AUTOMATIC GENERATION OF FUZZY INFERENCE RULES IN A RESHORING DECISION CONTEXT

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ABSTRACT

This paper presents a decision-support system for reshoring decision-making based on fuzzy logic. The construction and functionality of the decision-support system is briefly outlined and evaluated in a high-cost environment contemplating six specific decision criteria, namely cost, quality, time, flexibility, innovation and sustainability. A major challenge with fuzzy logic solutions has to do with the construction of the fuzzy inference rules. In the relocation domain, the fuzzy inference rules represent the knowledge and competence of relocation experts and they are usually created manually by the same experts. One obstacle is that the complexity of the fuzzy inference rules increases with the number of decision criteria. To overcome this complexity issue, this paper presents a solution whereby the fuzzy inference rules are automatically generated by applying one hundred reshoring scenarios as input data. The reshoring decision recommendations produced by the fuzzy logic decision-support system are demonstrated to be close to those of human reshoring domain experts.

Keywords: Decision-support system, Fuzzy inference rule generation, Fuzzy logic inference system, Membership function generation, Reshoring.

1. INTRODUCTION

An important activity that is often left in the hands of experts is decision-making, that is, to make correct and resilient decisions based on some key input information. The transformation of input information to an output decision recommendation is commonly realized relying on expert knowledge and competence. One specific decision-making application domain within manufacturing is related to the relocation of manufacturing capabilities. The movement of manufacturing from high-cost environments to low-cost environments, so called offshoring (Ketokivi et al., 2017), started already in the 60's and has continued ever since. A contributing factor for this relocation movement was a desire to reduce manufacturing cost, especially labor cost (Ellram et al., 2013; Engström et al. 2018a; Engström et al. 2018b). With all the facts on hand, however, it has become evident that many of these relocation decisions were based on insufficient, or sometimes even erroneous, data (Eriksson et al., 2018). One origin for these failures has sometimes been the use of too simplistic calculations, where all the costs related to the relocation decision were not contemplated (Platts and Song, 2010).

In recent years there has been an intense discussion concerning the opposite movement, that of moving production back to the manufacturers' home country (reshoring) or an adjacent country (nearshoring) (Wiesmann et al., 2017). On occasions, reshoring projects are managerial corrections of offshoring decisions that overemphasized cost and undervalued important, yet difficult-to quantify, performance challenges (Gray et al., 2017). Johansson et al. (2019) determined that that while cost is the key component during offshoring discussions, reshoring discussions are primarily focused on value-related factors, such as quality, flexibility and time.

In most cases, manufacturing location or relocation decisions are based on uncertain, vague and imprecise data, something that does not simplify the decision task for upper management. This uncertainty can be manifested in different ways (Ross, 2016): it can be fuzzy (not sharp, unclear, imprecise, and approximate), vague (not specific, amorphous), ambiguous (too many choices, contradictory), of the form of ignorance (dissonant, not knowing something), or due to natural variability (conflicting, random, chaotic, and unpredictable). Whatever the type of uncertainty, it has an impact on the data and makes it difficult to capture, manage and use in a digitized tool or platform.

Apart from the problem with the uncertainty issues, there is a lack of decision-support tools to enable fast and correct relocation decisions (Liu et al., 2011). The solution to vaguely formulated problems is often complex as the number of decision variables could rapidly grow and make it difficult, or potentially impossible, to manually identify a correct solution. To be able to handle complex reshoring decision-making in a formal and structured manner, several systematic frameworks, mostly manually handled, have been proposed (e.g., Foerstl et al., 2016). Having stated this, most complex problem-solving tasks would highly benefit from an automatic and digitized decision-support tool or platform. Several solutions to this type of problem have been proposed over the years, many based on a branch of mathematics known as fuzzy logic that was originally developed by Zadeh (1965). Apart from having the capacity of modeling and emulating the internal decision process of a domain expert, fuzzy logic has the advantage of lacking the expert's disposition to occasionally make irrational or even erroneous decisions. Thus, the repeatability of the decision process is maintained by applying fuzzy logic.

In an article by Hilletofth et al. (2019), fuzzy logic was applied to the reshoring domain and its feasibility in the reshoring decision domain was demonstrated while increasing the interpretability of the fuzzy inference rules as well as reducing the complexity when designing the same rules. Fuzzy inference rules constitute an essential part of the inference engine of a fuzzy logic system by concretizing the knowledge and competence of domain experts, in this case reshoring experts, and enabling the possibility to produce correct and resilient decisions. The task of defining the fuzzy inference rules is often a collaboration between domain experts and fuzzy logic experts. Through discussions between both types of experts, the fuzzy inference rules are defined. This is not an easy task, however, as the amount of possible input variables (so called linguistic variables), together with the different values for each of the input variables (so called linguistic labels), could easily grow to unsurmountable numbers, thus making it very hard to fathom the level of complexity and come up with the fuzzy inference rules.

To overcome the difficulty of manually defining fuzzy inference rules, an automatic solution is presented in this paper. To demonstrate the procedure, a decision-support system for reshoring decision-making based on fuzzy logic is used. The more intrinsic details of the decision-support system are explained in Hilletofth et al. (2019). The main contribution of this paper is to demonstrate the possibilities of automatically creating fuzzy inference rules with the help of input data in the form of reshoring decision scenarios. The reshoring context is that of a high-cost environment, in this case represented by Sweden. The decision recommendations, that is, the output from the system, are presented and compared to those of professionals competent in the reshoring domain, to validate the accuracy and performance of the fuzzy logic reshoring decision-support system.

The remainder of the paper is structured as follows. Section 2 introduces research results related to the creation of fuzzy inference rules. Section 3 presents the development of the fuzzy logic reshoring decision-making system with a special focus on the details behind the creation of the fuzzy inference rules. The accuracy and performance of the fuzzy logic reshoring decision-making system are presented and discussed in section 4 and the paper ends with some conclusions in section 5.

2. RELATED LITERATURE

The theory behind fuzzy logic is based on fuzzy set theory, which is a natural extension of classical set theory, developed by Zadeh (1965). Fuzzy logic provides a powerful tool to understand, quantify and handle numerous and uncertain data (Dutt and Kurian, 2013). Fuzzy logic expresses that nothing can be firmly stated as being either entirely right or entirely wrong. The key goal of a fuzzy logic inference system is to provide a decision-making platform that is made up of five functional units (see Figure 1).

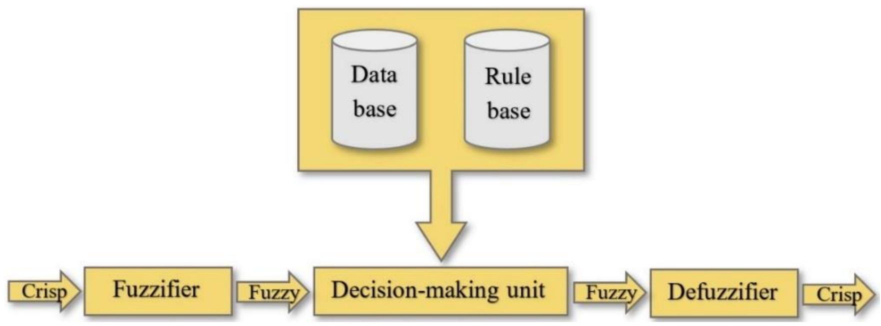

Figure 1. Fuzzy logic inference system

From the point of view of this paper and its contributions to the reshoring research domain, the most interesting unit is the rule base which includes the fuzzy inference rules and to some extent the database that harbors the membership functions. Some examples of how to generate fuzzy inference rules are described in continuation.

There exist many different methods to create fuzzy inference rules, rules that are necessary to infer new knowledge from a fuzzy logic system (Mendel, 2017). The fuzzy inference rules can be created manually by domain experts or automatically, making use of training data if available.

The most straightforward method to manually create fuzzy inference rules is with the help of domain experts that validate the logic behind the rules and the reasonability and accuracy of the inferred knowledge or results (Liao, 2005). The size of the set of rules in the rule base depends on the number of decision criteria and membership functions. If the numbers are low, for example 3 criteria with 2 membership functions each, the total number of rules is 8 (2^3) and is therefore quite manageable. But when the number of criteria and membership functions increase, so does the total number of rules. For example, if we have 7 criteria with 3 membership functions each, we end up with 2,187 rules (3^7). One way to circumvent the problem with an unmanageable number of fuzzy inference rules is to automatically assign ‘correct’ consequents to the rules (Hilletofth et al., 2019). The results presented by Hilletofth indicate that *linguistic variable weights* can reduce the complexity when designing fuzzy inference rules while still providing accurate results that coincide with those of domain experts.

Instead of relying on human expertise, semi-automatic or automatic extraction of fuzzy inference rules from a set of training data could be used. Wu et al. (2001) presented a method to automatically generate fuzzy inference rules from sample patterns using generalized dynamic fuzzy neural networks. A similar approach, making use of genetic algorithms, was presented by Odeh et al. (2015). An example of an adaptive fuzzy system was presented by Duţu et al. (2018) where the authors described a method called the *selection-reduction rule base learning method*. In the selection stage, the most relevant rules from each input subspace are identified in a five-step procedure. When all the five steps have been executed, an optimized version of a fuzzy rule base has been obtained. In the reduction stage, the fuzzy rule base is pruned, meaning that a reduced fuzzy rule base is obtained while still complying with a predefined level of accuracy but at the same time increasing the overall interpretability of the fuzzy logic system.

3. DECISION-SUPPORT SYSTEM

This section outlines the process of implementing a reshoring decision-support system in the form of a fuzzy inference system. In the example presented in this paper, the developed decision-support system has been based on knowledge acquired from experts in the reshoring domain. The system was created using the Fuzzy Logic Toolbox found in MATLAB®. The implementation process consisted of five steps, each carried out by fuzzy logic experts with the involvement of professionals competent in the reshoring domain.

3.1 Define linguistic variables

In the first step, the linguistic variables should be defined. From the point of view of this paper, a linguistic variable is the same thing as a relocation criterion. Relocation criteria are factors that influence reshoring decisions and could be identified among the drivers, enablers and barriers of reshoring (Benstead et al., 2017; Barbieri et al., 2018; Stentoft et al., 2016; Wiesmann et al., 2017). The six high-level decision criteria that are used in this paper correspond to common competitive priorities within the operations strategy field (Miller and Roth, 1994; Frohlich and Dixon, 2001). The reason for choosing common competitive priorities is that they provide a holistic view on how to create competitiveness, which is usually the main goal of any manufacturing relocation decision. The six criteria used are: cost, quality, time, flexibility, innovation and sustainability (Hilletofth et al., 2019).

The color coding of the six high-level relocation criteria (green: cost, quality; yellow: time, flexibility, innovation; orange: sustainability), see Table 1, indicates their order of importance in a high-cost environment. This order of importance has been confirmed by many researchers, for example Johansson et al. (2019). Their results, covering three high-cost countries, namely Sweden, Norway and Finland, indicate that cost is the most important criterion when considering offshoring while quality is the most important criterion when considering reshoring. Thus, green indicates the most important criteria as both cost and quality stands out from a relocation point-of-view. Next comes the yellow criteria that indicate lesser important criteria, as indicated in, for example, Johansson et al. (2019). Finally comes orange that indicates the least important criterion, sustainability. Placing sustainability as the least important criterion is a decision that was made in this paper but for some companies, where environmental aspects are paramount, sustainability might be rated higher. The output criterion indicates whether a specific combination of input criteria values, called an input scenario further on, is enough to recommend a reshoring evaluation (i.e., output = evaluate) or not (i.e., output = do-not-evaluate) (the lower part of Table 1).

3.2 Define linguistic labels

In the second step, the linguistic labels should be defined. In this study, *relative linguistic labels*, that is, negative, neutral, positive, have been applied (Hilletofth et al., 2019). The reason for choosing relative labels is that the opposite, so called 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 might cause misinterpretations. One example of this is that an absolute label, such as 'medium', may have different meanings to different people (Rodríguez et al., 2013; Chen et al., 2014; Pei and Zheng, 2017; Wang et al., 2018). One way to capture these different interpretations is to establish a weight for criteria or importance from every system user (Wu and Mendel, 2007). Another problem is that an absolute label, such as 'high', could have both positive and negative connotations depending of the variable considered (Rodríguez et al., 2016). 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 among system users. Relative linguistic labels, however, circumvent these issues. Relative labels eliminate the need for creating unique and specific linguistic labels for each variable. The inherent meaning of a relative label is also the same to any system user. This means that their semantics are consistent among human decision makers and eliminates the confusion aspect associated with absolute labels. For instance, the relative label 'positive' means that the variable (for example, cost or quality) has a positive impact on the decision (that is, decrease in cost or increase in quality). Apart from avoiding these common issues, the relative labels could be used for all the six criteria presented in the previous step, without a need for creating unique and specific labels for each criterion.

3.3 Define membership functions

In the third step, the membership functions should be defined. When defining memberships functions, three questions should be answered: 1) the number of linguistic labels per linguistic variable, 2) the shape (i.e., distribution) of the membership functions, and 3) the parameters defining the membership functions. The three questions can be answered by domain experts (i.e., manually) or by extracting the answers from input data (i.e., automatically). In situations where input data is abundant, all three questions can usually be answered through an automatic procedure (see for example, Hong and Lee, 1996; Pazhoumand-Dar et al., 2016). In this study, the membership functions were manually created using one hundred reshoring decision scenarios as input. A scenario consists of a 6-tuple made up of input values of the 6 criteria ranging from -5 to +5. -5 indicates that the criterion would be affected in an extremely negative way if reshoring would take place while +5 is the complete opposite. A higher positive (or negative) output value provides a stronger indication whether to proceed with a possible reshoring process (or not). A reshoring recommendation value of $0 < x \leq +5$ indicates that it might be a good idea to proceed with the reshoring process while a value of $-5 \leq x \leq 0$ indicates that it is not recommended to proceed with the reshoring process. The three steps that answer the three questions are described in continuation.

1) Define the number of linguistic labels per linguistic variable. Three relative linguistic labels (negative, neutral, positive) were manually defined, as described in sub-section 3.2. The six input linguistic variables (criteria), defined and presented in sub-section 3.1, are all represented by the same three membership functions. Each of the membership functions represents a linguistic label, that is, 'negative', 'neutral' or 'positive' (Figure 2, left). The membership functions in Figure 2 (left) are the same for the six linguistic variables. The singleton output linguistic variable, evaluation, is represented by two membership functions (Figure 2, right).

2) Define the shape of the membership functions. The Gaussian distribution was manually chosen for the membership functions for the linguistic labels as the reshoring domain experts considered the distribution to be the most adequate for the specific problem domain (Figure 2, left). The membership functions for the output variable were chosen to have a triangular distribution for

reasons of simplicity (Figure 2, right). Furthermore, and as can be observed, there exist no overlap between the two membership functions as there exist no middle solution; either a recommendation is to 'evaluate' or 'do-not-evaluate'.

3) Identify the membership functions' parameters. The parameters of the membership functions were manually calculated (that is, σ, which controls the width of the 'bell' of the curve, and μ, which defines the position of the center of the peak of the curve) by examining the data sets (that is, the 100 reshoring scenarios). Hence, the calculations identified that σ (negative) = 2.5, σ (positive) = 2.5 and σ (neutral) = 0.8. The values of μ were manually fixed due to simple observations, such as, 'neutral' has to lie in the middle of the defined range [-5,+5], thus μ(neutral) = 0, and 'negative' and 'positive' cannot pass the limits of the defined range, thus, μ(negative) = -5 and μ(positive) = +5. The result is illustrated in Figure 2 (left).

3.4 Define fuzzy inference rules

In the fourth step, the fuzzy inference rules should be defined. The definition of fuzzy inference rules is the cornerstone in the development of any fuzzy inference system. In this study, the fuzzy inference rules were automatically created using one hundred reshoring decisions scenarios as input. For the fuzzy inference system, a set of six-input, one-output fuzzy inference rules were generated. The rules were first identified as 'and' rules (i.e., logical conjunction, which is denoted as &) by a knowledge engineering expert. The result is that all six criteria need to be met simultaneously. After that, the rules were automatically generated from the training data set applying a method adapted from a method proposed by Wang and Mendel (1992) but consisting of three steps (as described in Tarasov et al., 2019). The Wang-Mendel (VM) method is a one-pass method, meaning that it uses the test data once and directly generates the fuzzy inference rules.

The three steps are presented in continuation. Step 1 and 2 correspond to the rule evolution stage while step 3 corresponds to the rule pruning stage (see section 2). The method is simple and straightforward in the sense that it is a one-pass, buildup procedure that does not require any time-consuming training.

1) Generate a rule for each input-output data pair (x_1, x_2, x_3, x_4, x_5, x_6; y) in the training data set (i.e., the 100 reshoring scenarios and the output results provided by five professionals competent in the reshoring domain):

IF x_1^i is A AND x_2^i is B AND x_3^i is C AND x_4^i is D AND x_5^i is E AND x_6^i is F THEN y^i is G,

Where μA(x_1^i), μB(x_2^i), μC(x_3^i), μD(x_4^i), μE(x_5^i), μF(x_6^i), and μG(y^i) are membership functions with the maximum membership degree for each value, respectively.

For example, Figure 2 illustrates scenario 8: ($x_1^8, x_2^8, x_3^8, x_4^8, x_5^8, x_6^8$, y^i) = (2, -1, 3, 0, 1, 5; 3).

The left part of the figure shows the three membership functions for the six criteria while the right part shows the two membership functions for the singleton output criterion. The maximum degrees of the $x_1^8, x_2^8, x_3^8, x_4^8, x_5^8, and\ x_6^8$ membership functions are described by the vertical colored lines, one for each of the six input criteria, plus the output criterion (y^8). The colored lines are placed in accordance with the values in a scenario. For example, the green Cost line is placed at 2 while the yellow Innovation line is placed at 1. The degree is where the colored lines cross the highest point of the three overlapping membership functions. For example, the green Cost line crosses negative at 0.02, neutral at 0.05 and positive at 0.47, thus, the degree is 0.47 (positive); the yellow Innovation line crosses negative at 0.05, neutral at 0.45 and positive at 0.27, thus, the degree is 0.45 (neutral).

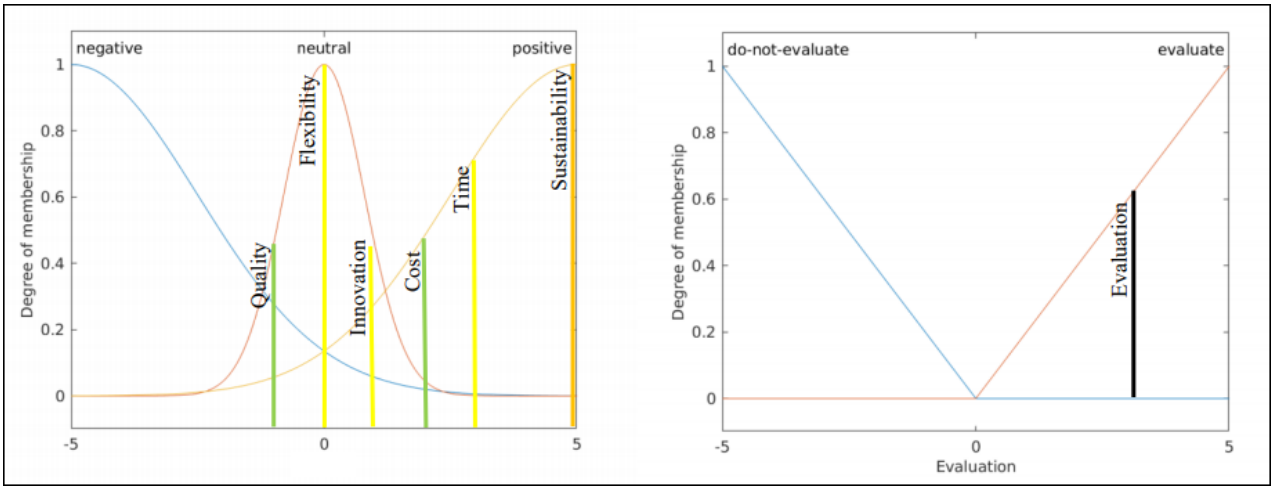

Figure 2. The membership degree in each of the three membership functions for the six criteria (left), the membership degree of the two membership functions for the singleton output criterion (right)

Table 1 demonstrates the membership degree in each of the three membership functions for the six criteria (top part) as well as the membership degree in each of the two membership functions for the output criterion (bottom part). The integers in the second column (i.e., Impact on decision) refer to one specific reshoring scenario, in this case number 8. The numbers in the third, fourth and fifth columns (i.e., negative, neutral and positive) refer to the membership degrees (see Figure 2).

Table 1. The membership degrees for reshoring scenario 8

Criteria	Impact on decision	Linguistic label		
		negative	neutral	positive
Cost	2	0.02	0.05	0.47
Quality	-1	0.27	0.45	0.05
Time	3	0.01	0.01	0.70
Flexibility	0	0.13	1.00	0.13
Innovation	1	0.05	0.45	0.27
Sustainability	5	0	0	1.00

	Recommendation	Linguistic label	
		do-not-evaluate	evaluate
Evaluation	3	0	0.60

Thus, the rule obtained from the input-output data pair for reshoring scenario 8 becomes:

IF (Cost is positive) AND (Quality is neutral) AND (Time is positive) AND (Flexibility is neutral) AND (Innovation is neutral) AND (Sustainability is positive) THEN (Evaluation is evaluate)

The same procedure as described above was performed for the remaining 99 reshoring scenarios.

2) Calculate a degree for each rule

$D(rule^i) = \mu_A(x_1^i) \times \mu_B(x_2^i) \times \mu_C(x_3^i) \times \mu_D(x_4^i) \times \mu_E(x_5^i) \times \mu_F(x_6^i)$, for example for scenario 8

$$D(rule^8) = \mu_A(x_1^8) \times \mu_B(x_2^8) \times \mu_C(x_3^8) \times \mu_D(x_4^8) \times \mu_E(x_5^8) \times \mu_F(x_6^8) =$$
$$0.47 \times 0.45 \times 0.70 \times 1.00 \times 0.45 \times 1.00 \approx 0.07$$

If some prior information from a domain expert about the input-output data pairs exists, the expert may suggest that while some pairs are very useful and crucial, others are very unlikely and may be the results of measurement errors. One could therefore assign a degree to each data pair that represents the belief of its usefulness. If we want to emphasize the objectivity of the system, and not want a human to judge the numerical data, the strategy still works by setting all the degrees of the data pairs equal to unity.

3) Generate a final list of rules. Initially, one rule was created from each data point, that is, the 100 scenarios (step 1). Then, if there are more than one rule with the same antecedent, the rule that has the maximum degree (step 2) is selected for the final list, thus, four rules were removed (step 3). Hence, all in all 96 fuzzy inference rules were created.

3.5 Configure the fuzzy logic inference system

In the fifth and final step, the fuzzy logic reshoring decision-support system should be configured. Once all the parts of the fuzzy logic inference system are defined, the system was implemented in MATLAB®. As could be observed in the previous sub-sections, the one hundred reshoring scenarios served as training data for the manual creation of the membership functions and the automatic generation of the fuzzy inference rules but also as input to the fuzzy logic reshoring decision-support system, to validate its accuracy and performance. The output, that is, the reshoring decision recommendations, could then be compared with the recommendations provided by five reshoring experts, to measure the accuracy and performance of the fuzzy logic reshoring decision-support system. The findings are presented in section 4. The fully configured fuzzy logic reshoring decision-support system was made up by the following parameters: *Linguistic variables*: cost, quality, time, flexibility, innovation, sustainability; *Linguistic labels*: negative, neutral, positive and do-not-evaluate, evaluate; *Membership functions*: Gaussian and triangular; *Fuzzy operator*: and (i.e., minimum); *Fuzzy inference rules*: 96 unique rules; *Implication*: min; *Aggregation*: max; *Defuzzification*: centroid. The selected implication method was 'min', which truncates the fuzzy output set. The selected aggregation method was 'max', which means that the strongest rule 'wins', that is, the result is the maximum level of firing. The centroid defuzzification method is the most widely used method and was therefore chosen.

4. RESULTS

This section describes the evaluation of the constructed decision-support system by applying the three step method described in sub-section 3.4. The method for learning the fuzzy inference rules from data is general, simple and straightforward. The implementation was done applying MATLAB® which automatically developed the rules in a fast manner and with a significant reduction in both time and effort. For example, if 'all' fuzzy inference rules would have been created, that is, all possible combinations of linguistic variables (6) and linguistic values (3) each, there would have been $3^6 = 729$ unique rules, thus, a saving of 86.8% was achieved.

The quality of the generated fuzzy inference rules was validated by comparing the output of the rules with the output of the rules manually created by a knowledge engineer. The created fuzzy inference system made use of the 100 data points (scenarios), both for fuzzy inference rule generation and testing.

To measure the accuracy, the Mean Absolute Error (MAE) was used. MAE is a model evaluation metric used in regression analysis which can help determine the degree to which an independent variable (or variables) is influencing a dependent variable (or variables). The dependent variable in this case is Target while the independent variable is Output. In MAE the error is calculated as an average of absolute differences between the target value (Target, i.e., the evaluation from the data set) and the prediction (Output, i.e., the evaluation recommendation computed by the fuzzy logic reshoring decision-support system). The MAE indicates how big of an error, in this case 0.94, that can be expected from the fuzzy logic reshoring decision-support system on average. The 'MAE scaled by the mean of the evaluation' gives an indication of the how close to the MAE mean value of 0.94 the one hundred measurements lie, in this case 26.11%. Figure 3 illustrates the performance measurements of the fuzzy logic reshoring decision-support system. The ideal situation is when the Target is the same as the Output. In Figure 3, the dotted line corresponds to 100% accuracy while the blue solid line is the actual, estimated accuracy.

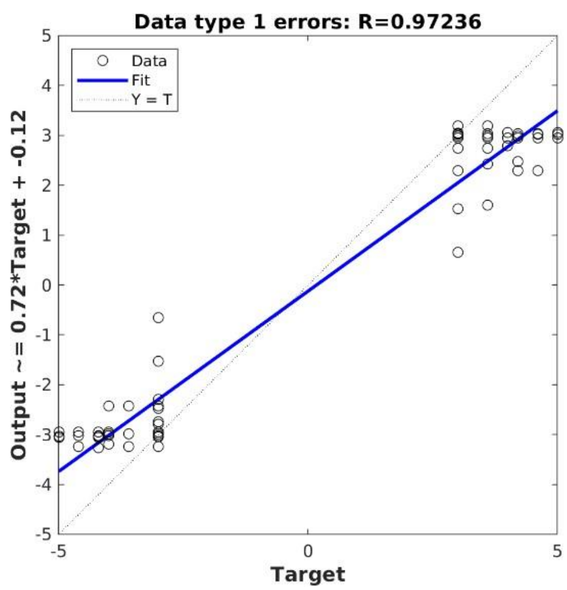

Figure 3. Performance of the fuzzy logic reshoring decision-support system

Correlation is a statistical method used to assess a possible linear association between two continuous variables (in this specific case Output and Target). It is a reciprocal relation between two or more things; a statistic representing how closely two variables co-vary; it can vary from −1 (perfect negative correlation) through 0 (no correlation) to +1 (perfect positive correlation). There are two main types of correlation coefficients: Pearson's product moment correlation coefficient and Spearman's rank correlation coefficient. The correct usage of correlation coefficient type depends on the types of variables being studied. Pearson's product moment correlation coefficient is used when both variables being studied are normally distributed while Spearman's rank correlation coefficient is appropriate when one or both variables are skewed or ordinal and is robust when extreme values are present. In this paper, the Pearson's product moment correlation coefficient was applied because of the nature of the Output and Target variables. When it comes to the value of a correlation coefficient, a value between 0.9 and 1.0 indicates a very high positive correlation (Hinkle et al., 2003). Thus, the acquired results indicate that the accuracy of the fuzzy logic reshoring decision-support system is very good (see Figure 3, where R = 0.97236).

What is more important than the accuracy of the results or the improved interpretability because of a reduced set of fuzzy inference rules, however, is that no consequent (i.e., output result) from any of the 96 fuzzy inference rules were contradictive. To conclude, all the recommendations provided by the fuzzy logic reshoring decision-support system turned out to be equal to those of the reshoring experts, thus no contradictions were observed.

5. CONCLUSIONS

The results presented in Hilletofth et al. (2019) indicated that the application of fuzzy logic to reshoring decision-making issues is viable and that the developed decision-support system is useful to management. This paper builds on the work by Hilletofth by automatically generate the fuzzy inference rules. The created fuzzy logic system maps the manual reshoring decision process well and is capable of accurately predicting reshoring decision recommendations.

Potential future research could evolve around an automatic generation of membership functions using reshoring scenarios as training data (e.g., Herrera et al., 1995; Hong and Lee, 1996). A comparison of the performance of the fuzzy logic model with the performance of manually constructed models as well as models built using, for example, heuristic methods (e.g., Nozaki et al., 1997), genetic algorithms (e.g., Zhang et al., 2009) or artificial neural networks (e.g., Wu et al., 2001) could also be considered. Furthermore, future cooperation with industry stakeholders that have performed, or are currently evaluating reshoring will provide more extensive test data for the fuzzy logic modelling of the reshoring decision process and the evaluation of the reshoring decision recommendations.

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