Reshoring Decision Support in a Swedish 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 are described, and the functionality is evaluated in a high cost environment exemplified through a Swedish context. Ten different reshoring scenarios, provided by Swedish reshoring experts, are entered into the decision-support system and the decision recommendations provided by the system are presented. The confidence that can be put on the recommendations is demonstrated by comparing them with those of the reshoring experts. The positive results obtained indicate that fuzzy logic is both feasible and that the quality of the results are sufficiently good for reshoring decision-making.

Keywords: Decision-Support Systems, Fuzzy Logic Systems, Reshoring

Introduction

In the past three decades, a significant movement of manufacturing from high to low cost environments (offshoring) has taken place (Ketokivi et al., 2017). The main reason for this relocation has been to reduce manufacturing cost, or more specifically labor cost (Ellram et al., 2013). When looking in the mirror, it has become clear that many of these relocations have been unsuccessful. One reason for this has been the use of too simplistic calculations where the total cost was under-estimated (Platts and Song, 2010). In more recent years, there has been an intensified discussion concerning the opposite movement, that is when companies decide to move production back to their home country, reshoring (Gray et al., 2013; Wiesmann et al., 2017). It has been argued that manufacturing location decisions often are based on vague grounds and that there is a lack of decision support for the evaluation of this type of decision (Liu et al., 2011).

A lot of effort has been put into developing methodologies and tools for decision-making problems that are based on uncertain, vague and imprecise information. This type of information is common and difficult to manage. An example of this in a reshoring context is the following situation: ‘if product quality is high [that is, high in the home country as compared to the current location] and transportation costs are high [from the current location to the home market], then reshore production [that is, move back to the home country or a nearby country]’. The nature of vagueness and the inability of traditional Boolean logic to cope with imprecise or vague concepts and perceptions, have been discussed in length by many authors (e.g. Williamson, 1994; Kenney and Smith, 1996).

In a reshoring scenario, the solution to the problem is complex as the number of decision variables could grow and make it cumbersome to manually identify an optimal solution. These types of problems are known as Multiple Criteria Decision Making (MCDM) or Multiple Attribute Decision Making (MADM) (e.g. Triantaphyllou, 2000; Mardani et al., 2015). To be able to handle complex reshoring decision-making in a formal and structured manner, several systematic frameworks, although manually handled, have been proposed (e.g. Tjader et al., 2010; Foerstl et al., 2016). Complex problem-solving tasks, however, would benefit from an automatic decision-support platform. As an answer to this, many solutions have been proposed based on a branch in mathematics known as fuzzy set theory that was originally developed by Zadeh (1965). Just to exemplify this, a review of solutions to the ‘supplier evaluation and selection’ problem, applying fuzzy set theory, was presented by Keshavarz Ghorabaee et al. (2017).

This paper presents a decision-support system, based on fuzzy logic, that can be used by, for example, upper management when evaluating the suitability of reshoring. The end goal of the research undertaken is to provide decision-makers with a tool to make well thought through decisions. The theoretical background, implementation and use of the decision-support system are outlined. To demonstrate the usefulness of the system, it has been configured in accordance with high-cost environments, such as Sweden. Following the configuration, a set of ten reshoring decision scenarios, provided by Swedish reshoring experts, have acted as input to the system. The decision recommendations, i.e. the output from the system, are presented and compared to those of the experts to validate the accuracy which is close to the experts’ recommendations.

Reshoring

One question that has been receiving quite a lot of attention in the existing reshoring literature is ‘what are the reasons for reshoring’. To answer that question, Fratocchi et al. (2016) built a framework consisting of 31 motivations, separated into internal and external environment, and cost efficiency and customer perceived value. Wiesmann et al. (2017) instead separate, what they call drivers, into the categories global competitive dynamics, host country, home country, supply chain and firm-specific. Among the more prominent motives are quality-related issues (Arlbjørn and Mikkelsen, 2014), reduced competitive advantages (e.g. Kinkel, 2012) and political incentives (Bailey and De Propris, 2014). This type of research highlights important criteria (or factors) to consider in a reshoring decision situation.

Within the operations strategy field, there are several frameworks outlining how to create a competitive advantage (e.g. Barney, 1991). These frameworks have later been updated, to specifically consider competitive advantages in a high-cost environment (Sansone et al., 2016), making them especially interesting to reshoring research. These frameworks focus on competitive priorities, such as cost, quality, delivery, flexibility, service, innovation and sustainability (Sansone et al., 2017). Quality has been considered the most important priority in a high-cost environment, closely followed by cost, which is more important than delivery, flexibility, service and innovation, sustainability being considered the least important (Sansone et al., 2016). The different drivers or criteria for reshoring mentioned above could be grouped under these competitive priorities.

Fuzzy logic and manufacturing

The following subsections introduce the basics of fuzzy logic and how fuzzy logic has been applied to a range of application domains in manufacturing, such as supply chain management, sustainability in manufacturing and reshoring of manufacturing facilities. The theory behind fuzzy logic is based on fuzzy set theory, which is a natural extension of classical set theory.

Fuzzy inference systems

Fuzzy logic provides a powerful way of understanding, quantifying and handling vague, ambiguous and uncertain data (Dutt and Kurian, 2013). Fuzzy logic expresses that nothing can be firmly stated as being either right or wrong.

The key unit in a fuzzy logic system is the fuzzy inference system (FIS), having decision-making as its primary work in this paper. The output from a FIS is always a fuzzy set, irrespective of its input which can be fuzzy or crisp. The basic structure of a FIS consists of five functional blocks (Figure 1).

- A rule base that contains several fuzzy if-then rules (Mamdani, 1976);
- A database that contains membership functions. Each membership function defines a fuzzy set used in the fuzzy if-then rules;
- A decision-making unit that performs the inference operations on the rules;
- A fuzzification interface that transforms the crisp inputs into degrees of match with linguistic variables;
- A defuzzification interface that transforms the fuzzy results into a crisp output.

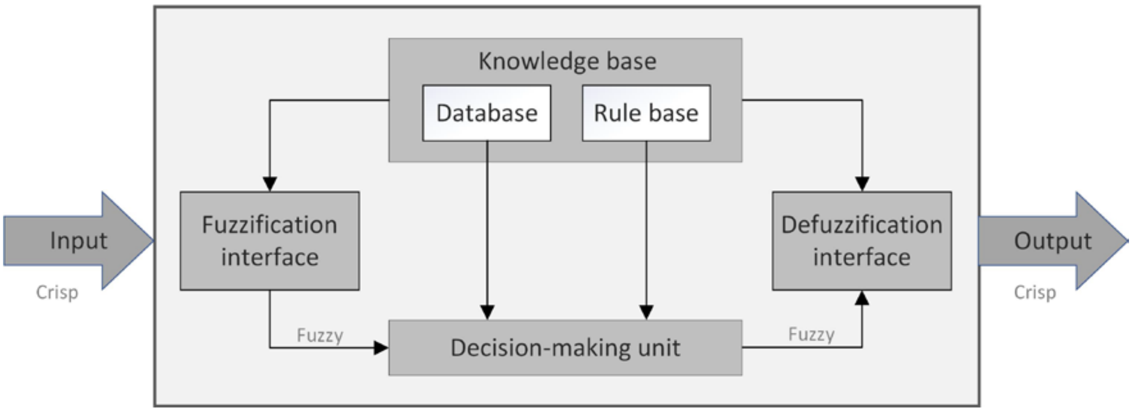

Figure 1 – Fuzzy inference system

Fuzzy inference rules are formulated in terms of linguistic variables. A linguistic variable is a variable whose values are not expressed in numbers but words, i.e. in linguistic terms (e.g. a single-input, single-output rule: ‘if the political risk is very high [that is, high at the current location], then production should move back [that is, move back to the home country or a country nearby]’). The concept of a linguistic variable is very useful when dealing with situations that are too complex or undefined to be understandably described by conventional quantitative expressions.

The five reasoning steps in a FIS are:

1. The membership functions are applied to crisp inputs to compute membership values.

2. The membership values in the antecedent (i.e. input) of each fuzzy inference rule are combined using fuzzy operators.
3. The combined antecedent values are applied to scale output fuzzy sets in the consequent (i.e. output) of each fuzzy rule.
4. The scaled fuzzy sets from each consequent are aggregated into a single fuzzy set.
5. The aggregated fuzzy set is defuzzified for each output.

The key idea of fuzzy sets is that an element has a degree of membership (a value between 0 and 1), representing the grade of membership of the element in the set. The determination of the membership function of a linguistic term for a linguistic variable is generally based on three factors: (1) the decision-makers previous knowledge of the linguistic variable; (2) simple geometric forms having slopes (e.g. triangular, trapezoidal, gaussian or s-functions) as per the nature of the variable; and (3) trial and error learning processes.

A fuzzy system must be both interpretable (i.e. readable by humans) and accurate (regarding the veracity of the results). In literature, two main approaches binding the issues of accuracy and interpretability can be identified (Cpałka, 2017).

- Precise fuzzy modelling. The main purpose is to obtain fuzzy models distinguished by good accuracy.
- Linguistic fuzzy modelling. The main purpose is to obtain fuzzy models distinguished by good interpretability (e.g. a Mamdani-type system).

When designing an interpretable fuzzy system, it should be characterized by high accuracy, good readability and low complexity. However, the development of such a system is not possible in practice for several reasons, including:

- High accuracy requires a complex structure of the fuzzy system (e.g. a larger rule base), which is not conducive to its readability.
- Good interpretability requires a simple structure of the fuzzy system, which is not conducive to its accuracy.

In literature, many solutions addressing the issue of interpretability have been proposed, such as reducing the number of fuzzy sets, reducing the number of fuzzy rules, reducing the number of antecedents in fuzzy rules, distinguishability and interdependence of fuzzy sets (e.g. their overlapping), varying the membership functions (to the antecedent input data or consequent output data) or assigning different weights to the fuzzy rules.

Another key issue that must be handed in a fuzzy system is inconsistency (Casillas et al., 2009). When a flexible fuzzy rule structure, such as those with antecedent in conjunctive normal form is used, the interpretability of the obtained fuzzy model is significantly improved. However, some important problems appear related to the interaction among this set of rules. Indeed, it is relatively easy to get inconsistencies, lack of completeness, redundancies, etc. Mostly these properties are ignored or mildly faced. Two fuzzy rules are inconsistent when their antecedents overlap, i.e. if their antecedents are equal, if they coincide in some labels for each input variable, or if one rule is subsumed by another (i.e. one antecedent is completely contained in a larger and more comprehensive antecedent) but the consequent is different. All types of inconsistency cause a linguistic contradiction that should be avoided.

Fuzzy logic applications in manufacturing

Fuzzy logic has been applied to a wide range of application domains. In this subsection the focus will be on related work in the manufacturing domain, examples being supply chain management, sustainability in manufacturing and reshoring of manufacturing facilities. An ampler description of fuzzy logic applied to production management and manufacturing can be found in Guiffrida and Nagi (1998) or in Azadegan et al. (2011).

Supply chain management (SCM) is 'the design, planning, execution, control, and monitoring of supply chain activities with the objective of creating net value, building a competitive infrastructure, leveraging worldwide logistics, synchronizing supply with demand and measuring performance globally' (Supply chain, 2018). Hence, the research area of SCM is vast. Just one of many examples, where fuzzy set theory has been applied, dealt with performance measurements in SCM (Ganga and Carpinetti, 2011). The authors proposed a supply chain performance model based on fuzzy logic to predict performance based on causal relationships between metrics of the Supply Council Operations Reference model (SCOR) model. The main contribution and originality of their proposal related to the application of fuzzy logic to predict performance based on performance metrics levels 1 and 2 of the SCOR model.

Sustainability in manufacturing. In recent years, sustainability has grown in importance, much depending on the negative impact that human activities have had on environment but also the impact on the social dimension and economy. 'Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs' (Brundtland, 1987). The report expressed the belief that social equity, economic growth and environmental maintenance are simultaneously possible, thus highlighting the three fundamental components of sustainable development, namely environment, economy, and society, which later became known as the triple bottom line (Elkington, 1994). One example where fuzzy logic was applied to the sustainability domain was presented in a study by Singh et al. (2014). The study proposed a FIS-based model for the evaluation of manufacturing sustainability of small and medium enterprises (SMEs). To assess the manufacturing SMEs, decision makers' opinion of the importance of sustainability measures and indicators and the performance of enterprise with respect to indicators were gathered using linguistic variables. The results from the study identified weak areas of performance which required appropriate strategies to enhance the overall sustainability. Another example, where the social dimension of sustainability was addressed, was presented in Cao et al. (2016). The authors presented a social sustainability assessment framework from the perspective of ergonomics. The proposed assessment framework consisted of three aspects, i.e., work task, work environment and human-machine interaction. A weighted Mamdani FIS was designed to obtain a social sustainability score, which was further translated into a social sustainability index.

Reshoring of manufacturing facilities. Only a few papers have been published on fuzzy theories applied to reshoring decision-making, one being White and Borchers (2016). The authors based their analysis on the work of Ellram et al. (2013) that identified 29 motivational factors for relocation decisions grouped into eight dimensions, namely input/product, cost, labor, logistics, supply chain interruption risk, strategic access, country risk, and government trade policies. The authors applied a technique resembling that of fuzzy set theory known as fuzzy AHP (Analytic Hierarchy Process, by Saaty, 1980) for the analysis. Their findings indicated that the surveyed participants placed the factor of labor cost, and the entire cost dimension, as the most crucial factors influencing manufacturing relocation decisions. The results from the fuzzy AHP analysis also showed that cost was the most important criteria to manufacturers when making manufacturing location decisions. The survey data also indicated that the participants found currency stability and input/product dimension to be the biggest risk to decision-makers. Another paper, by Adlemo et al. (2018), demonstrated the possibility of using fuzzy logic to create a decision-support system for reshoring decision-making. One key feature in the paper was the introduction of relative linguistic labels, such as 'negative, neutral, positive', instead of absolute linguistic labels, such as 'low, medium, high' where the labels could be interpreted differently by different persons. Another feature in the paper was the solving of inconsistencies among the fuzzy rules by assigning different weights to them. The implications of these two features are returned to later.

Fuzzy logic and reshoring decision-making

The process of implementing a decision-support system in the form of a FIS is presented in continuation. The FIS-solution is the result after having applied a case provided by 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 performed by fuzzy logic experts with involvement of professionals competent in the reshoring domain.

1. Define linguistic variables,
2. Define linguistic labels,
3. Define membership functions,
4. Define fuzzy rules,
5. Assign weights to the fuzzy rules.

The five steps are briefly described in continuation. More detailed descriptions can be found in Adlemo et al. (2018).

Define linguistic variables

The first step in the process was to identify linguistic variables. A linguistic variable, in the scope of this paper, is equivalent to a reshoring criterion. In this study we have chosen to use seven criteria, corresponding to the common competitive priorities introduced earlier and described in Sansone et al. (2017), namely Cost, Quality, Delivery, Flexibility, Service, Innovation and Sustainability. These (high-level) criteria comprise several sub-criteria, but the model described in this paper only contemplates the (high-level) criteria. Apart from the seven input criteria, there exist one output criterion, called Output decision.

The reason for choosing the common competitive priorities as our 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 location decision. Limiting the study to these criteria is considered appropriate for evaluating the usefulness of fuzzy logic in reshoring decisions. In the future, a thorough study on reshoring criteria and sub-criteria should be conducted.

Define linguistic labels

Each linguistic variable can have a set of linguistic values associated to it (usually expressed as adjectives), called linguistic labels. In this paper are applied relative labels, i.e. negative, neutral, and positive. One advantage with the relative labels is that they can be used for the seven criteria, without the need of unique label-names. Furthermore, the inherent meaning of a relative value is the same to any decision-maker, e.g. a manager, of the decision-support system. To provide an example, in a reshoring context this means that 'positive quality' (referring to that the quality of a product or process will improve if moved back to the country of origin of the company) is an acceptable and commonly understood term by any manager. Moreover, relative values are especially relevant in the reshoring domain as the current manufacturing situation is usually something that is already known; what is important to be aware about is whether the absolute level of a criterion will increase or decrease in relation to its current state and to ascertain the effect of the combined criteria on the final decision recommendation.

Define membership functions

Each membership function defines a fuzzy set that is denoted by one label. Thus, each of the seven input linguistic variables is represented by three membership functions and the output linguistic variable by two membership functions. The task of the research presented in this paper is to demonstrate the possibility of applying fuzzy logic to the reshoring domain. To reduce the complexity of the problem at hand, only Gaussian membership functions were used for the input labels and triangular membership functions for the output labels.

Define fuzzy rules

The definition of fuzzy rules is the cornerstone in the development of any FIS. In this study, instead of defining all possible combinations of fuzzy rules, only the rules that make sense to the users of the decision-support system are created which also augments the interpretability of the rules.

Different criteria have different importance to different people in different countries. In this paper, the importance of each criterion was assigned in accordance to the reshoring experts. Cost and Quality considered to be the most important (labeled green). This is common in high-cost countries like Sweden (De Backer et al., 2016; Sansone et al., 2016). Delivery, Flexibility, Service and Innovation were decided to lie 'in the middle' of the importance scale (labeled yellow) while Sustainability was the least important criterion (labeled orange). Swedish companies that have reshored during the period 2010-2015 also indicated Quality as the main driver (Johansson and Olhager, 2018).

Next, a set of high-level rules were defined in 3 steps based on the experts' knowledge in the domain.

Step 1: Define high-level rules that are 'obvious'

(1) if no criterion is positive, don't evaluate

(2) if no criterion is negative, evaluate

Step 2: Define high-level rules that include the 'most important criteria'

(3) if Quality is negative, don't evaluate

(4) if Cost is negative and Quality is positive, evaluate

Step 3: Define high-level rules that include the rest of the criteria and that make sense

(5) if Cost is negative and 2 yellow criteria are positive and 2 yellow criteria are neutral, evaluate

(6) if Cost is negative and 3 yellow criteria are positive, evaluate

(7) if one green criterion is positive and no green criterion is negative and 2 yellow criteria are negative, evaluate

(8) if 2 green criteria are positive and 3 yellow criteria are negative, evaluate

(9) if 2 green criteria are positive and 4 yellow criteria are negative and Sustainability is not negative, evaluate

(10) if 4 yellow criteria are negative and Sustainability is negative, don't evaluate

Several of the high-level rules were converted into single fuzzy rules, which was the case for (1), (2), (3), (4), (9) and (10). The rest of the high-level rules were translated into multiple fuzzy rules, ranging from 4 (for high-level rules (6) and (8)), to 6 (for high-level rule (5)) up to 12 fuzzy rules (for high-level rule (7)) because of all the possible combinations. In total, the 10 high-level rules were translated into 32 fuzzy rules.

Assign weights to the fuzzy rules

When analyzing the high-level rules, it is noticeable that some of them are inconsistent with each other, as described earlier in this paper. One way to avoid the problem is to assign different weights to the individual fuzzy rules, giving some of them preference over the others. This way of solving the problem was presented in Adlemo et al. (2018) and the same weights are applied here. The weights applied are 1.0 for high-level rules (1) and (2) (i.e. fuzzy rules 1 and 2), 0.8 for high-level rules (3) and (4) (i.e. fuzzy rules 3 and 4) and 0.5 for high-level rules (5) to (10) (i.e. fuzzy rules 5 through 32).

Results

This section describes the evaluation of the constructed decision-support system by applying the process described in the previous section. The goal of the decision-support system is that an output decision recommendation closely resembles that of a reshoring expert. If there is a discrepancy, the decision-support system needs to be tuned. To achieve this, ten different input scenarios were provided by experts. A scenario consists of a 7-tuple made up of input values of the 7 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 is the complete opposite. The output value ranges from -5.00 to +5.00 where values between -5.00 to -0.01 indicate 'don't evaluate' while 0.00 to +5.00 indicate 'evaluate'. A higher (or lower) value gives a stronger indication to evaluate (or not evaluate) reshoring. The recommendations (evaluate / don't evaluate), provided by the decision-support system, were validated by the experts. The results are shown in Table 1.

Table 1 – Expert opinions and Evaluation recommendations (System output 1 & 2)

	Criteria										
Input scenario	Cost	Quality	Delivery	Flexibility	Service	Innovation	Sustainability	Expert opinion	System output 1	System output 2	**Output decision**
1	-5	+1	-3	-2	-2	-3	3	-4	-0.54	-3.65	Don't evaluate
2	+2	+5	-1	+3	-1	+4	0	+4	+2.84	+3.50	Evaluate
3	0	-4	-3	+1	-2	+4	-1	-5	-3.21	-4.50	Don't evaluate
4	+3	-4	-3	-3	+1	-5	-3	-5	-3.25	-4.50	Don't evaluate
5	-4	-2	+5	-1	-5	+5	+5	-4	-1.81	-4.30	Don't evaluate
6	+4	+2	-4	+2	+4	+2	-5	+4	+1.54	+2.60	Evaluate
7	-4	+2	+1	-5	+4	-5	+5	+2	+2.87	+4.30	Evaluate
8	+1	-2	+3	+2	+4	+1	+5	-3	-0.61	-4.30	Don't evaluate
9	+3	+5	+5	+2	+3	+5	-3	+5	+2.52	+2.55	Evaluate
10	+3	-5	+3	-2	0	+5	-2	-5	-3.31	-4.50	Don't evaluate
								MAE	1.86	0.96	

'Expert opinion' indicates what the experts advocate, given the specific scenarios. 'System output 1' indicates the result from the decision-support system without any modifications of the rules while 'System output 2' use the weights as previously explained. The output results under 'System output 1' all indicate the correct evaluation recommendations when compared with the experts' opinions. However, the differences between the experts and the system is relatively high; for example, in input scenario 1 the experts' opinion is a strong recommendation not to evaluate reshoring (output: -4) while the decision-support system recommend the same (don't evaluate) but less strong (output: -0.54). By introducing weights to the fuzzy rules, the precision of the recommendations increases, as indicated by the output results under 'System output 2'. In input scenario 1 the output is now closer to the experts' (output: -3.65).

Another way of indicating the accuracy of the results is by using MAE (Mean Absolute Error, see formula 1). The MAE for 'System output 1' is 1.86 while 'System output 2' has 0.96, thus indicating an improvement through the assignment of weights to the fuzzy rules.

$$MAE = \frac{1}{n}\sum_{j=1}^{n} | y_j - \hat{y}_j | \qquad n = 10 \qquad (1)$$

Concluding remarks

The results presented in this paper indicate that applying fuzzy logic to reshoring decision-making issues is viable. The quality of the recommendations, that is how well the output results adhere to decisions made by reshoring experts, is highly dependent on the tuning of the many properties of the system, such as the number of linguistic variables and labels, the form of the membership functions, the weights of the fuzzy rules, and so on. The weights of the fuzzy rules, as described earlier, made it possible to limit the negative impact of the inconsistencies between the fuzzy rules. The application of relative values for the linguistic labels helped mitigating potential misinterpretations. The results provided so far in the research project indicate that fuzzy logic is well suited when analysing different reshoring scenarios. To evaluate the usefulness of fuzzy logic in the reshoring domain, the seven criteria presented in the paper suffice. In the future, though, a more thoroughgoing study needs to be undertaken in relation to the reshoring criteria, and especially their related sub-criteria.

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