Extending Adaptive Interpolation: From Triangular to Trapezoidal

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Abstract

Fuzzy interpolative reasoning strengthens the power of fuzzy inference by enhancing the robustness of fuzzy systems and reducing systems complexity. However, during the interpolation process, it is possible that multiple object values for a common variable are inferred which may lead to inconsistency in interpolated results. A novel approach [10] was recently proposed for identification and correction of defective rules in the transformations computed for interpolation, thereby removing the inconsistencies. However, the implementation of this work is limited to rule models involving triangular fuzzy variables. This paper extends the adaptive approach as presented in [10], by introducing trapezoidal variables in the representation and manipulation of fuzzy rule models. This significantly improves the applicability of adaptive fuzzy interpolation reasoning, as many fuzzy systems are modelled with trapezoidal (as well as triangular) variables.

1 Introduction

Fuzzy rule interpolation significantly enhances the robustness of fuzzy reasoning. When given observations have no overlap with any antecedent values, no rule can be fired in classical inference. However, interpolative reasoning through a sparse rule base may still obtain certain conclusions and thus improve the applicability of fuzzy models. Also, with the help of fuzzy interpolation, the complexity of a rule base can be reduced by omitting those fuzzy rules which may be approximated from their neighboring rules. A number of important interpolating approaches have been presented in the literature, including [1, 2, 3, 6, 7, 8, 9]. In particular, the scale and move transformation-based approach can handle both interpolation and extrapolation which involve multiple fuzzy rules, with each rule consisting of multiple antecedents. This approach also guarantees the uniqueness as well as normality and convexity of the resulting interpolated fuzzy sets. However, it is possible that more than one object value of a single variable may be derived or observed in fuzzy interpolation. This implies that certain inconsistencies may result.

To address the aforementioned problem, recently, adaptive interpolative reasoning has been proposed [10]. This approach is capable of efficiently detecting inconsistencies, locating possible fault candidates and modifying the candidates in an effort to remove all the inconsistencies. It works by artificially viewing the interpolative inference procedures as system components, and then utilising assumption-based truth maintenance system (ATMS) [4] to record the dependencies between an interpolated value as well as contradictions and its proceeding interpolation components. From this, the classical algorithm of general diagnostic engine (GDE) [5] is employed to manipulate these sets of dependent components of contradictions to generate all possible defective rules.

However, the adaptive approach of [10] is limited in its implementation in that fuzzy models are assumed to involve only triangular fuzzy variables. Nevertheless, fundamentally, this is not restricted by the underlying approach. Having identified this fact, the work of [10] is herein extended to allow the use of fuzzy variables which are represented by trapezoidal membership functions. This will considerably widen the scope of the existing approach for adaptive fuzzy interpolation because in many practical applications of fuzzy systems, variables are typically not only represented in triangular membership functions but also in trapezoidal.

The rest of this paper is structured as follows. Section 2 reviews the mechanism of adaptive interpolative reasoning. Section 3 describes the extension of generalizing the previously pro-
posed adaptive approach to covering interpolations involving trapezoidal membership functions. Section 4 gives an example to illustrate the utility of this work. Section 5 concludes the paper and points out important future research.

2 Adaptive Interpolative Reasoning

Adaptive interpolative reasoning [10] provides a way to ensure inference results being consistent during the fuzzy interpolative process. Given a certain fuzzy contradiction metric, a \( \beta_0\)-contradiction is a contradiction whose corresponding degree \( \beta > \beta_0 \) for a predefined threshold \( \beta_0 \) (0 \( \leq \beta_0 \leq 1 \)). With the help of this concept, the adaptive approach can be summarized in Figure 1. Firstly, an interpolative reasoning tool performs inferences on a task and passes the inferred results over each step of interpolation to the ATMS for dependency-recording. Then, the ATMS relays any \( \beta_0 \)-contradictions as well as their dependent fuzzy reasoning components to the GDE which diagnoses the problem and generates all possible component candidates. After that, a modification process takes place to correct a certain candidate to restore consistency. A brief description of each of these key methods is given below.

\[
\begin{align*}
A & \Rightarrow \beta_0 \bot, \\
A' & \Rightarrow \beta_0 \bot.
\end{align*}
\]

A label is a set of environments each supporting the associated node. An environment contains a minimal set of fuzzy reasoning components that jointly entail the concerned node, thereby describing how the node ultimately depends on those fuzzy reasoning components. An environment is said to be \( \beta_0 \)-inconsistent if \( \beta_0 \)-contradiction is derivable propositionally by the environment and a given justification. An environment is said to be \( (1 - \beta_0) \)-consistent if it is not \( \beta_0 \)-inconsistent.

The label of each node is guaranteed to be \( (1 - \beta_0) \)-consistent, sound, minimal and complete by the label updating algorithm, except that the label of the special “false” node is guaranteed to be \( \beta_0 \)-inconsistent rather than \( (1 - \beta_0) \)-consistent. In particular, the label of the special “false” node gathers all \( \beta_0 \)-inconsistent environments. Its corresponding label-updating process is given as follows. Whenever a \( \beta_0 \)-contradiction is detected, each environment in its label is added into the label of “false” node and all such environments and their supersets are removed from the label of every other node. Also, any such environment which is a superset of another is removed from the label of the node “false”.

2.2 Candidate generation

GDE [5] generates minimal candidates by manipulating the label of the specific “false” node. A candidate is a particular set of assumptions which may be responsible for the whole set of current contradictions. Because a \( \beta_0 \)-inconsistent environment indicates that at least one of its assumption is faulty, a candidate must have a nonempty intersection with each \( \beta_0 \)-inconsistent environment. Thus, each candidate is constructed by taking one assumption from each environment in the label of “false” node. Supersets removal then ensures such generated candidates to be minimal. In light of this, a successful correction of any single candidate will remove all the contradictions (see later).

2.3 Candidate modification

Consistency can be restored by successfully correcting any single candidate because each single candidate explains the entire set of current contradictions. Given a set of candidates, the modification procedure is shown in Figure 2. For convenience, in the rest of this paper, \( A_{ij}' \) is used to denote the modified consequence of a culprit interpolated rule whose consequent value is \( A_{ij} \), and \( A_{ij}'' \) and \( A_{ij}''' \) are used to denote the corresponding modified intermediate rule consequence and the relative placement factor of \( A_{ij}'' \), respectively. Suppose that the neighboring rules \( A_{11} \Rightarrow A_{21} \) and \( A_{1n} \Rightarrow A_{2n} \) are the two base rules used by a defective fuzzy reasoning component, that \( A_{12}, A_{13}, \ldots, A_{1(n-1)} \) are observations or previously interpolated results located in between \( A_{11} \) and \( A_{1n} \), and that \( A_{1j} \) (2 \( \leq j \leq n - 1 \))
CONSISTENCY\textsc{Restoring}(Q)

Q, the candidate set in a FIFO descending queue in cardinality, each element of which is a set of fuzzy reasoning components (f);
MODIFY(f), the modification procedure for single fuzzy reasoning component (f). Return \texttt{true}
when modification succeeds and return \texttt{false}
otherwise.

1. \(\text{success} \leftarrow \text{false}\)
2. \(\text{do}\)
3. \(\text{C} \leftarrow \text{Dequeue}(Q)\)
4. \(\text{foreach } f \in \text{C} \text{ do}\)
5. \(\text{success} \leftarrow \text{MODIFY}(f)\)
6. \(\text{if } (\text{success} == \text{false})\) \(\text{break}\)
7. \(\text{until } ((\text{success} == \text{true}) \text{ or } (Q == \text{\varnothing}))\)
8. \(\text{return } \text{success}\).

Figure 2: The \textsc{Consistency\textsc{Restoring}} procedure is the middle most one. The modification procedure for single fuzzy reasoning component is summarized as follows.

\textbf{1.} Find out the rule \((A_{ij} \Rightarrow A_{2j})\) whose antecedent locates in the middle most of the neighborhood of the antecedents of the two base rules with respect to their representative values. Assume that the relative placement factor of its consequence \(\lambda_{i2}\) is modified to \(\lambda_{i2}'\).

\textbf{2.} Calculate the correction rate pair according to the relative placement factor modification of rule \(A_{1j} \Rightarrow A_{2j}\): \[
\begin{align*}
    c^- &= \frac{\lambda_{i2}'}{\lambda_{i2}}, \\
    c^+ &= \frac{1 - \lambda_{i2}'}{1 - \lambda_{i2}}.
\end{align*}
\]

\textbf{3.} Calculate the modified relative placement factors of consequences of all other interpolated rules which are generated based on the same defective interpolative reasoning component as per the correction rate pair computed above, where \(i \in \{2, 3, ..., j-1\}\) and \(k \in \{j+1, j+2, ..., n-1\}\):
\[
\begin{align*}
    \lambda_{i2}' &= \lambda_{i2} \cdot c^- \\
    1 - \lambda_{i2}' &= (1 - \lambda_{i2}) \cdot c^+.
\end{align*}
\]

\textbf{4.} Calculate the modified consequences of all interpolated rules which are generated based on the same defective interpolative reasoning component as per their modified relative placement factors:
\[
\begin{align*}
    A'_{ij} &= (1 - \lambda_{i2}') A_{2j} + \lambda_{i2}' A_{22} \\
    T(A'_{ij}, A_{1j}) &= T(A'_{ij}, A_{12}).
\end{align*}
\]

\textbf{5.} Restrict the modified consequence to be consistent with the context. Suppose that \(m\) object values \(A_{11}, A_{12}, ..., A_{1m}\) are obtained for variable \(x_i\). If they are \((1 - \beta_0)\)-consistent, they must satisfy:
\[
\bigcap_{j=1}^{m} (A_{ij})_{\beta_0} \neq \varnothing,
\]

where \((A_{ij})_{\beta_0}\) denotes the \(\beta_0\)-cut of \(A_{ij}\).

\textbf{6.} Restrict the propagation of the modified consequence to be consistent with the context. For simplicity, let function \(I(A_{ij}, R_i R_j) = A_{kij}\) denote the standard interpolation from the antecedent fuzzy set \(A_{ij}\) to the consequent value \(A_{kij}\), based on the fuzzy reasoning component involving the neighboring rules \(R_i\) and \(R_j\). Suppose that \(m\) object values \(A_{11}, A_{12}, ..., A_{1m}\) of variable \(x_i\) are modified which are located between the antecedent values of rules \(R_i\) and \(R_j\), that the corresponding modified object values of variable \(x_k\) are \(A_{kij}\) \(j \in \{1, 2, ..., m\}\), and that \(n\) object values \(A_{kl}\) \(l \in \{1, 2, ..., n\}\), of variable \(x_k\) are already obtained one way or another. If the modified consequences \(A_{kij}\) are all \((1 - \beta_0)\)-consistent, then they must satisfy:
\[
\left\{ \bigcap_{j=1}^{m} (A_{kij})_{\beta_0} \right\} \bigcap \left\{ \bigcap_{l=1}^{n} (A_{kl})_{\beta_0} \right\} \neq \varnothing.
\]

\textbf{7.} Solve all these simultaneous equations generated above. The result is the modified solution which ensures inconsistency-free.

\section{The Extension}

It is potentially very useful to extend this adaptive approach to apply to fuzzy variables with trapezoidal fuzzy membership functions. This is because trapezoidal membership functions are also practically popular to model fuzzy systems apart from triangular. The extension is relatively straightforward due to the generality of ATMS, GDE, and the scale and move transformation-based interpolation, but there are still issues that require clarification, especially in the implementation of the approach. These points are discussed as follows.

\subsection{Representative value and relative placement factor}

The representative value captures the overall location of the fuzzy set. Consider a trapezoidal fuzzy set \(A_{ij}\), denoted as \((p_{0(ij)}, p_{1(ij)}, p_{2(ij)}, p_{3(ij)})\), where \(p_{0(ij)}\) and \(p_{3(ij)}\) are the left and right coordinates of the start and end points of its support \((\forall x \in (p_{0(ij)}, p_{3(ij)}), \mu_{A_{ij}}(x) > 0)\) while \(p_{1(ij)}\) and \(p_{2(ij)}\) are the coordinates of the start and end points of its normal range \((\forall x \in (p_{1(ij)}, p_{2(ij)}), \mu_{A_{ij}}(x) = 1)\). The left support, right support and top support of \(A_{ij}\) are defined as \(p_{1(ij)} - p_{0(ij)}, p_{3(ij)} - p_{2(ij)}, p_{2(ij)} - p_{1(ij)}\) respectively. Note that this generic trapezoidal representation covers triangular fuzzy sets as its specific case, where \(p_{1(ij)} = p_{2(ij)}\). Different definitions for representative values may be applied to meet different realistic requirements [6]. In order to be
compatible with triangular representation situation, the representative value of a trapezoidal fuzzy set is defined as follows:
\[ \text{Rep}(A_{ij}) = \frac{1}{3} (p_{0(ij)} + \frac{p_{1(ij)} + p_{2(ij)}}{2} + p_{4(ij)}). \] (8)

The relative placement factor reflects the relative location of the interpolated rule compared to its neighboring rules, which is calculated from the representative values of the relevant fuzzy sets. The relative placement factor \( \lambda_{ij} \) of the antecedent (or consequence) \( A_{ij} \) of an interpolated rule, with respect to its two neighboring rule antecedents (or consequences) \( A_{im} \) and \( A_{in} \), is defined as the ratio of \( d(A_{im}, A_{ij}) \) to \( d(A_{im}, A_{in}) \):
\[ \lambda_{ij} = \frac{d(A_{im}, A_{ij})}{d(A_{im}, A_{in})} = \frac{\text{Rep}(A_{im}), \text{Rep}(A_{ij}))}{\text{Rep}(A_{im}), \text{Rep}(A_{in}))} \] (9)

where \( d(A_{ix}, A_{iy}) \) is the distance between fuzzy sets \( A_{ix} \) and \( A_{iy} \) (for a given distance metric).

3.2 Interpolation with trapezoidal fuzzy variables

Let \( x_i, i \in \{1, 2, ..., n\} \), be a variable and \( A_{11}, A_{12}, ..., A_{im} \) be the fuzzy sets in the domain of \( x_i \). If \( A_{11} \Rightarrow A_{21} \) and \( A_{12} \Rightarrow A_{22} \) are two adjacent fuzzy rules in a sparse rule base, given an observed object value \( A_{13} \) of variable \( x_i \), which does not match any existing rule and which is located between fuzzy sets \( A_{11} \) and \( A_{12} \), the object value \( A_{23} \) of variable \( x_2 \) can be derived through fuzzy interpolative reasoning. The procedure of calculating \( A_{23} \) is summarized as follows:

1. Calculate the antecedent value of the intermediate rule \( A_{13}' = (p_{0(13)'}, p_{1(13)'}, p_{2(13)'}, p_{3(13)'}) \) which has the same representative value as the observation \( A_{13} \). For this, the relative placement factor \( \lambda_{13} \) of the observation \( A_{13} \) is calculated first according to (9) with respect to its flanks \( A_{11} \) and \( A_{12} \). Then:
\[ 
\begin{align*}
    p_{0(13)'} &= (1 - \lambda_{13})p_{0(11)} + \lambda_{13}p_{0(12)} \\
    p_{1(13)'} &= (1 - \lambda_{13})p_{1(11)} + \lambda_{13}p_{1(12)} \\
    p_{2(13)'} &= (1 - \lambda_{13})p_{2(11)} + \lambda_{13}p_{2(12)} \\
    p_{3(13)'} &= (1 - \lambda_{13})p_{3(11)} + \lambda_{13}p_{3(12)} \\
\end{align*} \] (10)
which are collectively abbreviated to:
\[ A_{13}' = (1 - \lambda_{13})A_{11} + \lambda_{13}A_{12}. \] (11)

2. Calculate the consequence of the intermediate rule \( A_{23}' \) by analogy to the calculation of \( A_{13}' \) except letting the relative placement factor \( \lambda_{23} \) of the conclusion \( A_{23} \) be equal to \( \lambda_{13} \):
\[ \lambda_{23} = \lambda_{13}. \] (12)

Then,
\[ A_{23}' = (1 - \lambda_{23})A_{21} + \lambda_{23}A_{22}. \] (13)

By the first two steps, the intermediate inference rule \( A_{13}' \Rightarrow A_{23}' \) is constructed.

3. Calculate the similarity degree between \( A_{13}' \) and \( A_{13} \) through two steps of transformation. Let \( A_{13}'' = (p_{0(13)''}, p_{1(13)''}, p_{2(13)''}, p_{3(13)''}) \) denote the fuzzy set generated by scale transformation. This transformation transforms the current bottom support \( (p_{0(13)'}, p_{1(13)''}) \) into a new bottom support \( (p_{0(13)''}, p_{1(13)''}) \), and the top support \( (p_{2(13)'}, p_{3(13)''}) \) into a new top support \( (p_{2(13)''}, p_{3(13)''}) \) while keeping the representative value and the ratio of left-support \( (p_{0(13)'}, p_{1(13)''}) \) to right-support \( (p_{2(13)''}, p_{3(13)''}) \) of the transformed fuzzy set \( A_{13}'' \) the same as those of its original. This transformation is measured by scale rates \( s_8 \) and \( s_1 \), and scale ratio \( S \) which are calculated by:
\[ S_8 = \frac{p_{3(13)''} - p_{1(13)''}}{p_{3(13)''} - p_{2(13)''}}, \quad S_1 = \frac{p_{3(13)''} - p_{1(13)''}}{p_{3(13)} - p_{1(13)''}}, \] (14)

\[ (if \frac{p_{2(13)''} - p_{1(13)''}}{p_{3(13)''} - p_{1(13)''}} \geq 0, \quad S_1 = \frac{p_{3(13)''} - p_{1(13)''}}{p_{3(13)''} - p_{1(13)''}}, \] (15)

\[ (otherwise). \] (otherwise).

Move transformation shifts the current bottom support from \( (p_{0(13)'}, p_{1(13)''}) \) to \( (p_{0(13)}, p_{3(13)''}) \), and top support from \( (p_{2(13)'}, p_{3(13)''}) \) to \( (p_{2(13)}, p_{3(13)''}) \) while keeping the same representative value, that is, transforming fuzzy set \( A_{13}'' \) to fuzzy set \( A_{13} \). The move ratio \( M \) measures this transformation which is calculated by:
\[ M = \frac{p_{3(13)''} - p_{2(13)''}}{p_{3(13)} - p_{2(13)''}}, \] (16)

\[ otherwise. \] (otherwise).

4. Transform \( A_{23}' \) to \( A_{23} \) with the same transformation function \( T \) as used for transforming \( A_{13}' \) to \( A_{13} \): \( T(A_{23}', A_{23}) = T(A_{13}', A_{13}) \). (17)

3.3 Candidate modification with trapezoidal fuzzy variables

The solution of defective fuzzy reasoning component modification results from solving a group of simultaneous equations which are linear for triangular representations. However, the complexity of this group of equations is raised to quadratic when using trapezoidal fuzzy sets. The reason for this is the introduction of scale ratio \( S \) (15). Following the description in last subsection, and taking a similar approach to the triangular representation situation, the scale rate \( s_6 \) between the intermediate consequence \( A_{23}' \) and the transformed consequence \( A_{23} \) is set to that between its intermediate antecedent \( A_{13}' \) and its transformed antecedent \( A_{13}'' \), but unlike triangular representation case, the scale
rate $s'_i$ between $A_{23}'$ and $A_{23}''$ is calculated under the condition that the scale ratio $S$ between $A_{23}$ and $A_{23}''$ is set to that between $A_{13}'$ and $A_{13}''$. This is followed by:

$$
\begin{align*}
    s'_0 &= s_0, \\
    s'_i &= \frac{\sqrt{i\pi (x_i - s_0)}}{\sqrt{i\pi (x_i - s_0) + 1}} + s'_0, \quad (s_i \geq s_0) \\
    s'_i &= \sqrt{\frac{4}{s_0}} s_0, \quad (s_i \geq s_0).
\end{align*}
$$

(18)

It is clear that the above equation is quadratic. Although higher computational complexity is incurred, this extension is worthwhile due to the allowance of utilizing the practically popular trapezoidal fuzzy variables.

4. An Illustrative Example

To illustrate the potential of this extended adaptive interpolative reasoning method, the problem given in [10] is reconsidered such that the original triangular fuzzy variables are replaced with trapezoidal fuzzy sets. The rule base is given as follows:

$$
\begin{align*}
    &R_1: (x_1 = A_{13}) \Rightarrow (x_2 = A_{21}); &R_2: (x_1 = A_{12}) \Rightarrow (x_2 = A_{22}); &R_3: (x_2 = A_{23}) \Rightarrow (x_3 = A_{31}); &R_4: (x_2 = A_{24}) \Rightarrow (x_3 = A_{32}); \\
    &R_5: (x_3 = A_{33}) \Rightarrow (x_5 = A_{51}); &R_6: (x_3 = A_{34}) \Rightarrow (x_5 = A_{52}); &R_7: (x_4 = A_{43}) \Rightarrow (x_5 = A_{53}); &R_{10}: (x_4 = A_{44}) \Rightarrow (x_5 = A_{54}).
\end{align*}
$$

4.1 Dependency recording by ATMS

In Figure 3, an arrow line flanked by two rules $R_i$ and $R_j$ represents a fuzzy reasoning compo-

4.2 Candidate generation by GDE

Two minimal candidates can be generated according to the “false” node of the ATMS and its labeling $\{R_1, R_2, R_3, R_4\}, \{R_1, R_2, R_3, R_6\}$: $C_1 = [R_1, R_2], C_2 = [R_3, R_4, R_6]$, $C_3 = [R_1, R_2, R_3, R_4, R_6]$. Two rules have been interpolated based on this fuzzy reasoning component, both of which need to be modified: $R_{11}: (x_1 = A_{14}) \Rightarrow (x_2 = A_{27})$; $R_{12}: (x_1 = A_{14}) \Rightarrow (x_2 = A_{28})$.

Following the modification procedure of single fuzzy reasoning component outlined in Section 2.3, the following simultaneous equation group can be set:

$$
\begin{align*}
    &c' = \frac{e_2}{e_3}; \\
    &\lambda^{27} \cdot e' = \frac{1 - \lambda^{28}}{\lambda^{28}} \cdot e = \frac{1 - \lambda^{27}}{\lambda^{27}} \cdot e; \\
    &\lambda^{27} = (1 - \lambda^{28}) \lambda^{27} + \lambda^{28} A_{14}; \\
    &A_{14}^\alpha = (1 - \lambda^{27}) A_{14} + \lambda^{27} A_{28}; \\
    &T(A_{13}, A_{14}) = T(A_{47}, A_{42}) = T(A_{47}, A_{48}); \\
    &T(A_{47}, A_{42}) = T(T(A_{47}, A_{42}), (A_{45}^\alpha)_{\eta} \cap (A_{45}^\alpha)_{\eta} \neq \emptyset; \\
    &A_{47} = I(A_{37}, R_3 R_4); \\
    &A_{45} = I(A_{28}, R_3 R_4); \\
    &A_{42} = I(A_{28}, R_3 R_4); \\
    &A_{42} = I(A_{28}, R_3 R_4); \\
    &A_{45} = I(A_{28}, R_3 R_4); \\
    &A_{42} = I(A_{28}, R_3 R_4); \\
    &A_{45} = I(A_{28}, R_3 R_4); \\
    &A_{42} = I(A_{28}, R_3 R_4).
\end{align*}
$$

Solving all these equations listed above simultaneously leads to no solution. Therefore, candidate $C_1$ is discarded and $C_2$ is then taken.
A for tentative modification. Four rules have been interpolated through the two fuzzy reasoning components that comprises the candidate, which need to be modified:

\( IR_3: (x_2 = A_{27}) \implies (x_3 = A_{35}) \);
\( IR_4: (x_2 = A_{28}) \implies (x_3 = A_{36}) \);
\( IR_5: (x_2 = A_{27}) \implies (x_4 = A_{45}) \);
\( IR_6: (x_2 = A_{28}) \implies (x_4 = A_{47}) \).

The following equations can be set according to the modification procedure of single fuzzy reasoning component outlined in Section 2.3.

\[
\begin{align*}
\mu_{A_0} &= \lambda_{A_0} + \lambda_{A_0} x_0, \\
\mu_{A_1} &= \lambda_{A_1} + \lambda_{A_1} x_1, \\
\mu_{A_2} &= \lambda_{A_2} + \lambda_{A_2} x_2, \\
\mu_{A_3} &= \lambda_{A_3} + \lambda_{A_3} x_3.
\end{align*}
\]

Solving these simultaneous equations leads to one solution which is illustrated in Figure 5. It is clear from this figure that there is no contradiction any more and thus consistency has been restored. This means that the original inconsistent interpolation process has been corrected with consistent interpolated results throughout.

![Figure 5: The solution for the running example](image)

5 Conclusion

This paper has extended the recent work on adaptive interpolative reasoning, by allowing fuzzy variables to be represented by trapezoidal membership functions (instead of just the triangular form). The approach uses the classical ATMS-based GDE method to detect and isolate faults during the process of fuzzy interpolation. It modifies the identified culprit interpolated rules in an effort to restore consistency. The working of this method is illustrated with a practically significant example.

While the proposed approach is promising, further improvements may enhance its potential. Currently, all base rules which are provided in the initial rule base for interpolation are assumed to be totally true and are fixed. However, this may not be the case in certain real-world problems, despite the fact that it is a common assumption made in the literature of interpolative reasoning. Thus, it is important to extend the proposed work to allow base rules to become themselves diagnosable and modifiable. In addition, it is of great interest to develop an unified inconsistency diagnosis and fault correction mechanism for both standard fuzzy inference and fuzzy interpolation. Also, issues such as how to deal with rules with multiple antecedent variables and how to extend the proposed method to be used in fuzzy extrapolation require further research.

References


