2,24	5,00
8	3	0,89	3,00	1,17	1,00	1,11	5,00	1,93	5,00	1,33	1,95	0,96	0,95	2,49	5,00	2,55	5,00
9	5	2,87	4,00	2,69	4,00	3,04	5,00	3,00	5,00	2,87	4,00	2,79	4,00	3,04	5,00	3,04	5,00
10	-4	-2,85	-4,00	-2,52	-3,00	-3,01	-5,00	-2,86	-5,00	-2,87	-4,00	-2,86	-4,00	-3,04	-5,00	-3,03	-5,00
11	-3	-2,17	-5,00	0,01[a]	0,00	-2,40	-5,00	-0,01	-5,00	-2,17	-5,00	-0,43	0,00	-2,40	-5,00	-0,78	-5,00
12	-3	-2,50	-3,50	-1,53	-2,00	-2,86	-5,00	-2,20	-5,00	-2,00	-2,65	-1,74	-2,15	-3,01	-5,00	-2,89	-5,00
13	3	1,94	4,00	1,80	3,00	2,17	5,00	2,35	5,00	1,94	4,00	1,78	3,00	2,17	5,00	2,32	5,00
14	-3	-0,89	-3,00	-0,49	-1,00	-1,11	-5,00	-0,75	-5,00	-1,75	-2,90	-1,21	-1,05	-2,24	-5,00	-1,79	-5,00
15	-5	-2,63	-3,50	-2,27	-3,50	-3,04	-5,00	-2,98	-5,00	-2,63	-3,50	-2,41	-3,50	-3,04	-5,00	-3,04	-5,00
16	4	2,87	4,00	2,84	4,00	3,04	5,00	3,03	5,00	2,87	4,00	2,74	4,00	3,04	5,00	3,04	5,00
17	3	0,89	3,00	-0,77[a]	0,00	1,11	5,00	-1,38[a]	-5,00[a]	-1,40[a]	-2,00[a]	-0,88[a]	-1,00[a]	-2,54[a]	-5,00[a]	-2,49[a]	-5,00[a]
18	-3	-2,30	-3,00	-2,11	-3,00	-3,04	-5,00	-3,01	-5,00	-2,30	-3,00	-2,13	-3,00	-3,04	-5,00	-3,04	-5,00
19	3	2,30	3,00	1,98	3,00	3,04	5,00	3,00	5,00	2,30	3,00	2,02	3,00	3,04	5,00	3,04	5,00
20	-3	-0,89	-3,00	0,44[a]	0,00	-1,11	-5,00	0,83[a]	5,00[a]	0,92[a]	2,00[a]	0,16[a]	0,45[a]	1,43[a]	5,00[a]	0,55[a]	5,00[a]
MAE		1,49	0,48	2,10	1,50	1,16	1,35	1,64	1,95	1,68	1,11	1,88	1,33	1,34	1,95	1,37	1,95

5. CONCLUSSION

The aim of this study is to investigate the feasibility of using fuzzy logic for reshoring decision-making. To achieve this a fuzzy logic system for reshoring decision-making was conceived and implemented. The system was configured in two different ways to cover the two main fuzzy logic modeling approaches (i.e., precise and linguistic) and sixteen fuzzy inference settings were used in each configuration. The research shows that fuzzy logic is a feasible method for reshoring decision-making. It does not matter so much whether a complete or reduced rule base is used, it is more important that the right setting is chosen. The reduced rule base configuration was somewhat more accurate than the complete rule base configuration. However, the reduced rule base also generated more conflicts in particular settings. Among all the fuzzy inference settings used in this research, one of the settings (i.e., AND method Min; OR method Max; Implication method Min; Aggregation method Max; and Defuzzification method Mom) outperformed the others. With regard to the particular inference methods, the research show that maximum is the preferred aggregation method while middle of maximum is the preferred defuzzification method in a reshoring decision- making context.

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