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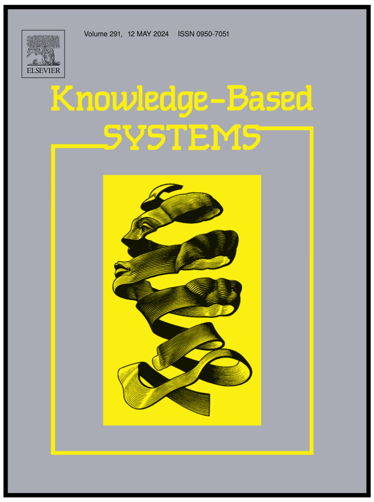

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Integrated Fuzzy Condition Assessment and Decision Support for Water Pipe Mains

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Abstract

This paper presents a novel Integrated Fuzzy Condition Assessment and Decision Support (IFCADS) method that has been applied to predicting the condition of large prestressed concrete cylinder water pipes. IFCADS encodes human expertise within fuzzy rules to emulate human reasoning and solve condition problems when data are scarce. It is based on a new, simple and intuitive elicitation method for: (i) converting both input variables and hierarchical concept memberships into fuzzy linguistic values and (ii) determining the relative influences or weights of each child node on the parent compared to their siblings. These tasks are scalable to high-dimensional and complex hierarchical knowledge domains because all the associated rules can be automatically generated without any further human input.

Additional innovations of IFCADS involve improved representation and processing of fuzzy uncertainties. Fuzzy equality has been made more consistent with other fuzzy comparisons by ensuring fuzziness extends equally on both sides of the mid-point. The integrity of fuzzy values is maintained even when the combined fuzzy influence of children on their parent concept has an upper triangular extension beyond the parent's value range. And there is no interim defuzzification during the inference process, which means full fuzziness is carried through from inputs to outputs.

IFCADS uses this combination of fuzzy numbers, linguistic variables, and If-Then rules to facilitate elicitation of uncertainties associated with decision-making and convert expert knowledge into a mathematical formalism. It was applied to the challenges of assessing buried water pipe conditions using limited and imprecise data from the Libyan Man-Made River Project (MMRP), which manages thousands of kilometres of pipes carrying water from the desert to coastal conurbations. IFCADS performed better than the existing model used by the MMRP and, more pertinently, better than similar fuzzy approaches that lack the full-fuzzification innovations of IFCADS. The application demonstrates a method that has the flexibility and tractability to be applied in many different knowledge-rich and high-dimensional domains of human expertise.

Keywords: Asset Management, Condition Prediction, Fuzzy Systems, Knowledge Elicitation, PCCP, Water Pipes

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1. Introduction

Deterioration and failure of buried water pipes is a complex process that depends heavily on pipe material, environmental surroundings, and operational conditions. Continuous evaluation of their structural integrity and performance is important because they degrade and fail even under normal service conditions (Makar and Kleiner, 2000). The American Society of Civil Engineers (ASCE) recently gave America's drinking water infrastructure a grade of "C-", Mediocre, because of its risk of failure (ASCE, 2021). US water systems currently lose at least 6 billion gallons of water every day and an estimated $7.6 billion of treated water in 2019 due to leaks. This is an indication of the complexity of the water mains condition assessment problem and the economic impact on society.

Many water utilities around the world use large diameter Pre-stressed Concrete Cylinder Pipe (PCCP) as the transmission backbone of their water supply systems due to its high capability for resisting large internal pressure and external forces. They have been deployed for more than 70 years in the U.S., Mexico, Canada, the Middle East, North Africa and China (Zarghamee et al., 2012).

The Man-Made River Project (MMRP), located in the northern African state of Libya, is one of the largest water supply projects that uses PCCP as a main transmission system. The project encountered a series of ruptures ten years after installation of the pipes (Essamin and Holley, 2004), which are significant due to the large diameter and high internal operating pressure of PCCPs. Figure 1 shows scenes of the damage caused by pipe rupture at the MMRP.

Figure 1: Pipe rupture and damage at the MMRP.

To date, there is no prescribed method for water utilities to assess their buried pipes. Alternative approaches include destructive and nondestructive testing (Rizzo, 2010; Liu et al., 2012; Liu and Kleiner, 2013; Loganathan et al., 2022). The field observations obtained from inspections are related to the condition of pipes and converted into an overall condition rating so that an appropriate course of action regarding repair and maintenance is undertaken. However, obtaining such observed data is not always feasible due to the prohibitive costs of applying direct inspections and/or inability to apply them while the pipeline is operating. In these situations, knowledge from experienced engineers can be exploited to model the relationships between influencing factors and pipe condition.

Past experience and lessons learned at the MMRP showed that pipes with only a few wire breaks are still capable of sustaining operating conditions with low risk of failure and do not need urgent intervention. Nondestructive inspection methods such as electromagnetic or acoustic monitoring can detect wire breaks but excavating every single pipe showing them is costly, time consuming, and unnecessary. At the same time, corrosion and pipe damage leading to ruptures can remain undetected in large areas of pipelines where no assessments or excavations have been conducted.

The substantial challenge facing water utilities in general, and the MMRP in particular, is to find an effective and reliable decision support tool for pipe condition assessment that incorporates direct distress data (e.g. breaks, leaks, corrosion etc.) together with indirect distress data (e.g. soil properties, environmental surrounds, etc.) for accurately assessing the condition of each individual pipe. Utilizing indirect distress data accounts for corrosion possibilities that cannot be detected by electromagnetic and acoustic monitoring inspection technologies. The upshot is more accurate and feasible inferences about different pipe components and the formulation of future renewal, repair and inspection requirements for each individual pipe.

Most data and knowledge concerning water pipe condition assessment and deterioration processes are associated with uncertainties. These originate in: (1) the relative reliability and calibration methods of inspection technology; (2) the natural variability of data (time-dependent); (3) the imprecision of natural language that describes and measures qualitative data; and (4) the conversion of test signals into quantitative numbers using human judgement. In addition, data are scarce for large buried pipes such as PCCP and so exploiting experts' intuitive understanding and experience is an important supplement to formulating the relationships between variables. However, this introduces uncertainty relating to the organisation and representation of that human expertise.

The principle motivation for this paper is to model and exploit these different uncertainties more effectively. It is a continuation of the preliminary work presented by Amaitik and Buckingham (2017). It introduces an improved fuzzy-based methodology for modelling human expertise in solving water pipes condition assessment when historical data are scarce, or not available. The proposed methodology is intended to be generically applicable for other knowledge domains with similar qualities.

The developed methodology has the advantage of employing tractable and simple methods for knowledge engineering that allow the system to generate multiple rules itself. The complexity of rule generation is reduced and means the methodology can be used for high-dimensional systems, where a large number of rules might be required to produce accurate results; eliciting them directly from experts would be difficult, impractical and often impossible.

The pioneering part of the novel Integrated Fuzzy Condition Assessment and Decision Support (IFCADS) method is that its fuzzy computations for transforming and combining model parameters during knowledge construction and inference ensure full information about uncertainty is maintained from inputs right through to outputs. This leads to more accurate model outcomes compared to existing methods, which lose precision during fuzzy computations. It also provides better explanations for how different representations of the model parameters affect the performance of the model.

Although many fuzzy-based MCDM models exist, few manage hierarchical expert knowledge, full fuzzification, and uncertainty propagation in a unified framework. This study is motivated by the need to support robust decision-making under data scarcity and subjective expert knowledge, where conditions often encountered in infrastructure condition assessment. Our aim is to build a tractable, scalable, and fully-fuzzy inference framework that mimics expert reasoning from incomplete or indirect observations.

The next section provides a literature survey on the methods used for water pipe condition assessment and decision support. A discussion on methods for modelling human expertise within the decision support system is presented in Section 3. Section 4 details the proposed one for IFCADS. Section 5 evaluates the application of IFCADS on real-world pipes data to predict the pipe condition and rehabilitation actions required. It also compares the performance of IFCADS with other models. Section 6 draws conclusions from the research, summarises the new contributions made, and discusses future work.

2. Modelling Approaches for Water Pipe Condition Assessment and Decision Support

Various approaches have been proposed for modelling the condition of buried water pipes and supporting decisions regarding maintenance and rehabilitation. These can generally be classified into statistical and artificial intelligence (AI) approaches (Liu et al., 2012; Dawood et al., 2020). These are summarised in this section, including how fuzzy approaches link with human expertise to provide a strong synergistic approach when the available data do not provide full understanding of the domain.

2.1. Statistical Modelling Approaches

Statistical modelling is widely used in solving engineering problems and has expanded rapidly since the 1970s for predicting system failures (Lawless, 2003). Several models have been used to quantify the condition or deterioration of water mains by forecasting the number of pipe failures (breaks). They are usually applied when historical failure records and/or condition data are much easier to obtain (Kleiner and Rajani, 2001). They include survival analysis using Weibull/Exponential equations (Le Gat and Eisenbeis, 2000; Pelletier et al., 2003), regression models (Wang et al., 2009; Liu et al., 2009), simple time-linear and time-exponential models (Poulton et al., 2007; Wood and Lence, 2009), and physical probabilistic models (Davis et al., 2007; Moglia et al., 2008). Most are simple mathematical models and can be used for any type of pipe materials.

They are less effective without large amounts of historical pipe condition/failure data recorded over a long period of time. It reduces the variety of variables required for accurate analysis Kleiner et al. (2007) and they are unable to account properly for the subjective and probabilistic nature of pipe deterioration and condition. Even if data are available, they may not be linked to known outcomes, which affects model training.

Another limitation is that data do not provide information about pipes that have not yet failed Dawood et al. (2020). One of the motivations for the present work is to produce a model capable of inferring the condition of pipes when they do not indicate any signs of distress.

2.2. Artificial Intelligence Modelling Approaches

Artificial intelligence (AI) covers a multitude of approaches, many of which have been effective in modelling complex problems. Choosing the appropriate one depends mainly on the type and availability of data.

Artificial Neural Networks (ANNs) have been recently used for modelling the condition and deterioration of water pipe infrastructures (Najafi and Kulandaivel, 2005; Achim et al., 2007; Geem et al., 2007; Amaitik and Amaitik, 2008; Jang et al., 2018; Kerwin et al., 2020). They are appropriate when there are no clearly stated rules or mathematical steps that lead to the solution of a problem, and also when there is no exact knowledge about probabilistic relationships between predictors and the dependent variables. They can determine model structure and learn cause-effect relationships from past data and generalise results. On the other hand, ANN models are hard to interpret and usually require a large amount of historical data for training to obtain the most accurate network architecture (Haykin, 2007; Tang et al., 2007; Jang et al., 2018).

Case-Based Reasoning (CBR) is a useful AI technique when a large and varied database of experienced cases (case library) about the problem is available. The condition assessment of pipes given input data can be predicted by retrieving and adjusting relevant information obtained from the case library. It has been applied to a variety of infrastructures (Morcous et al., 2002a,b) but it requires a large library of previously experienced cases that is regularly updated to generate accurate results.

Bayesian Belief Networks (BBNs), also called causal probabilistic networks, are graphical models that are popular for evaluating water-pipe systems (Francis et al., 2014; Kabir et al., 2015; Demissie et al., 2017; Elmasry et al., 2017; Balekelayi and Tesfamariam, 2022). They can be effective when causal relationships between variables are clear and well understood, or enough complete data are available to infer variable relationships and conditional probabilities.

Fuzzy-based approaches come into their own when historical data are not available or, if available, they are ambiguous or imprecise. It has been widely applied to water pipes infrastructure (Kleiner et al., 2004; Najjaran et al., 2004; Kleiner et al., 2006; Rajani et al., 2006; Fares and Zayed, 2010; Amaitik and Buckingham, 2017; Xu, 2022; Dawood et al., 2023). Fuzzy sets and fuzzy logic technologies are the tools for handling both quantitative and qualitative data types and enable expert judgements to formulate cause-effect knowledge of system variables (Zimmermann, 2001; Siler and Buckley, 2005; Amaitik, 2020).

Recent developments in fuzzy-based multi-criteria decision-making (MCDM) have expanded their utility in uncertain and complex environments. Lin et al. (2020a) proposed a TODIM-based model with hesitant fuzzy linguistic term sets to allow decision-makers to express uncertainty across multiple linguistic evaluations. Although hesitation is not explicitly modelled in the present study, the use of fuzzy linguistic rules in our approach similarly aims to accommodate expert uncertainty in evaluating buried pipe conditions.

In parallel, Lin et al. (2020b) also applied MULTIMOORA under a picture fuzzy environment to the problem of car-sharing station site selection. Picture fuzzy sets allow representation of membership, non-membership, and neutrality degrees, which enrich the model's ability to reflect real-world decision-maker behaviour. While our work does not implement picture fuzzy theory directly, it shares the motivation of preserving uncertainty through the inference process, using full fuzzy propagation from input to output.

Another notable contribution is the integration of entropy and correlation weighting into Pythagorean fuzzy TOPSIS, as explored by Lin et al. (2019). These techniques support better balance between expert judgment and data-derived weights. Our method echoes this philosophy by employing fuzzy analytic hierarchy process (FAHP) to establish expert weights, while maintaining linguistic fuzziness through rule-based inference.

Furthermore, Lin et al. (2018) introduced a group decision-making framework using probabilistic uncertain linguistic term sets (PULTS). This model captures uncertainty by allowing linguistic evaluations to be expressed as probability distributions, an approach conceptually related to the graded membership in fuzzy rule-based systems like ours.

More recently, Fan et al. (2025) proposed an opinion dynamics model for group decision-making with probabilistic uncertain linguistic information, addressing how expert consensus evolves through multiple iterations. Similarly, Qin et al. (2023) developed a probabilistic linguistic multi-attribute decision-making approach based on generalized MSM operators, offering enhanced aggregation strategies for uncertain linguistic evaluations. These studies reflect a growing emphasis on decision robustness and flexible linguistic modelling, key principles that also guide the development of the IFCADS model proposed in this work.

The advantage of our approach lies in combining these principles, uncertainty modelling, expert weighting, and interpretability, within a hierarchical and fully fuzzy rule-based architecture that can be scaled to infrastructure-level systems, such as condition assessment of buried water pipes.

3. Modelling Human Expertise

The previous section showed how different mathematical models are dependent on the amount, quality, and richness of data. It concluded with fuzzy approaches that have the potential to supplement data paucity with human expertise. This section will review how this expertise can be modelled to provide the required synergy.

Human expertise is high level cognitive understanding of a subject in the form of concepts, facts and their relationships. Modelling the knowledge base is a complex task in the construction process of knowledge-based decision support systems (Pradier et al., 2021). Generally, the knowledge base can be established either by eliciting it, directly or indirectly, from domain experts, or by learning it from historical data using one of the machine-learning techniques. The former is more complicated and challenging because it requires knowledge engineers to find an appropriate mechanism for converting and combining experts' knowledge so that it simulates human reasoning efficiently, taking into account experts' uncertainty and imprecision about the domain.

3.1. Knowledge Representation

Determining how the knowledge base is organised and represented is a significant challenge(Pradier et al., 2021). Since the 1960s, hierarchical structures have been widely used for cognition-based domains (Cohen, 2000). Categorising data and information into different concepts (groups) is a basic characteristic of hierarchical structures, which is also a fundamental function of human cognition and thinking (Voorspoels et al., 2011). It allows people to view missing data as a problem only involving the concept and any concept can be processed independently.

In large buried PCCP water pipes, data and information about the pipes are naturally hierarchical, with meaningful concepts encapsulating related data. The lower levels of the hierarchy represent more specific and detailed concept information, which becomes more general when moving up to the target concept: the overall pipe condition and recommended actions.

Hierarchical models of human expertise include probabilistic graphs and rule-based approaches. Bayesian belief networks are graphs capturing causal relationships between variables/concepts and their associated probabilities. Targeted concept predictions or probabilities (the hypothesis) can be inferred by transmitting probabilities throughout the network based on certain evidence (observed data). However, in the absence of data, specifying causal relationships and conditional probabilities by experts requires large amount of questions to be answered and experts are not able to provide the required probabilities easily, let alone reliable conditionally independent chains.

Rule-based approaches are an alternative hierarchical representation. They capture human expertise in the form of "IF-Then" rules consisting of simple linguistic terms. The set of rules are combined within an inference engine that simulates human reasoning to reproduce the expert's solution of the problem. MYCIN was a seminal rule-based expert system (Shortliffe, 1976) providing diagnoses and advice about bacterial infections. It comprised of around 600 rules elicited directly from human practitioners, each one associated with a certainty-factor encapsulating uncertainty. It was a goal-directed expert system based on backward-chaining where the system reasons by first matching the available information to the conclusion part of the rule and then searching for conditions relevant to the problem. The system demonstrated a performance commensurate with the human expert and stimulated a well-populated field of similar rule-based expert systems. This paper follows in that tradition but with a different "fuzzy" approach to eliciting and propagating uncertainty. It is justified in the next section.

3.2. Why Use a Fuzzy Rule-based Approach?

Fuzzy set theory originated with Zadeh (1965), where items are assigned to sets based on a membership function that has a continuous grade varying between 0 and 1. This "membership grade" determines how much an item belongs to the set. Fuzzy logic (also called multi- or many-valued logic) calculus is similar, with assertions having multiple truth or membership values. These partial truths extend traditional Aristotelian two-valued logic where statements can either be true or false and nothing in between.

The philosophy of fuzzy logic provides an appropriate framework for reasoning about uncertain or inexact knowledge rather than traditional approaches that concentrate on exact or absolute solutions (Ross, 2004; Amaitik, 2020). It is the main motivation for our research using fuzzy linguistic variables and fuzzy numbers, and also because they resonate with human cognition. Fuzzy numbers apply membership functions to create approximations that efficiently process imprecise or vague input data and their ranges. They also encapsulate partial knowledge where human experts are not certain about the contribution of variables to the different potential outcomes, which is the case in the water-pipes domain.

Linguistic variables play a fundamental role in modelling fuzzy systems. They provide a sensible way of describing the behaviour of complex systems by representing uncertain variables in terms of propositions that humans use and understand. These propositions (phrases) expressed in natural language are then converted into fuzzy meaning (fuzzy numbers) for processing using fuzzy mathematics (Ross, 2004; Amaitik, 2020). An important goal is to eliminate loss of uncertainty information gleaned from human experts at the rule construction phase when propagating uncertainty through the hierarchy.

In solving real-world problems, producing an exact representation of the system's structure and parameters (i.e. assuming that the system under study is known with certainty) is rarely feasible for systems of any complexity. A complete description or understanding of the system's behavior depends on many interacting parameters that humans are not able to perceive and process simultaneously. At the same time, machines are unable to elicit them without a sufficiently large data set and some prior understanding of its structure. An intermediate method that converts available knowledge into a mathematical or logical formalism is our proposed solution. It captures uncertainty and then processes it formally so that there is a transparent relationship between input data, hierarchical rule-based processing, and output advice. The next section explains the methodology.

4. Proposed Methodology

This section presents an innovative combination of fuzzy-based approaches resulting in an integrated, simplified and effective fuzzy methodology for supporting the elicitation of human expertise and adapting uncertainty propagation during knowledge processing. The proposed IFCADS employs linguistic variables and fuzzy numbers for knowledge-base representation and processing, and fuzzy logic for the inference process. It is mainly composed of three phases (Figure 2): 1) defining inputs, membership functions, and the tree structure; 2) fuzzy rule construction; and 3) the inference process. A detailed description of the IFCADS methodology is given next, along with illustrative examples from the water pipes domain.

4.1. Phase 1: Defining Inputs, Membership Functions, and the Tree Structure

The structuring of data can have a significant effect on model performance. This research adopts a hierarchical approach that is suited to fuzzy modelling and integration of various types of uncertainties. The conceptual hierarchy is elicited from experts through interviews and subsequent thematic analysis that explore their understanding of the domain variables, how they are organised into concepts, and the overall relationships of those concepts Buckingham et al. (2008, 2013).

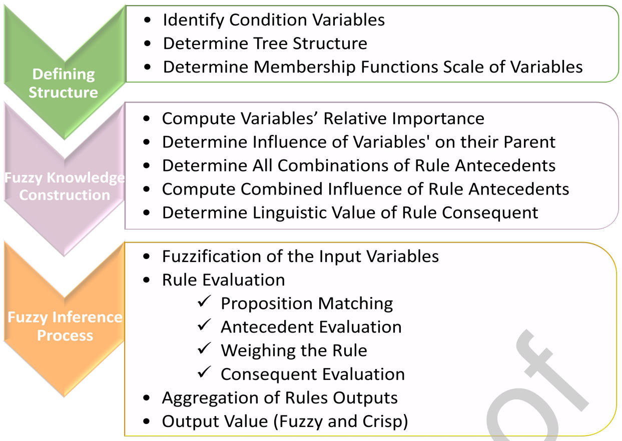

Figure 2: The main steps of IFCADS Methodology.

Figure 3 shows a typical tree structure composed of variables and concepts. A concept is defined as an aggregate effect of a group of variables and/or other concepts. Input variables contribute to the condition of their parent concept at intermediate levels up to the final system output level.

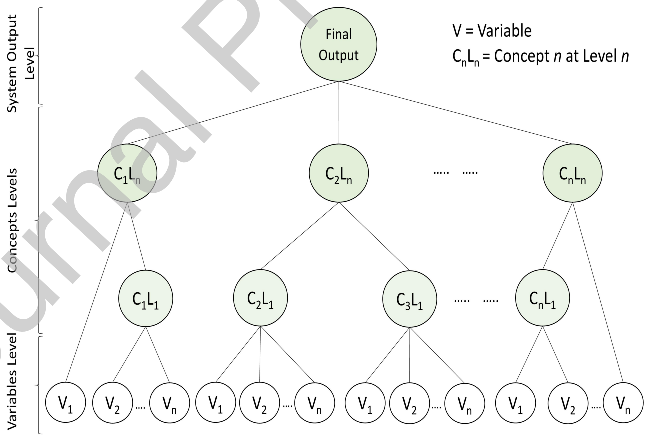

Figure 3: A typical condition/risk assessment tree where variables and concepts interact towards the final output. The white ovals show input variables and light-green ovals represent intermediate concepts at different levels of the tree up to the final output.

4.1.1. *Determine Membership Function Scale for Variables and Concepts*

Having identified the problem tree structure, we need to establish the values associated with each variable and concept along with the scales for measuring variables. A proposed three-step method for creating the membership functions (MFs) for the variables and concepts is manageable and possible to automate due to the simple way of eliciting information required from experts. The method employs triangular fuzzy numbers to express the linguistic values associated with the concepts and variables. They are fast in computation and give more intuitive and natural interpretation due to the simple shape of the MF.

Step 1: Ask the expert to specify the minimum and maximum values of a variable's values, beyond which there is no change to the variable's influence on the concept being assessed (which may just be the limits of those values or some intermediate range). Figure 4 shows this for the number of wire breaks in a pipe section where the range of values covering zero to maximum influence on condition is 0 to 400 wire breaks.

Step 2: Ask the expert to determine how many distinctive linguistic values (categories) should be used to encompass the meaningful range of values for the variable/concept. These capture the division of variable values into psychological scales such as low, medium, and high. In our example, Figure 4 divides the scale into five linguistic categories from minimum to maximum.

Step 3: Create the Triangular Fuzzy Numbers (TFNs) for each linguistic value of the variable/concept so that the membership grade (MG) distributions are placed evenly across the scale. This is done automatically by dividing the range of values by the number of linguistic values minus 1, ($\frac{Max-Min}{Linguistic\ Values-1}$). The resulting value is then added to the minimum value, determined in Step 1, to determine the middle value of the TFN next to the minimum value, and then added to this middle value to get the middle value of its next variable and so on until all middle values of the TFNs are determined, as shown by Figure 4. Now, the TFNs are evenly distributed across the scale, such that the lines of the TFN for both sides are extended to the middle values of the neighbouring TFN, giving a half-way overlapping between adjacent TFNs. it means the MG of a value always adds up to one across the associated linguistic variables. For the illustration in Figure 4, the three parameters and their values for the number of wire breaks are: minimum value = 0, maximum value = 400, number of linguistic values = 5. Accordingly, the distance between middle values is ($\frac{400-0}{5-1}$=100) and the resulting Membership Functions (MFs) are: ($\frac{0,0,100}{Minimum}$, $\frac{0,100,200}{Low}$, $\frac{100,200,300}{Moderate}$, $\frac{200,300,400}{High}$, $\frac{300,400,400}{Maximum}$).

Membership scales effectively capture the degree to which variables belong to specific fuzzy sets, which aligns with the primary goal of representing expert judgments in condition assessment. For this domain, our approach has stuck with the traditional "special case" fuzzy-set methodology where there is a single membership function, and non-membership is $1-$ membership. Intuitionistic fuzzy sets (Atanassov, 1986) are a generalisation that allows for separate functions for membership and non-membership where the sum does not have to equal unity. This additional complexity has not been needed for the current domain as yet but we acknowledge that it may be something worth exploring in future applications. Separate non-membership functions could complement the current approach and further enhance the model's flexibility and applicability.

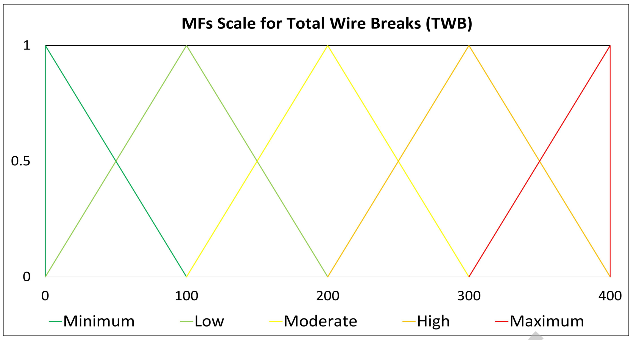

Figure 4: The MFs scale of TWB.

4.2. *Phase 2: fuzzy rule construction*

The general fuzzy rule structure in IFCADS is as follows:

IF x_1 is A_{1k} AND x_2 is A_{2k} ..... AND x_n is A_{nk} THEN y is B_k

where, x_i is the i^{th} input variable (i=1, 2, ..., n), y is the output variable, A_{ik} is the linguistic value (fuzzy set) of the i^{th} input variable in k^{th} rule, B_k is the linguistic value (consequent fuzzy set) of the output variable in k^{th} rule and n is the number of input variables. Constructing the rules will be illustrated with the Pre-stressed Wires Condition, "PWC", concept and its child variables, Total Wire Breaks, "TWB", Maximum Wire Breaks per Positions, "$MWBpP$", and Number of Wire Breaks Positions, "$NWBP$".

IFCADS adopts a five-step method that is based on a full fuzzy processing environment to build the knowledge base of the system (fuzzy rule-base). Figure 5 illustrates the steps and will be fully explained later. Step 1 determines the fuzzy influence (FI) of each child's values on its parent concept. Step 2 identifies every combination of each child's fuzzified values with every combination of the siblings' fuzzified values. The combinations are separate rules, mapping those particular input variable values to the output parent concept. In Step 3, the children of a concept have their fuzzy relative importance (FRI) calculated with respect to each other. These are fuzzy scales that moderate the influence of the child's value depending on how much influence that child has on the parent node compared to its siblings. Step 4 finds the total influence of each combination of input variable values on the parent concept. It is the combined fuzzy influence, CFI, of the input variable values calculated by multiplying the FI of the input variable linguistic value by the FRI of that variable and summing them across all the input values. The resulting CFI is shown in Figure 5 as a fuzzy number in bold. Step 5 maps the CFI fuzzy number onto the MF scale of the parent to determine the maximum support for the linguistic values describing the condition of the parent. Accordingly, for the first variable FRI in the figure, the particular combination of values of Rule 1 have more support for the "Excellent" condition of PWC than for any of the others. And therefore, the "Excellent" condition has been selected to be the consequent linguistic value for Rule 1. These 5 steps are described in detail next.

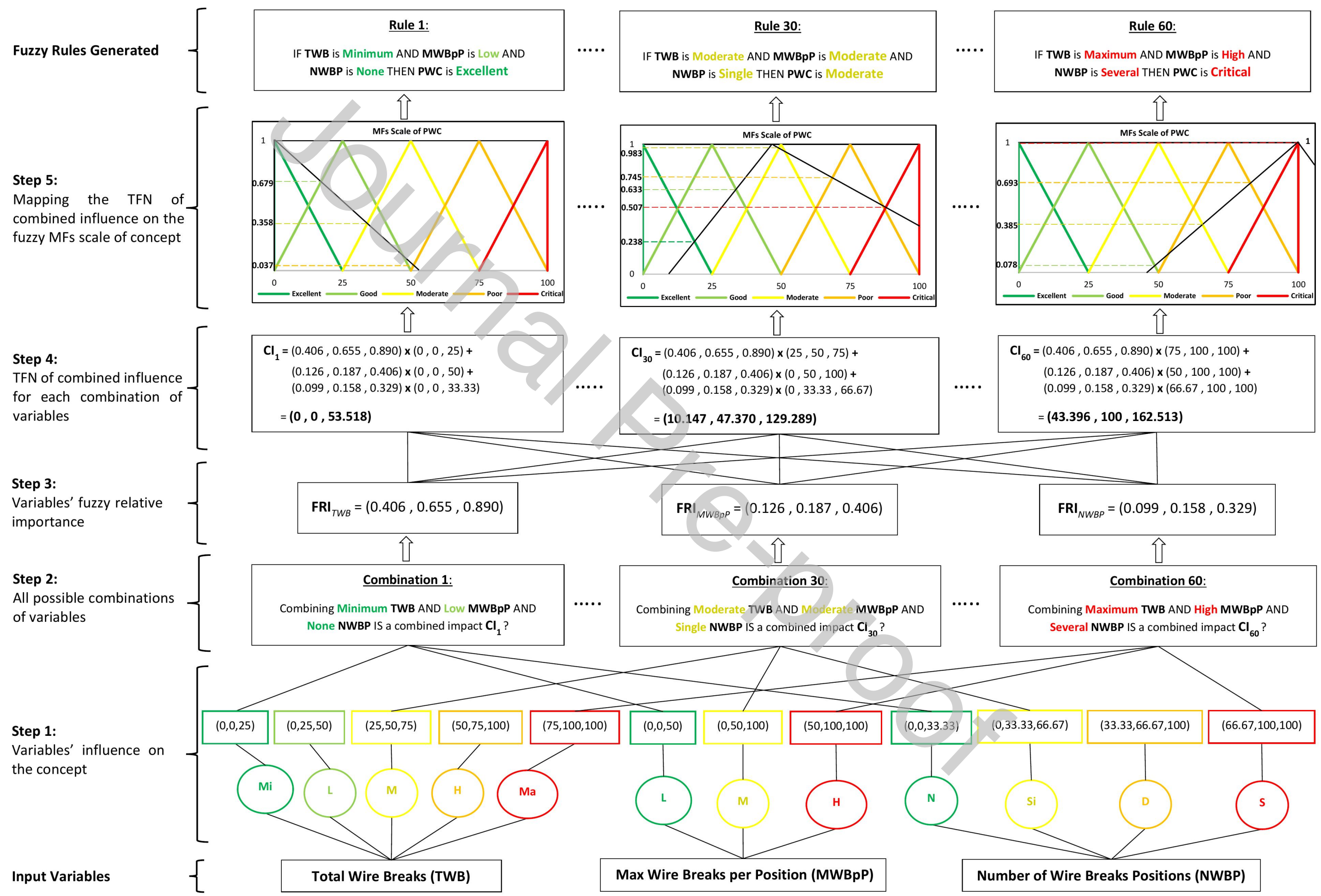

Figure 5: Illustration of how fuzzy rules are generated for the parent concept PWC, Pre-stressed Wires Condition. The ovals in the first row of Step 2 represent the linguistic values associated with the variables, and their acronyms shown are: $Mi = Minimum, L = Low, M = Moderate, H = High, Ma = Maximum, N = None, Si = Single, D = Double$ and $S = Several$. And the rectangles in the second row represent the influence TFNs distribution of the variables on the parent concept PWC.

4.2.1. Step 1: Determine the Influence of Variables' Values on the Concept

In general, the influence of a child's particular value on its parent concept is determined by a membership function (MF) specifying the child's influence distribution across all its values. The innovation of IFCADS is its manageable and simple method for generating the MF. It maps linguistic values of the child variable or concept to the parent membership grade distribution using minimal information from the expert.

The approach is similar to the GRiST (Galatean Risk and Safety Tool) clinical decision support system for mental-health risk assessment (Buckingham, 2002; Buckingham et al., 2013) where the MF of risk factors is specified using the least number of reference points for generating the distribution. The difference for IFCADS is the use of linguistic values that map to intuitive rules rather than the numerical MG distributions of GRiST. There are two tasks that need to be carried out for IFCADS.

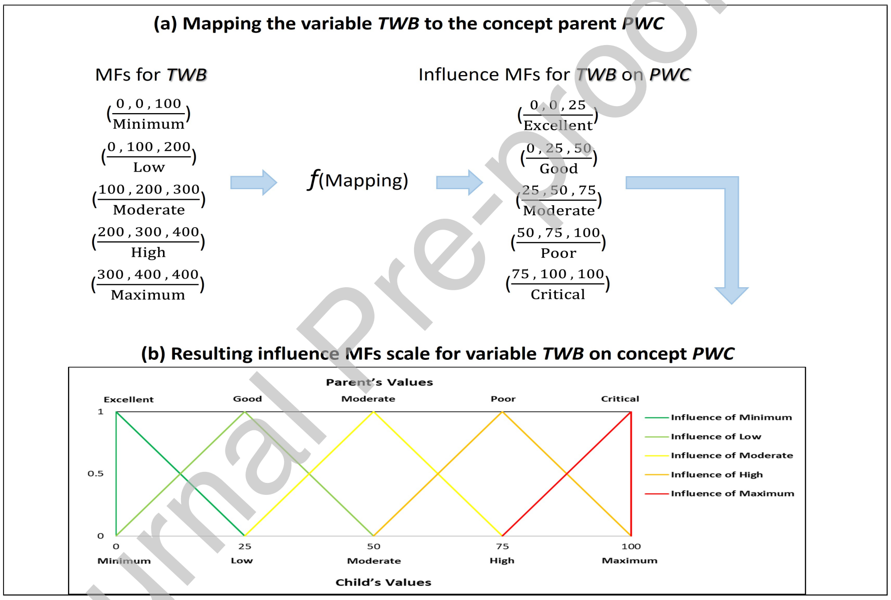

Figure 6: Proportional mapping where extreme values of TWB map to the best and worst of PWC. (a) illustrates mapping process, (b) shows resulting influence MFs.

<u>Task 1:</u> Ask the expert to identify the variable values that are associated with least and most influence on the parent concept. In the simplest case, the extremes of the child range map to the extremes of the parent range, as shown in Figure 6. The "$Minimum$" value of TWB has an "$Excellent$" influence value on the parent PWC. Similarly for the other extreme value, where "$Maximum$" of TWB maps to "$Critical$" of PWC.

The child always has to map to the extreme values of the parent but not necessarily with each pole of its own range. For example, a child value of high might map to the maximum influence on the parent and any value above the child's high (e.g. maximum) will also map to the same influence. Unusually, but still possible, is the case where a child's intermediate value maps to the parent's extreme and one above the child's intermediate value maps to a parent value below the extreme. In other words, the influence reaches a maximum for an intermediate child value and then decreases above it. As a purely hypothetical example, the moisture of soil might have the largest influence on pipe corrosion at an intermediate level where the influence reduces as the soil becomes more saturated, as shown in Figure 7-b.

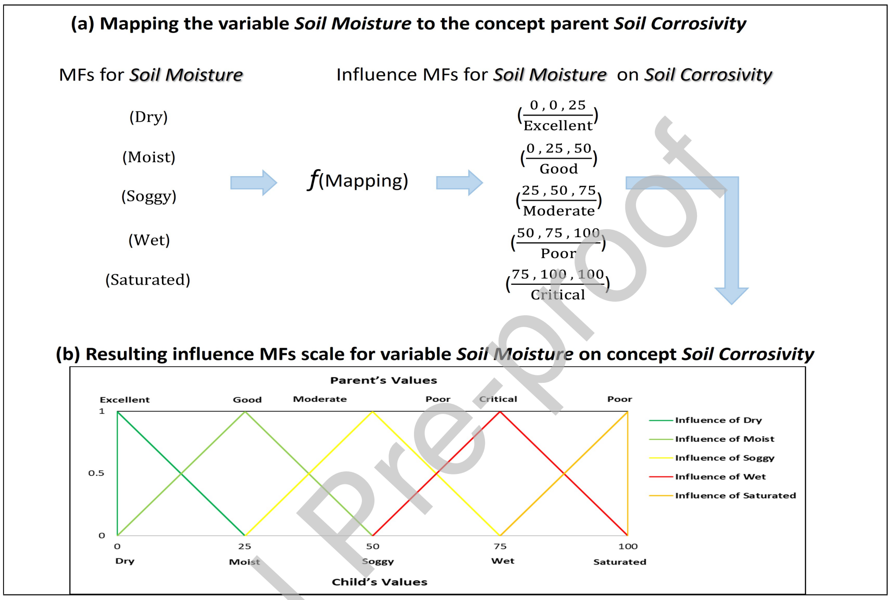

Figure 7: Example of $SoilMoisture$ influence on $SoilCorrosivity$ where the largest influence is at an intermediate level and reduces as the soil becomes more saturated. (a) illustrates mapping process, (b) shows resulting influence MFs.

Task 1 establishes mappings between all child and parent values. However, the child values may not have a linear influence on the parent, which is explored in the next task.

Task 2: Ask the expert whether the child's influence on its parent changes proportionately between all its values.

(a) If the expert wants an even distribution of the fuzzy influence of the variable's values on the parent concept, then it is automatically generated, as shown in Figure 6-a and described in Section 4.1.1.

(b) If the expert thinks the influence of a variable on the parent concept is not proportionally increasing or decreasing with the values, then the expert is asked to give the variable values that define the different shape. They just need to specify the additional mappings that are causing the uneven influence and the algorithm then works out the proportional changes in between these values. For example, Figure 8-a shows the child's Moderate mapping to Good and then the High mapping to Critical. We apply the same process mentioned in (a), but for two intervals, where the mapping within the intervals are proportionate. The resulting influence MFs are compressed or stretched, ensuring that the total MGs across the linguistic values always add up to 1.

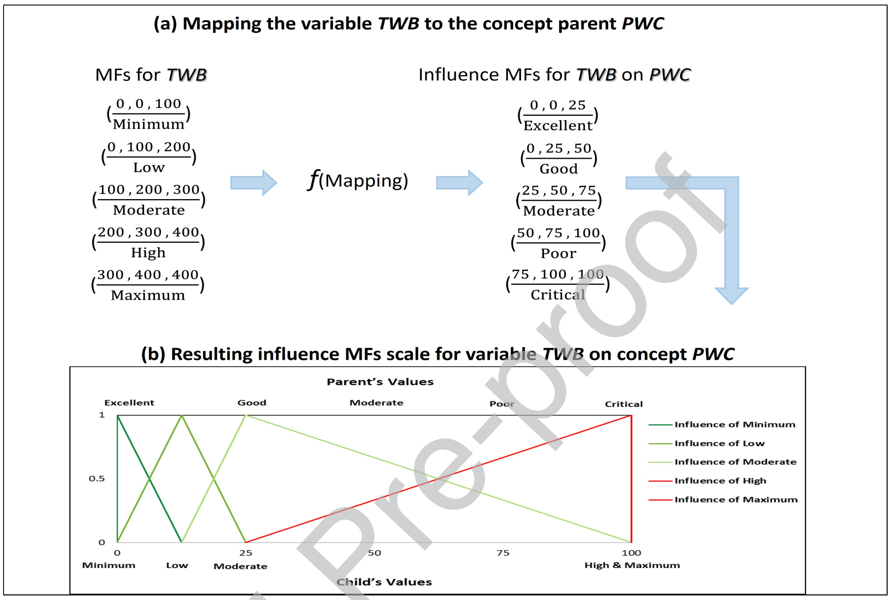

Figure 8: Disproportional mapping where non extreme values of TWB map to the best and worst of PWC. (a) illustrates mapping process. (b) shows resulting influence MFs.

Having established the individual fuzzy influences of each child on its parent, the next step determines all the different combinations of children values that can occur for a parent. Each combination will be a separate rule for the parent.

4.2.2. Step 2: Specify All Combinations of Sibling Variable Values

In our example, the variables TWB, $MWBpP$ and $NWBP$ have 5, 3 and 4 linguistic values, respectively. This means there will be 60 combinations of variable values that represents the entire relationship between the siblings, as shown in Figure 9. Each one is computer generated and will become a rule with its own certainty propagation, as explained next.

4.2.3. Step 3: Compute Variables' FRI

IFCADS employs the Fuzzy Analytic Hierarchy Process (FAHP) to calculate the FRI of variables and concepts needed to build the fuzzy rule-base of the system. The process is similar to the Analytic Hierarchy Process (AHP) introduced by Saaty (1980). However, the pairwise comparison matrix of variable relative importance is obtained in the form of linguistic values, which is next translated into TFNs according to a fuzzy

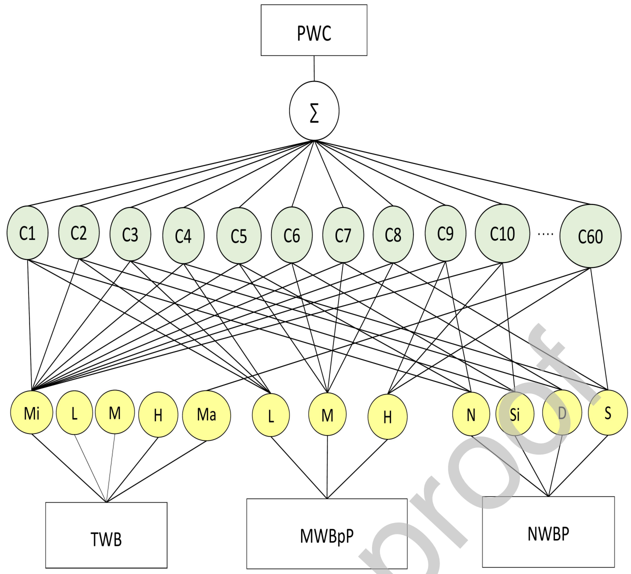

Figure 9: Variable combinations of the parent concept PWC. The yellow ovals are the linguistic values associated with each variable, and their acronyms shown are: $Mi = Minumum, L = Low, M = Moderate, H = High, Ma = Maximum, N = None, Si = Single, D = Double, and\ S = Several$. The green ovals are the summed influence of their particular combination of variable values on the parent concept.

comparison scale. Finally, the TFNs comparison ratios are normalised to produce FRIs across all the child variables/concepts of a parent.

Task 1: Determine the fuzzy comparison scale used to conduct the comparisons and specify the extent of the importance or domination of one variable/concept over another with respect to the parent concept. Many fuzzy comparison scales have been developed and used in solving decision support problems (Cebeci, 2009; Güngör et al., 2009; Cinar and Ahiska, 2010; Ablhamid et al., 2013; Kengpol et al., 2013; Taibi and Atmani, 2017), based on the original crisp (absolute) numbers scale introduced by Saaty (1980).

All fuzzy comparison scales mentioned above had the same TFNs for preference judgment except for the comparison of equality, where they either use a fuzzy singleton (1,1,1) with ($l = m = u$), or an imbalanced fuzzy value such as (1,1,2) or (1,1,3) with ($m - l \neq u - m$). In the latter case, the values are unbalanced because the TFN is stretched out in one direction only (u=2 or 3), which leads to an inconsistency in resulting FRIs for equal importance variables. Our innovation is to address this by keeping the middle value as one (m=1) and extending the fuzziness equally on both sides. We created a new fuzzy comparison scale for the TFN representing equality, TFN (1/3, 1, 3), as shown in Table 1. It is applied within the framework of IFCADS to compute the set of FRIs for variables and concepts. It improves the consistency of fuzzy propagation and is a novel contribution of our research to fuzzy AHP comparison algorithms.

Table 1: The fuzzy comparison scale used in IFCADS methodology.

Intensity of Importance	Definition
(1/3,1,3)	Equal Importance
(1,3,5)	Moderate Importance
(3,5,7)	Strong Importance
(5,7,9)	Very strong Importance
(7,9,9)	Extreme Importance

Task 2: Obtain the pairwise Fuzzy Relative Influences (FRIs). In our example using the parent concept PWC, to compute the FRI of its variables TWB, $MWBpP$ and $NWBP$, we first construct a square matrix where the rows and columns contain the same variables, TWB, $MWBpP$ and $NWBP$, in the same order. Then, for each row, the experts compare the importance of the variable in the row with respect to each variable in the columns for assessing the parent concept. For group preference, judgments can be aggregated using a weighted averaging method (e.g. establishing weights for experts based on their years of experience). The expert judgments are then translated into TFNs according to the fuzzy comparison scale (Table 1).

Only half of the comparison matrix is filled directly by the experts' judgments, while the other half is filled automatically by taking the reciprocal values of comparisons. For example, if comparing TWB to $NWBP$ was given a relative importance of (3,5,7), then comparing $NWBP$ to TWB has to be given a reversed order of relative importance, (1/7,1/5,1/3), because the inverse of the strongest value is the weakest. Our three example variables, require experts to answer three pairs of comparisons. Equation 1 determines the number of pairwise comparisons, NoC, needed for n variables. The fuzzy pairwise comparison matrix, M, of the variables is shown in Table 2.

$$NoC = \frac{n(n-1)}{2} \tag{1}$$

Table 2: Fuzzy pairwise comparison matrix for the variables TWB, MWBpP and NWBP

Variable	TWB	$MWBpP$	$NWBP$
TWB	(1,1,1)	(1,3,5)	(3,5,7)
$MWBpP$	(1/5,1/3,1)	(1,1,1)	(1/3,1,3)
$NWBP$	(1/7,1/5,1/3)	(1/3,1,3)	(1,1,1)

Csutora and Buckley (2001) proved that the fuzzy pairwise comparison matrix is considered consistent if the corresponding crisp pairwise comparison matrix is consistent. The crisp format of the fuzzy pairwise comparison matrix is constructed by considering the middle value of the TFN, and the consistency ratio is calculated based on Saaty (1980); it was found to be within the range of consistency for our method.

Task 3: Calculate the normalised FRI of variables. Normalising the fuzzy values takes into account the weights of all their siblings. This is done using the pairwise comparison matrix. Three slightly different methods have been evaluated: (a) Fuzzy Row

Means of Normalised Columns with Geometric Fuzzy Division Normalisation (FRM-GFD); (b) Fuzzy Row Means of Normalised Columns with Fuzzy Division Normalisation (FRM-FD); and (c) Fuzzy Geometric Row Means with Fuzzy Division Normalisation (FGRM-FD) (Chang and Lee, 1995).

First, the Mean Relative Fuzziness of the pair-wise comparison data, FuD, is calculated using Equation 2, where l_{ij}, m_{ij} and u_{ij} are the lower, middle and upper-bound of the pairwise comparison TFN.

$$FuD = \frac{1}{n^2} \sum_{i,j=1}^{n} \frac{u_{ij} - l_{ij}}{m_{ij}} \tag{2}$$

This FuD is then compared with the Mean Relative Fuzziness of normalised FRIs, $FuRI$, from the three different methods of generating the FRIs. The $FuRI$, are calculated using Equation 3, where l_i^{FRI}, m_i^{FRI}, u_i^{FRI} are the lower, middle and upper-bound of the FRIs TFN, respectively.

$$FuRI = \frac{1}{n} \sum_{i=1}^{n} \frac{u_i^{FRI} - l_i^{FRI}}{m_i^{FRI}} \tag{3}$$

The FuD is 1.202 and the $FuRI$ are 1.230, 2.710, and 2.498 for the three methods FRM-GFD, FRM-FD, and FGRM-FD, respectively. The FuD and $FuRI$ calculated using FRM-GFD are very close, which means this normalisation approach is best at preserving the fuzziness experts have in their judgments. Hence it was selected for normalising the pair-wise comparison data in IFCADS and Equations 4 and 5 show how it is calculated.

$$\begin{aligned} GF = (l_{ij}^{GF}, m_{ij}^{GF}, u_{ij}^{GF}) = \\ (\frac{l_{ij}}{(\sum_{i=1}^{n} l_{ij} \sum_{i=1}^{n} u_{ij})^{1/2}}, \frac{m_{ij}}{\sum_{i=1}^{n} m_{ij}}, \frac{u_{ij}}{(\sum_{i=1}^{n} l_{ij} \sum_{i=1}^{n} u_{ij})^{1/2}}) \end{aligned} \tag{4}$$

$$FRI_i = (l_i^{FRI}, m_i^{FRI}, u_i^{FRI}) = (\frac{\sum_{j=1}^{n} l_{ij}^{GF}}{n}, \frac{\sum_{j=1}^{n} m_{ij}^{GF}}{n}, \frac{\sum_{j=1}^{n} u_{ij}^{GF}}{n}) \tag{5}$$

where, GF is the matrix of normalised comparison ratios using geometric fuzzy division, and l_{ij}^{GF}, m_{ij}^{GF} and u_{ij}^{GF} are the lower, middle and upper-bound of normalised comparison ratios TFN, respectively.

Table 3: Normalised FRIs of the variables.

Variable	Normalised FRI
TWB	(0.406,0.655,0.890)
$MWBpP$	(0.126,0.187,0.406)
MWB	(0.099,0.158,0.329)
Total	(0.632,1.000,1.625)

Table 3 presents the computed normalised FRIs for the example concept PWC and the variables associated with it. These values can be shown to satisfy the fuzzy numbers normalisation condition (Chang and Lee, 1995; Sevastjanov et al., 2010). For triangular fuzzy numbers, let $l_i^*(\alpha)$ and $u_i^*(\alpha)$ represent the α-level set of the fuzzy number. Then, the set of FRIs is normalised if equations 6 and 7 are satisfied:

$$\sum_{i=1}^{n} l_i^*(\alpha) \sum_{i=1}^{n} u_i^*(\alpha) = 1, \forall\, \alpha \in [0, 1] \tag{6}$$

where $l_i^*(\alpha) = \frac{l_i(\alpha)}{\sum_{i=1}^{n} u_i(\alpha)}$ and $u_i^*(\alpha) = \frac{u_i(\alpha)}{\sum_{i=1}^{n} l_i(\alpha)}$, and

$$\sum_{i=1}^{n} m_i^* = 1 \quad for\ \alpha = 1 \tag{7}$$

where $m_i^* = \frac{m_i}{\sum_{i=1}^{n} m_i}$, and l_i, m_i, u_i are the lower, middle and upper-bound of normalised FRI, and n is the number of variables in equations (6 and 7).

To test the conditions, we take the FRIs for variables TWB, $MWBpP$ and $NWBP$ and calculate the set of $l_i(0.75)$ and $u_i(0.75)$ values, as shown in Figure 10. Applying Equations 6 and 7 demonstrates that the set of FRIs are normalised, as illustrated in Table 4.

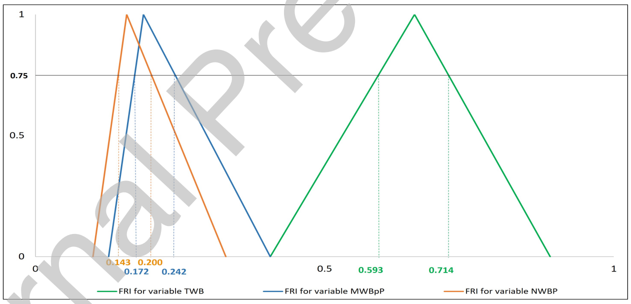

Figure 10: FRIs for variables TWB, $MWBpP$ and $NWBP$ and normalisation test at α=0.75.

Table 4: Test of normalisation for the FRIs.

FRI for	$l_i(0.75)$	$u_i(0.75)$	$l_i^*(0.75)$	$u_i^*(0.75)$	$\sum l_i^*(0.75) \times \sum u_i^*(0.75)$	m_i^*
TWB	0.593	0.714	0.513	0.787		0.655
$MWBpP$	0.172	0.242	0.149	0.267		0.187
$NWBP$	0.143	0.200	0.123	0.221		0.158
$\sum$	0.908	1.156	0.785	1.273	1.0	1.0

The fuzzy influences of the children on their parents are combined with the FRIs to establish the consequent part of the fuzzy rules associated with the parent and its children, as explained in the next step.

4.2.4. Step 4: Compute the Combined Influence of Each Combination of Variable Values

The aggregated influence for each combination of sibling variables and their values shown in Figure 9 is calculated using an aggregation operator. In this study, the aggregation strategy employed is the sum of products of the fuzzy values, where the FI (obtained in 4.2.1) and the FRI (obtained in 4.2.3) of each variable are multiplied and then summed to compute the combined fuzzy influence (CFI) of the variables' combination on the parent concept, represented as a TFN. This is implemented using Equation 8 as follows:

$$CFI_k = (l_k^{CFI}, m_k^{CFI}, u_k^{CFI}) = (\sum_{i=1}^{n} l_i^{FRI} l_i^{FI}, \sum_{i=1}^{n} m_i^{FRI} m_i^{FI}, \sum_{i=1}^{n} u_i^{FRI} u_i^{FI}) \quad (8)$$

where, CFI is the combined fuzzy influence of children on their parent concept, and l_{ij}^{CFI}, m_{ij}^{CFI} and u_{ij}^{CFI} are the lower, middle and upper-bound of the combined fuzzy influence TFN, respectively.

Consider the variables' combination in our example of the concept PWC, where $TWB = Minimum$, $MWBpP = High$ and $NWBP = Single$. Applying Equation 8 using arithmetic operations of fuzzy numbers, the $CFI = (l^{CFI}, m^{CFI}, u^{CFI}) = (12.954, 34.451, 95.765)$

In some cases we obtain a relaxed CFI that goes outside the range of the MFs scale of the concept PWC (refer to Step 5 in Figure 5 for an illustration, where the CFI is represented by a black-lined triangle). This is because the sum of the upper-bounds (u_i^{FRI}) of the normalised FRI of variables can be greater than 1. Our method does not adjust for this by changing the shape of the line, which would reduce the influence of the higher boundary on uncertainty. Instead, we keep the original combined value in the mapping process (next step). This ensures consistency of calculations and maintains untrimmed uncertainty information during processing. It is another distinction of our approach, with the same goal of maintaining consistent and complete uncertainty throughout the fuzzy processing.

4.2.5. Step 5: Determine the Linguistic Value of a Rule's Output

Determining the linguistic value of a rule's output is done by mapping the TFN of the CFI (obtained in 4.2.4) onto the fuzzy MFs scale of the concept, as shown in Figure 11 for the PWC concept. The linguistic values shown in the fuzzy MFs scale of the concept represent alternatives to the rule output and the MGs of their intersections could be interpreted as the degree of preference for alternatives. Accordingly, the resulting MGs of the intersections are ranked and the linguistic value with the highest MG of intersection is selected to be the output linguistic value of the rule, as shown in Equation 9.

$$\mu_k^{int-H} = max(\bigcup_{i=1}^{s} (\mu_k^{int})) \quad (9)$$

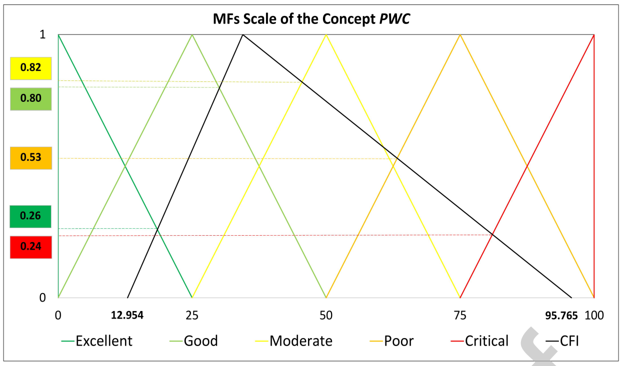

Figure 11: Mapping of CFI of variables on the PWC membership function scale. The resulting MGs of intersections are: 0.26/$Excellent$, 0.80/$Good$, 0.82/$Moderate$, 0.53/$Poor$ and 0.24/$Critical$, represent the degrees of influence of the variables combination on PWC.

where, μ_k^{int-H} is the highest MG of the intersections, μ_{ik}^{int}, between the MF of each linguistic value i of all s linguistic values and the combined fuzzy influence of a particular child combination of values, k.

The research explored an alternative criteria for selecting the output linguistic value of the rule, which was to evaluate the area of intersections with the fuzzy linguistic values rather than the single MG points of intersection. However, combining the MG intersections led to better model outcomes and is simpler.

Figure 11 provides a graphical interpretation of the combined influence for this combination of variables and values on their parent concept. The resulting output linguistic value is selected to be "$Moderate$" because it holds the highest MG intersection, μ^{int-H} = 0.82. The MG could also be interpreted as a degree of confidence in the selected linguistic value, and will be used as a rule weight. The mapping operation is carried out for all CFIs of the 60 variable combinations to generate the full set of fuzzy rules for the concept PWC.

4.2.6. Illustrative Summary of Fuzzy Rules Construction

Figure 5 summarises how expert knowledge is elicited and implemented in the full IFCADS fuzzy environment. First, the influence of every variable's value on the parent concept is generated as shown in Step 1 of the figure. For example, a Low number of wire breaks is indicated by L inside a light green oval shape in the figure and the variable TWB has an influence TFN as (0,25,50) on the parent concept PWC. In Step 2, all possible combinations of variables and values are formulated. Step 3 establishes the set of FRIs (fuzzy weights) for the variables.

The input from human experts is straightforward and scaleable for Steps 1 and 3. All other steps are executed computationally and need no further human involvement, which is a major advantage of IFCADS. Step 4 integrates the influences of each combination of values to generate a TFN for their joint influence by multiplying the variable's weights by their influence on the parent concept. The CFI for Rule 30, in the middle, is (10.147,47.370,129.289). The output TFN is then mapped on to the MFs scale of the parent concept linguistic variables and the MGs of their intersections are calculated, as shown by Step 5. The concept linguistic level associated with the highest MG intersection is selected as the linguistic value of the rule output, with the MG as the rule weight. For combination 30, this is "$Moderate$", weighted "0.983", which is the rule conclusion for the given set of input variable values as the conditions.

4.3. Phase 3: Fuzzy Inference Process

Phase 2 created the full fuzzy rule-based architecture. The next phase processes the input data by the rule hierarchy to produce output assessments. The first step is to convert variable values into fuzzy versions that can be input to the rules.

4.3.1. Step 1: Fuzzification of the Input Variables

The fuzzy hierarchy defined linguistic categories for the quantity levels of a variable, such as low, medium, high etc, which encompass the full range of values the variable can take. Step 1 uses these to generate the fuzzy MG associated with the variable's numerical value. The membership grade, μ_{ij}, of variable i associated with the linguistic value j is determined using Equation 10.

$$\mu_{ij} = max(min(\frac{x - l_{ij}^{LiV}}{m_{ij}^{LiV} - l_{ij}^{LiV}}, \frac{u_{ij}^{LiV} - x}{u_{ij}^{LiV} - m_{ij}^{LiV}}), 0) \tag{10}$$

where, l_{ij}^{LiV}, m_{ij}^{LiV} and u_{ij}^{LiV} are the lower-bound, middle and upper-bound of TFN of the variable's linguistic values, respectively.

Step 1 of the Figure 12 shows an example of how the real-world input values are converted into MGs having a value from 0 to 1. These MGs represent the variable's degree of support for one or more matching input variable's fuzzy linguistic categories. In the example presented, 280-wire breaks in the pipe generated 0.20 and 0.80 MGs for categories "$Moderate$" and "$High$", respectively. Each category (linguistic value) is represented by a triangular membership function.

4.3.2. Step 2: Rule Evaluation

Once the input data have been converted into the format required for the rules, Step 2 can evaluate the matched rules.

Task 1: The antecedent (condition) part of the rule is evaluated to determine its firing strength (activation degree) using the AND logical operator. The input to this operation is the membership grades for each membership function (obtained in 4.3.1) and the output is a single value representing the firing strength of the rule. The firing strength of the k^{th} rule, μ_k^{fs}, is calculated using the fuzzy intersection operation shown in Equation 11.

$$\mu_k^{fs} = \bigcap_{i=1}^{n} \mu_{ik} \tag{11}$$

Task 2: All fired rules in the rule set are weighted by multiplying their firing strength and the membership grade associated with their consequent linguistic value, μ_k^{int-H}, (rule weight obtained in 4.2.5). The weighted firing strength of the k^{th} rule, μ_k^{wt}, is calculated using the multiplication operation shown in Equation 12.

$$\mu_k^{wt} = \mu_k^{fs}(\cdot)\mu_k^{int-H} \tag{12}$$

Task 3: The output fuzzy set of the k^{th} rule, $F_k(y)$, is obtained by reshaping (truncating) the consequent membership function of the rule using the weighted firing strength. This operation is illustrated in Equation 13, where, μ_k^{QMF} is the consequent membership function of the rule k.

$$F_k(y) = \mu_k^{wt} \bigcap \mu_k^{QMF} \tag{13}$$

The rule evaluation process is illustrated in Step 2 of Figure 12, where the linguistice categories and their MGs are matched against the rule conditions and processed according to the rule inference algorithm. It can be seen that 4 rules are fired in this example. Consider Rule 32 on the left-side of the diagram: the conditions of the rule are matched with the input MGs and evaluated to give a firing strength of 0.2. This is multiplied by the rule weight, 0.918, producing a weighted firing strength of 0.184, which instantiates the output fuzzy set "$Moderate$" of the rule. The other fired rules are evaluated in the same way.

4.3.3. Step 3: Aggregation of Rules Outputs

All output fuzzy sets of the set of r rules are aggregated by using the fuzzy union operator. It generates a single fuzzy set, $F(y)$, for the output variable of the concept as illustrated in Equation 14.

$$F(y) = \bigcup_{k=1}^{r} F_k(y) \tag{14}$$

Step 3 of the Figure 12 shows how the output fuzzy sets of the fired rules are aggregated to get the fuzzy set of MG contributions to the parent concept, ($0/Excellent$, $0/Good$, $0.184/Moderate$, $0.703/Poor$, $0/Critical$). The concept PWC would thus be represented by two contiguous condition categories, "$Moderate$" and "$Poor$" with respective degrees of support of 0.184 and 0.703. The output fuzzy set of MGs would be passed up to the subsequent level as a fuzzy input value.

Starting with the first level of the hierarchy structure of the problem, these three steps of the fuzzy inference algorithm are applied for every concept in the level. Then, for subsequent levels, apply only (4.3.2) and (4.3.3), i.e. the output of the first level is passed to the second level as a fuzzy value so that fuzzification of the input variables (4.3.1) is no longer needed. The process continues until all levels of the hierarchy are evaluated and a fuzzy set of MGs representing the condition is obtained. In the final level, the output fuzzy set could be defuzzified into a single crisp value using an appropriate defuzzification method or it could be left fuzzy, depending on the application. A fuzzy version of the output might be helpful for additional explanation of the solution, especially for problems characterised by a subjective nature (which is invariably the case for expert-based systems). The next section applies the full method to the PCCP water-pipe domain for the MMRP.

5. Application of Integrated Fuzzy Methodology to PCCP Water Pipes

The £14 billion MMRP uses PCCP pipe sections of typically 7.5 metre lengths, with various diameters ranging from 1.6 to 4.0 metre (Figure 13). The project aims to extract and convey a total of 6 million cubic metres of high quality groundwater a day from deep aquifers in the Sahara Desert to the northern coastal strip. The total length of all project pipelines network is about 4,300 km, which represents 585,000 individual PCCP pipes. It also includes five open circular concrete reservoirs and ten tanks with total storage capacity of 56 million cubic metres (Essamin and Holley, 2004; Kuwairi, 2006).

This paper applies IFCADS to assessing these large buried PCCP water pipes. Predictions have been analysed and compared to actual outcomes as well as outcomes of alternative models in order to determine how well IFCADS can help explain and represent uncertainties inherent in the PCCP pipes domain.

- **Model-I (fully-fuzzified IFCADS)** is the main model proposed in this research work, where all model parameters are represented by fuzzy numbers in the computational processes and propagation of knowledge, as explained in Section 4.
- **Model-II (partially-fuzzified IFCADS)** is the same as Model-I except that it uses a defuzzified version of the FAHP relative importance of variables (An et al., 2011; Verma and Chaudhri, 2014) for rule construction.
- **Model-III** is based on Fares and Zayed (2010) approach, where parameters are represented by crisp values in the computational processes of rule construction. In the inference process, the output fuzzy set at each level is defuzzified into a single number and then propagated as a crisp value.
- **Model-IV** is the Pipe Risk Management System (PRMS) model used by the MMRP (Essamin et al., 2004, 2005). The PRMS was developed for the MMRP to estimate the level and rate of pipes deterioration using deterministic (structural) and statistical approaches. The system also incorporates a web-based GIS interface to access data and model results. The research work does not experiment with the model due to lack of details about methods used in its development: only the outcomes are used for comparison purposes.

Table 5 summarizes the main differences between Models I to III. Predictions of the models are compared with known outcomes obtained from the MMRP to determine how different types of uncertainty representation affect accuracy.

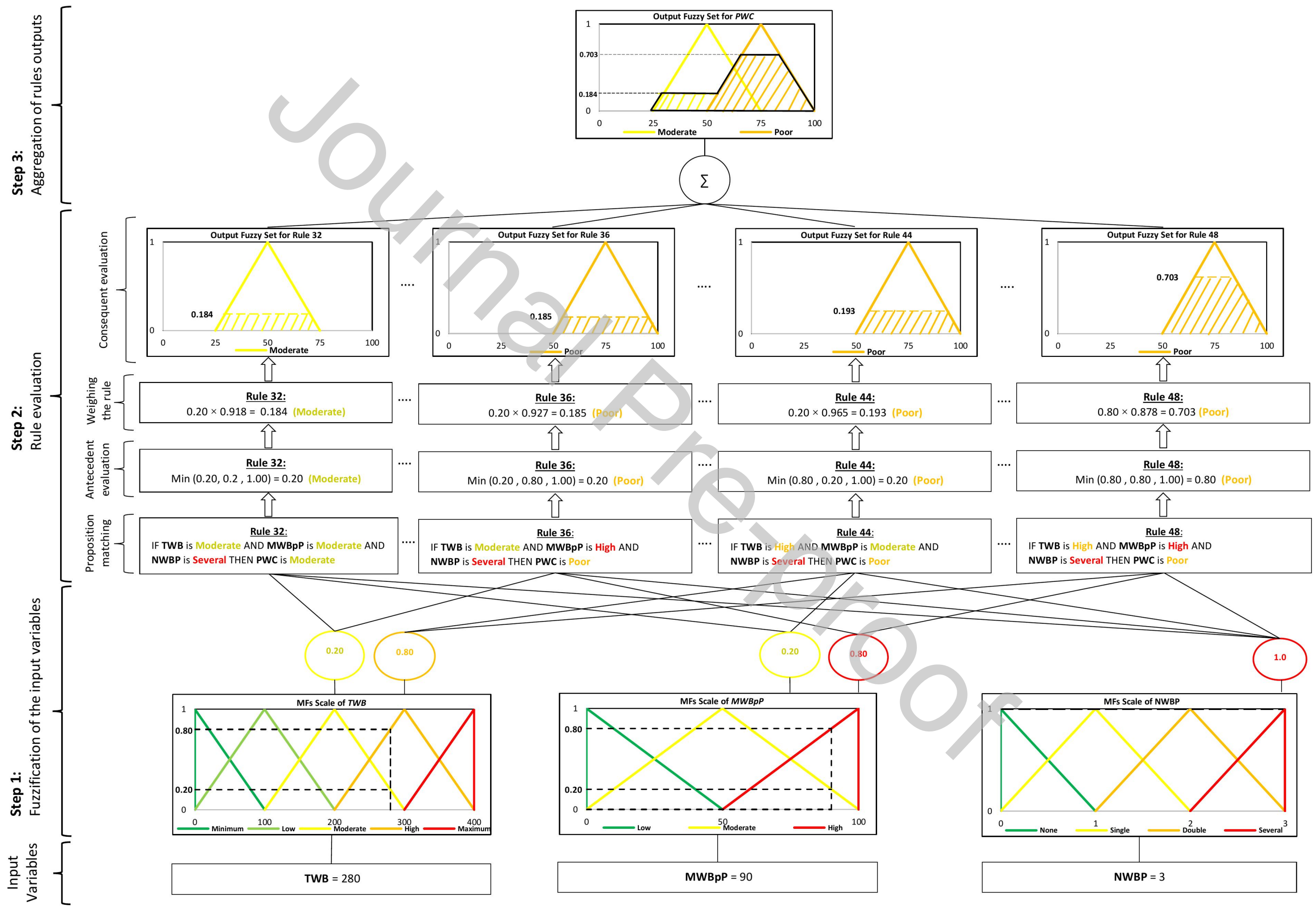

Figure 12: Illustration of how knowledge is processed using fuzzy inference to calculate the parent concept PWC. The values of input variables are shown in the rectangles next to the variable name, while the MGs produced during fuzzification process appear in the oval shapes.

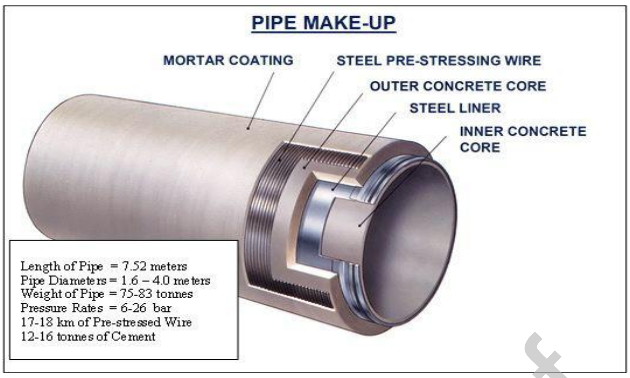

Figure 13: Cross section of the PCCP pipe.

Table 5: Differences between Model-I (IFCADS), Model-II and Model-III.

Element	Model-I and Model-II	Model-III
Variables relative importance	Represented as fuzzy numbers computed by FAHP	Represented as absolute numbers calculated by traditional AHP.
Variables influence	Represented as fuzzy numbers based on fuzzy influence MFs scale.	Expressed as absolute numbers based on crisp influence MFs scale.
Combining variables relative importance and influence	Model-I: Multiplues the fuzzy version of variables relative importance and their influence; Model-II: Multiplies the defuzzified crisp version of variables relative importance and their fuzzy influence.	Uses weighted average method to calculate the crisp value of the combined influence.
Determining rule consequent linguistic value	The resulting combined fuzzy influence is mapped onto the fuzzy MFs scale to determine the consequent linguistic value of the rule with its weight.	The resulting combined crisp influence is matched to a crisp scale to determine the rule consequent linguistic value. No weights are assigned to the rules.
Knowledge propagation during inference process	Model-I: The knowledge is propagated throughout the hierarchy in its fuzzy format. The output of the system is then obtained in a fuzzy format; Model-II: Same as Model-III	The knowledge at each level of the hierarchy is converted into a crisp value, and then propagated to the upper level as an absolute number. The final output of the system is then obtained in a crisp format.

5.1. PCCP Condition Variables and Model Tree Structure

Overall, 17 variables, including both direct distress data and inferential data, were selected to model the PCCP water pipe condition assessment. The output of the model is the "Recommended Action" required for rehabilitation. It is either "No Action Required", "Inspection/Monitoring", "Repair" or "Replace". The selected variables were organized into concepts based on their potential influence on condition and deterioration of the pipes as shown by Figure 14.

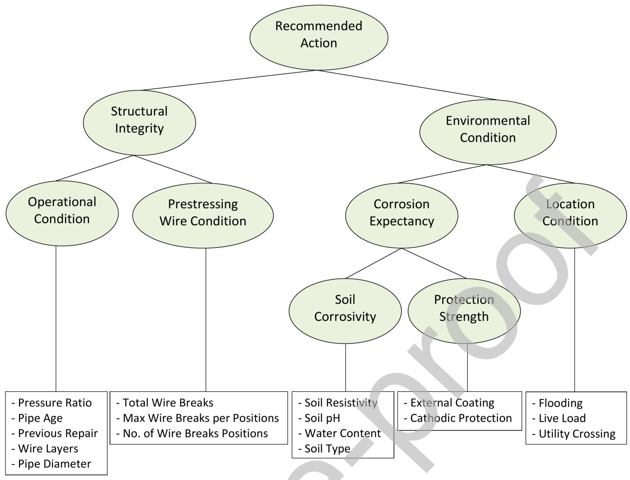

Figure 14: The hierarchical structure of the PCCP condition assessment. The rectangles at the bottom show basic input variables connected to their parent concepts, shown in light-green ovals. The top dark-green oval represents the model output.

5.2. Implementation and Results

Real-world sample data of one-hundred PCCP pipes collected from the MMRP were made available for testing the models. Software developed with the Visual Basic for Applications (VBA) programming language implemented the knowledge base development and inference process for the models.

The final output of each model is a rehabilitation prescription suggested for the pipe that explains the required action and the level of priority/urgency of that action. The "Recommended Action" is the category, or fuzzy subset, in the final fuzzy set of the inference that has the highest MG of support. The level of priority or urgency is based on the following criteria:

(a) Priority "Low". if the selected recommended action category has one or more lower level contiguous categories;

(b) Priority "Medium". if the selected recommended action category has any contiguous category, or lies between two categories;

(c) Priority "High". if the selected recommended action category has one or more higher level contiguous categories.

Figure 15 illustres how the priority level is determined for the selected "Recommended Action" category based on these criteria.

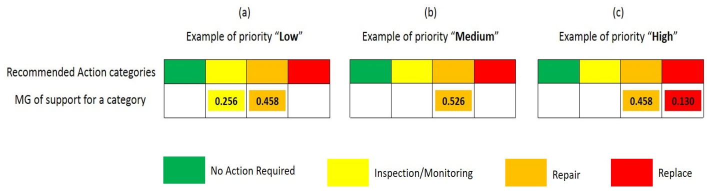

Figure 15: Examples of how priority level is assigned to the "Recommended Action".

Figure 16 compares outcomes and recommendations of the developed models. It shows the IFCADS model (Model-I) to have perfectly predicted 85 of the outcomes. This was higher than any other model: 68 for Model-II, 62 for Model-III and 37 for Model-IV. IFCADS also yielded the lowest number of false negatives, 5, compared to the others: 28 for Model-II, 36 for Model-III and 21 for Model-IV. False negatives are critical because they mean the model is underestimating the poor quality of pipes. An estimated pipe action of "Inspection/Monitoring" when it is really "Repair" or "Replace" could lead to a sudden failure of the pipe with the serious consequences described earlier. False positive outcomes have less effect because overestimating poor condition, such as "Repair" or "Replace", simply leads to the cost of an extra inspection and excavation.

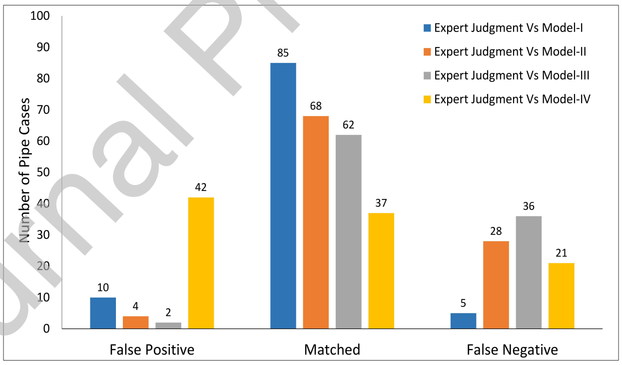

Figure 16: False positive and false negative analysis of results.

Figure 17 provides a clear illustration of how fuzzy parameter representation influences the accuracy of pipe condition predictions, particularly demonstrating the superiority of IFCADS (Model I) in minimising false negatives. The figure is useful as it provides a comparative analysis of different models, highlighting IFCADS' ability to enhance predictive reliability while preserving expert knowledge during processing. By illustrating the relationship between fuzziness and accuracy, the figure offers valuable insights into how varying degrees of fuzziness influence model performance, making it a practical reference for decision-makers in infrastructure management.

A key contribution of Figure 17 is its explicit depiction of the trade-off between fuzziness and precision. Traditional models often assume that increased fuzziness leads to greater uncertainty, but the figure demonstrates that an optimal level of fuzziness enhances predictive accuracy by capturing expert reasoning more effectively. Additionally, the figure demonstrates that IFCADS avoids premature defuzzification, ensuring that uncertainty is carried through the inference process rather than lost at intermediate stages. These findings suggest that the approach could be generalised to other domains, such as medical diagnostics or financial forecasting, where expert-driven assessments are critical.

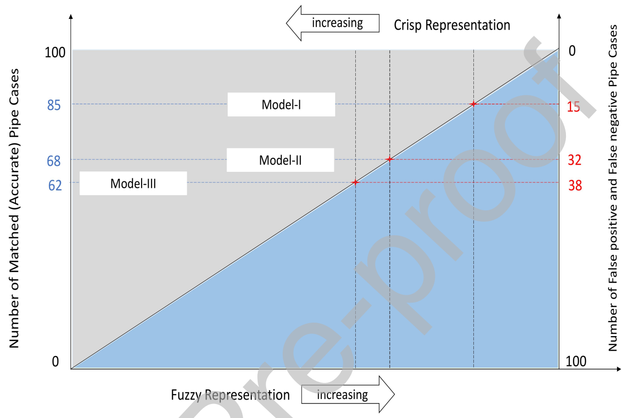

Figure 17: Relationship between fuzziness of parameter representation and accuracy of results.

6. Conclusion

The IFCADS methodology presented in this paper applies a new hierarchical fuzzy rule-based approach for condition assessment and decision support in representing and processing human expertise. It elicits human expertise using simple activities that are scalable for high-dimensional complex knowledge domains. The resulting system enables more precise risk management actions and has been successfully applied to the real-world problem of predicting the condition of large-sized buried PCCP water pipes. The dataset was obtained from the Libyan Man-Made River Project (MMRP). Analysis of the results demonstrated the ability of IFCADS to exploit human expertise and improve automated decision making.

More specifically, the significance and contributions of the IFCADS methodology can be summarised as follows:

1. Applying a simple and intuitive elicitation method for:
   (a) transforming input variables into fuzzy linguistic equivalents;
   (b) generating scales of fuzzy linguistic values for concept memberships within the knowledge hierarchy;

(c) mapping from child linguistic values into their individual fuzzy influence on membership of the parent concept;
(d) and determining the relative importance or weights of each child node using FAHP so that the combined influence of children on parent membership can be calculated.

2. Automating generation of rules based on the elicited conceptual hierarchy and fuzzy scales already given, meaning rule complexity is independent of the expert and modelling high-dimensional hierarchies is tractable.
3. Improving the representation of fuzzy equalities, so that the triangular fuzzy value extends equally on both sides from the crisp mid-point, which is not the case for existing fuzzy systems.
4. Maintaining the integrity of uncertainty information (fuzziness) throughout the rule construction and inference process even when the upper fuzzy triangular extension goes beyond the concept value range.
5. Processing fuzziness throughout the rule inference system without any interim defuzzification.
6. Introducing a new hierarchical model of PCCP pipe knowledge based on rigorous categorisation of data that affect the condition and deterioration process of pipes.
7. Showing that a fuzzy version of the relative influence of child nodes compared to their siblings leads to more natural representation of data and better model performance than a defuzzified crisp version.
8. Improving explanations of outputs to help decision makers analyse and understand their problems.
9. Demonstrating a method that has the flexibility and tractability to be applied in many different knowledge-rich and high-dimenstional domains of human expertise.

The IFCADS condition assessment model predicts the current condition of an entity with recommendations for the types of treatments required and their priority. Expanding the work by integrating time-to-failure predictions will improve the output of the model both for when to intervene and how. This involves modelling the deterioration process over time, which might be appropriate for a Markov chain (Sharabah et al., 2006; Tran et al., 2010; Setunge and Hasan, 2011; Edirisinghe et al., 2015; Liang and Parlikad, 2015) where the current condition state, estimated by the existing IFCADS model, flows to the new condition state at the next timepoint, with its associated IFCADS configuration. It would enable IFCADS to look ahead and plan accordingly, based on the current advice and the advice it would give if that predicted state did, indeed, arise.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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