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Sensitivity analysis of a fuzzy expert system for modelling dependencies in human operators' emergency tasks

Keywords

human reliability analysis, fuzzy expert system, sensitivity analysis

Abstract

This paper analyzes the behaviour of a fuzzy expert system for evaluating the dependence among successive operator actions, through a sensitivity analysis on the fuzzy input partitioning and assessment. Preliminary results are presented with respect to a case study concerning two successive tasks of an emergency procedure in a nuclear reactor. Work is in progress to perform a thorough sensitivity analysis to generalize the results obtained.

1. Introduction

Fuzzy logic (FL) [8] modelling has proven successful in a variety of industrial tasks where ambiguous, qualitative and linguistic data are used to represent the behaviour of the system or process [5]. One of the main strengths of FL compared with other modelling schemes is that the underlying knowledge base capturing the system input/output relations is in the form of simple IF-THEN rules, which are easy to examine and understand and which allow taking into account human expertise. Furthermore, the FL models explicitly include the uncertainty and vagueness of the analyst judgments input into the model [2], [4].

In this paper, a Fuzzy Expert System (FES) for modelling dependencies among human operator actions is considered. The FES is constructed through an expert elicitation procedure for identifying the main factors influencing the dependence between successive tasks and their relationships with the dependence level [9].

The design of the FES requires arbitrary choices in the definition of the partitioning of the involved variables into Fuzzy Sets (FSs). In this respect, the objective of the present work is to perform a sensitivity analysis to investigate the response of the model with respect to different choices. Preliminary results on a case study are presented. Work is in progress to generalize these results.

The paper is organized as follows. In Section 2, the FL framework of the FES is briefly recalled. Section 3 sketches the basics of the dependence level assessment procedure. The reference case study for the numerical application is illustrated in Section 4. Section 5 and 6 report the sensitivity analyses performed. Conclusions are drawn in the last Section.

2. The Fuzzy Expert System for modelling task dependence

The model underpinning the FES for task dependence assessment considers four input factors [6]: "closeness in time", "similarity of performers", "similarity of cues" and "similarity of functions/goals", the latter two making up the "tasks relatedness" factor, and one output, i.e. the dependence level (*Figure 1*).

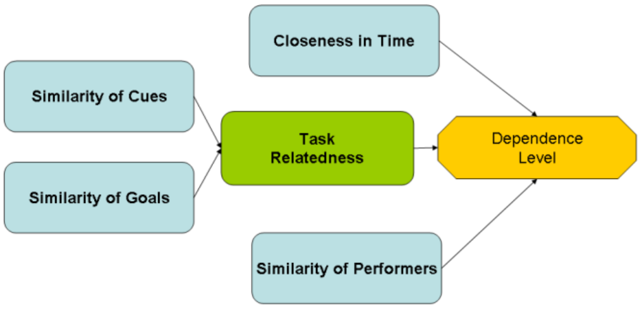


Figure 1. Functional relationships of the dependence model

Each of the four input factors is qualified in terms of linguistic variables with associated linguistic labels (*Table 1*).

Table 1. Linguistic Variables and associated linguistic labels of the input factors

Input Factor	Linguistic Variable	Short Format	Linguistic Labels
x_1	Closeness in Time	"Time"	WIDE (W) NEITHER (NT) CLOSE(CL)
x_2	Similarity of Cues	"Cues"	NONE (N) LOW (L) MEDIUM (M) HIGH (H) COMPLETE (C)
x_3	Similarity of Goals	"Goals"	
x_4	Similarity of Performers	"Performers"	

To the qualifying linguistic labels of each of the four input factors $x_k, k=1,2,3,4$, in *Table 1*, are associated FSs $X_k^v, v=1,2,...,k=1,2,...,4$, with Membership Functions (MFs) $\mu_{X_k^v}(x_k)$, $v=1,2,...$, $k=1,2,...,4$, on their Universes of Discourse (UODs) arbitrarily chosen to be [0,1].
The UOD of the output linguistic variable "Dependence" is formed by the labels y_i={ZERO, LOW, MEDIUM, HIGH, COMPLETE} representing the dependence levels. A singleton FS $Y^v, v=1,2,...,5$, with $\mu_{Y^v}(y_i)=0$ for $v \neq i$ and $\mu_{Y^v}(y_i)=1$ for $v=i$, is associated to each possible label y_i of y (*Figure 2*).
The "task relatedness" is derived from the "similarity of cues" and "similarity of goals" and it is qualified in terms of the linguistic labels contained in *Table 2*.

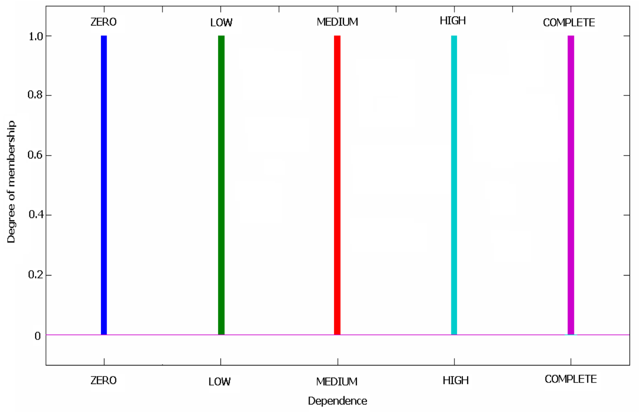


Figure 2. FSs of the discrete output "Dependence"

Table 2. Linguistic Labels of task relatedness

Linguistic Variable	Short Format	Linguistic Labels
Task Relatedness	"Task"	NONE (N) LOW (L) MEDIUM (M) HIGH (H) COMPLETE (C)

Table 3 summarizes the rules which have been identified by the expert to link the "Cues" and "Goals" input factors to the "Task relatedness" [5].

Table 3. Table of rules for the sub-model of "Task"

Cues | Goals	N	L	M	H	C
N	N	N	L	L	M
L	L	L	L	M	M
M	L	L	M	M	H
H	M	M	M	H	H
C	H	H	H	C	C

For example, the first rule has the linguistic form:

If Cues is NONE and Goals is NONE then Task is NONE

Table 4 – Table 8 contain the rules which have been set up by the expert to relate the "Time", "Performer" and "Task" factors to the dependence level.

Table 4. Complete Table of rules for “Task = C”

Perf | Time	W	NT	CL
N	L	L	M
L	L	L	M
M	M	M	H
H	M	M	H
C	H	H	C

Table 5. Complete Table of rules for “Task = H”

Perf | Time	W	NT	CL
N	Z	Z	L
L	Z	L	M
M	L	L	M
H	L	M	H
C	M	H	C

Table 6. Complete Table of rules for “Task = M”

Perf | Time	W	NT	CL
N	Z	Z	Z
L	Z	Z	L
M	Z	Z	L
H	Z	L	M
C	Z	L	H

Table 7. Complete Table of rules for “Task = L”

Perf | Time	W	NT	CL
N	Z	Z	Z
L	Z	Z	Z
M	Z	Z	Z
H	Z	Z	L
C	Z	Z	L

Table 8. Complete Table of rules for “Task = N”

Perf | Time	W	NT	CL
N	Z	Z	Z
L	Z	Z	Z
M	Z	Z	Z
H	Z	Z	Z
C	Z	Z	Z

For example, the first rule in *Table 4* reads:

If Time is WIDE and Performer is NONE and Task is COMPLETE then Dependence is LOW

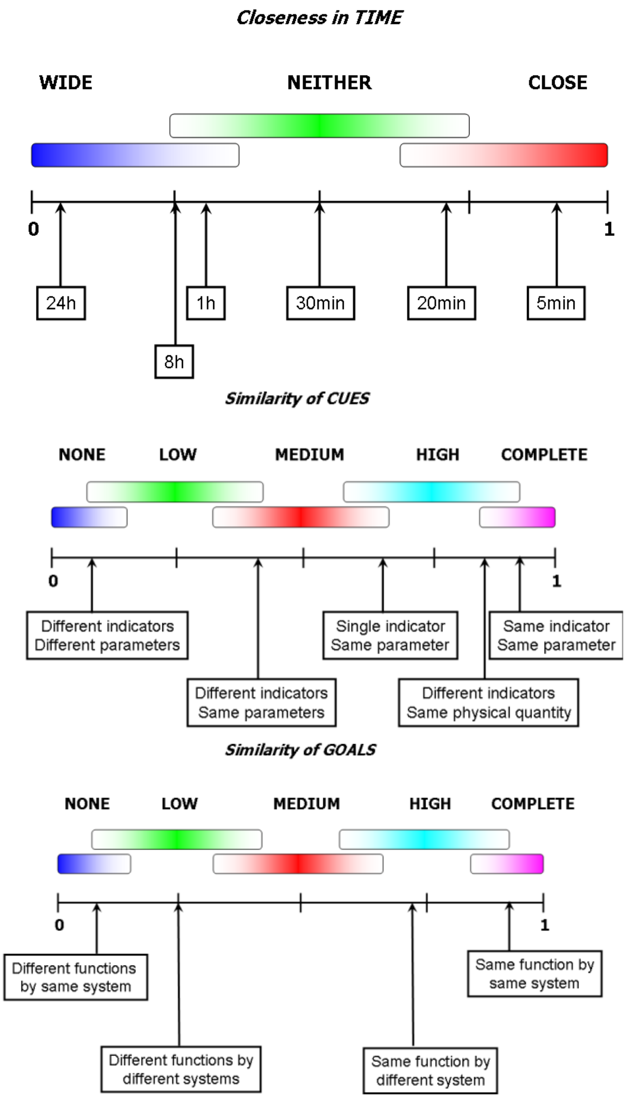
These rules are obtained by a “label interpolation” procedure founded on few, extreme situations elicited from the expert (grey cells in the *Tables*) [3], [9]. The expert knowledge concerning these extreme evaluations is elicited with few linguistic judgements on pre-specified prototype situations for the input factors. The prototype situations are represented by anchor points placed on the UODs of the input factors. Particular linguistic labels are associated to the anchor points, e.g. the anchor “Different indicators/Different parameters” of “Cues” input factors can be related to its linguistic label NONE(N) and so on (*Figure 3*). Given the correspondence between the anchor points and the linguistic labels, the rules elicited from the expert take the form:

If Cues is “Different indicators/Different Parameters” and Goals is “Different Functions by Different Systems” then Task is NONE

which is translated into a fuzzy rule of the form:

If Cues is NONE and Goals is NONE then Task is NONE

A “label interpolation” procedure is then used to smoothly spread the consequent labels over the fuzzy rules in order to complete the missing relationships. The complete *Tables* are then presented to the expert who can motivate adjustments and changes aimed at a more adherent representation of its beliefs.



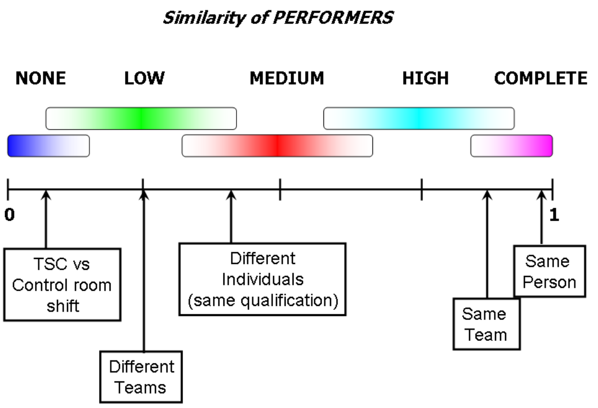


Figure 3. Anchored UODs with supports of FSs relative to the input factors

3. Assessment procedure

Once the UOD of the inputs and output have been partitioned into FSs and the Table of fuzzy rules has been established, the FES model is completed and ready for use. For a given sequence of tasks, the analyst is required to assign the proper numerical fuzzy values on [0,1] describing the input factors characteristics. This is the so called Fuzzy Fact which enters the model for its quantification. Granting the difficulty of providing such quantitative assessment when it is not possible to introduce a representative measure scale, the input procedure developed for the dependence fuzzy model is based on the same set of anchor points defined by the expert.
This way of proceeding provides an interface between the mathematical model and the analyst's input judgment: the latter is provided by the analyst in terms of point values $x_k^{'}, k = 1,2,3,4$, on the anchored UOD through comparison between the analyzed pair of tasks and the anchor points position (*Figure 3*).
Actually, in practice the analyst might be more comfortable with providing not just point values to describe the input conditions, but also intervals $[a_k^{'}, b_k^{'}]$ reflecting the uncertainty and the ambiguity of the description. In this case, these intervals are taken as supports of corresponding fuzzy input Facts with MFs equal to unity, at least, in correspondence of the analyst assigned point values. *Figure 4* shows an example of an ambiguous input provided by the analyst for the input factor "Performers" and its implementation as Fact in the FES.
On the basis of the FES developed in Section 4, the assessment of the dependence level for a generic Fuzzy Fact $\vec{x}^{'} = \left(x_1^{'}, \dots, x_4^{'}\right)$ is performed by a Mamdani fuzzy inference procedure [1] leading to the fuzzy Conclusion y is Y', where Y' is a discrete output FS constituted by the five values

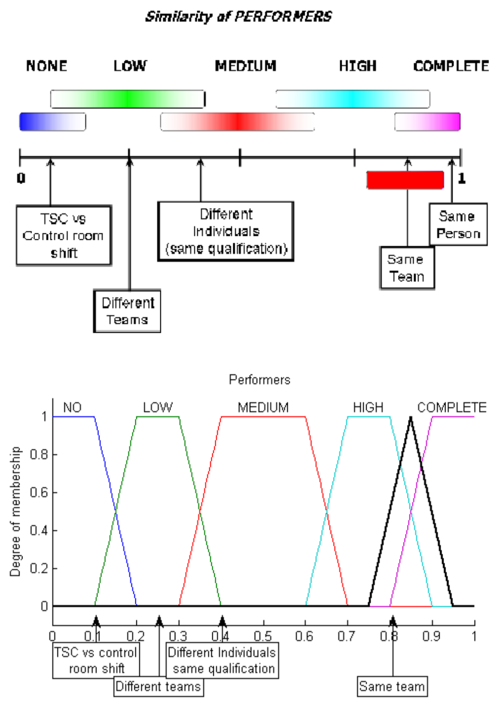


Figure 4. Uncertain input provided by the analyst on the anchored scale (top) with the indication of the support of the FSs; fuzzy input Fact built from the analyst input (bottom)

$\mu_{Y'}(y_i), i = 1,2,\dots,5$. Thus, the output of the FES consists of a discrete membership function $\mu_{Y'}(y_i)$ that represents the degree of activation of each dependence level y_i={ZERO, LOW, MEDIUM, HIGH, COMPLETE}.
The information available from this kind of output helps the analyst to identify the most activated dependence level that best matches with the input Fact FSs describing the tasks relationships and gives a representation of the uncertainty in the dependence assessment.

4. Case study

The case study considered in this work refers to a set of operator actions intended to avoid excessive boron dilution in the reactor cooling system in case of an Anticipated Transient Without Scram (ATWS) at a nuclear Boiling Water Reactor (BWR). In the considered scenario, the operators have successfully initiated the Standby Liquid Control System (SLCS) to shut the reactor down. To facilitate the reactor shut down, the operators are directed by the procedures to increase the voiding by reducing the level in the reactor to the Top of Active Fuel (TAF). Additionally, they are required to inhibit the actuation of the Automatic Depressurization System (ADS), which is activated by the signal of low water level in the reactor, generated while lowering the reactor water level to the TAF. In case of failure to inhibit the ADS, the reactor pressure would be automatically decreased and low pressure injection systems (e.g. the Core Spray System, CSS), would be activated. The injected water could lead to diluting the boron injected by the SLCS and the consequential failure of controlling reactivity. In case of failure to inhibit ADS actuation, the operators are called to control the level in the reactor using low pressure injection, tripping one of the CSS pumps and controlling the other pump.

The signal to activate the ADS is generated about 7 minutes after the event of failure to scram. At that point, the operators have about 15 minutes to take actions to limit the low pressure injection flow.

The pair of operator tasks involved in the dependence assessment, object of the present case study, is the preclusion of the ADS and the successive control of the reactor vessel level in order to prevent diluting boron concentration after the ADS failure. Both actions are part of the same emergency procedure.

The desired output of the dependence model is the probability of human failure in controlling the reactor vessel level after the failure to preclude the ADS.

4.1. Analyst judgment

The analyst assessment of the four factors entering in input to the dependence model for the scenario at hand (the so called Fact) is as follows:

- “Time”: control of low pressure injection would be achieved within about 15 minutes after depressurization of the reactor vessel. The available interval time is assumed from 5 to 20 minutes. Thus the analyst assessment is the interval [5 min, 20 min].
- “Cues”: the initial cues are related to the initial failure to scram. The operator is initially successful, the SLCS is properly initiated. The control of low pressure injection is related to maintaining the reactor vessel level. The analyst judgment is: very low (NONE) similarity of cues is present between the two tasks.
- “Performers”: the action is carried out by the same team. It is assumed that the Technical Support Center (TSC) does not reach the control room in the time available. The analyst judgment coincides with the anchor point ‘same team’.
- “Goals”: the two actions relate to different systems and have different goals (inhibit the ADS, the former and controlling the injection, the latter). On the other hand the function of the actions is the same: shut down the reactor by boron control. The analyst considers that the two actions correspond to a prototype situation of tasks with the same function but related to different systems.

5. Model sensitivity to different input UOD partitioning

The quantitative evaluation by the analyst of the Fact in the scenario considered is reported in *Figure 5* (light gray intervals on the interval [0,1]). Note how the interval quantification of the factors “Performers” and “Goals” made by the analyst with respect to the tasks conditions of the case study at hand coincides with the prototypes conditions of “same team” and “same functions by different systems”, respectively.

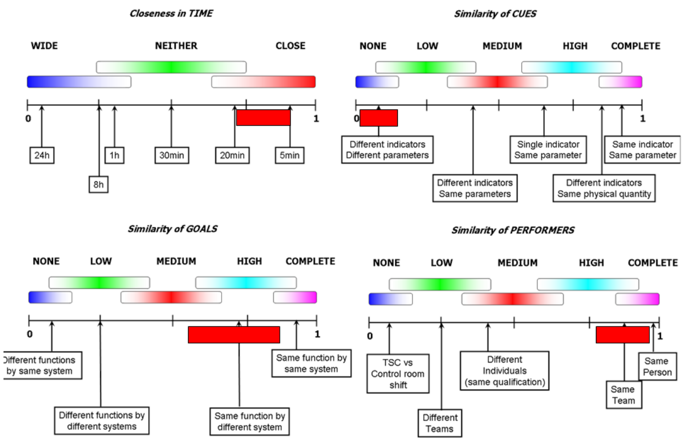


Figure 5. Analyst input assessment on the anchored scale

To investigate the sensitivity of the output FS Y' to variations in the input FSs quantifying the uncertainty in the dependence model definition, both trapezoidal and triangular FSs, are considered keeping the FSs supports fixed. *Figure 6* shows the fuzzification of the analyst interval judgment proposed in *Figure 5* in terms of trapezoidal FSs whereas *Figure 7* presents the case with triangular FSs. The fuzzification of the Fact is achieved by triangular FSs positioned at the centers of the assigned intervals of values.

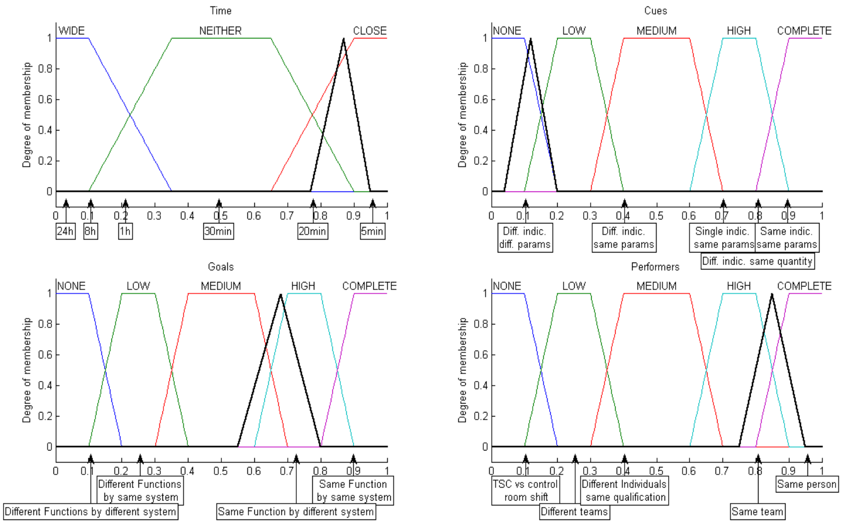


Figure 6. UOD partitioned by trapezoidal FSs. The thick-line triangle represents the FS of the Fact in input to the model

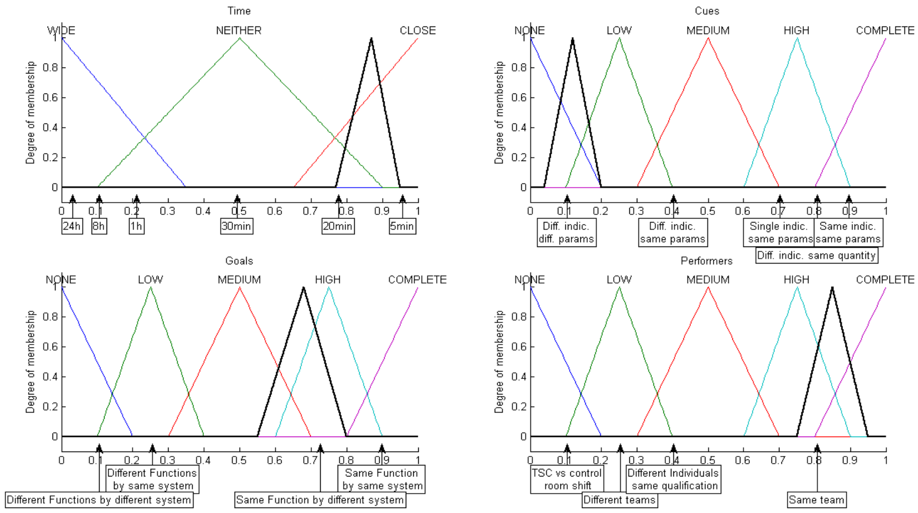


Figure 7: UOD partitioned by triangular FSs. The thick-line triangle represents the FS of the Fact in input to the model.

Figure 8 reports the discrete output FSs describing the dependence level of the actions, 'preclusion of the ADS' and 'control of the reactor vessel level', in the case of trapezoidal FSs (top) and triangular FSs (bottom).

The two cases present a similar representation of uncertainty, with the most activated dependence level being "LOW" and the highest dependence level with non-zero MF being "HIGH".

To further analyze the response of the model to the different (trapezoidal or triangular) input UODs partitioning, the value of the center of the triangular Fact FS of the input variable "Performer", $X_4^{'}$, is varied in the interval [0,1], while keeping constant the Fact FSs of the other three input variables, $X_1^{'}, X_2^{'}, X_3^{'}$.

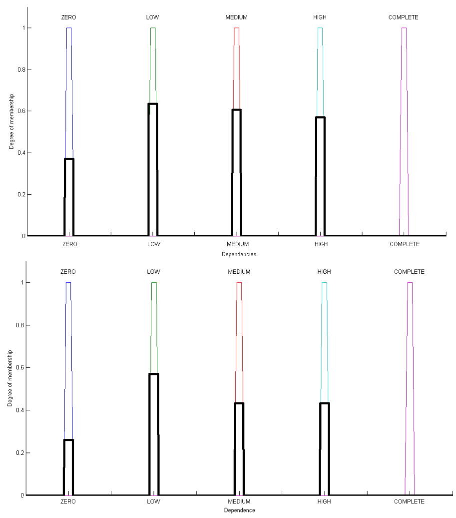


Figure 8. Output FSs of dependence level: input partition by trapezoidal FSs (top) and triangular FSs (bottom).

Figure 9 reports the effects of the variation: the circles represent the degree of activation by the Fact of the dependence levels for the trapezoidal FS input partitioning whereas the asterisks represent the dependence levels for the triangular FS partitioning. The activation degrees of the trapezoidal partitioning are always higher than those of the triangular partitioning. This is due to the fact that the trapezoidal membership functions of *Figure 6* include the corresponding triangular ones of *Figure 7*, as shown in *Figure 10*: this results in larger values of activation of the fuzzy rules and thus higher activation degrees of the output dependence levels.

Furthermore, when adopting a partitioning of the input variables UODs in trapezoidal FSs, the degrees of activation of the output dependence levels are locally more sensitive to variations of the input Fact than in the case of triangular partitioning. This is shown, for example, by the two dips at 0.15 and 0.35 of the "ZERO" dependence level activation degree appearing in *Figure* when the center of the input Fact $X_4^{'}$ is varied.

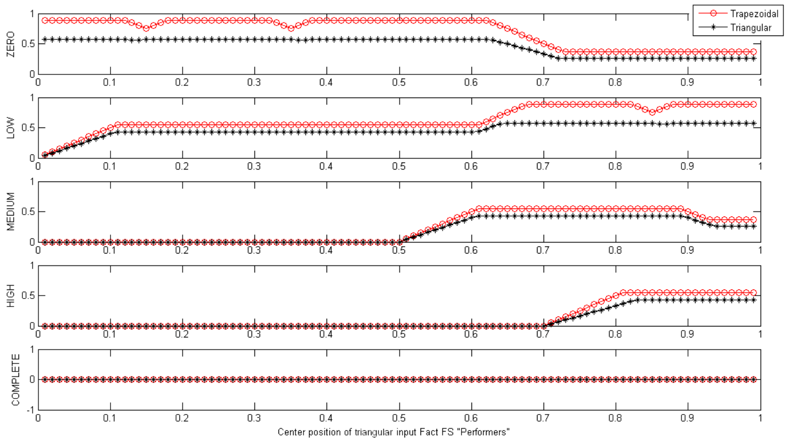


Figure 9. Degree of activation of the dependence levels "ZERO", "LOW", "MEDIUM", "HIGH" and "COMPLETE" as a function of the position of the center of the triangular "Performers" Fact FS. Circles: trapezoidal input partitioning. Asterisks: triangular input partitioning

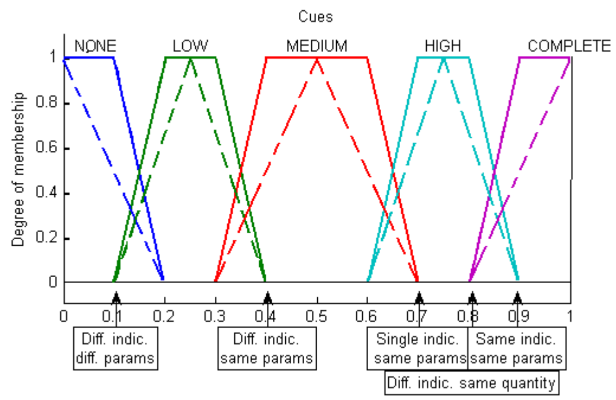


Figure 10. Trapezoidal (solid line) and triangular (dashed line) partitioning of the input factor "Cue"

The reason for this higher sensitivity is due to the more rapid changes of MF values in the side of the trapezoids than in those of the triangles. Thus, two Facts with contiguous centers activating a same rule, would do so with higher activation strengths in the case of trapezoidal MFs than in the case of triangular MFs (*Figure 11*).

A further peculiarity of the trapezoidal MF is the presence of an upper-base interval at constant, unitary value. The effects of this feature can be effectively highlighted by showing the variation of the degree of activation of the "ZERO" dependence level in correspondence of singleton facts ($X_1^{'}$, $X_2^{'}$, $X_3^{'}$, $X_4^{'}$).

Figure 12 shows the case in which the "Performers" Fact is varied in [0,0.2], on both the trapezoidal and triangular input partitioning, for comparison. In correspondence of a variation of the singleton Fact $X_4^{'}$ from 0.09 to 0.1, for example, the degree of activation of the "ZERO" dependence level remains constant and equal to 0.87 in case of trapezoidal MFs because the intersection between the input Fact FS $X_4^{'}$ and the trapezoidal FS "NONE" of the antecedent "Performer" X_4 is always 1 for $x_4^{'}$ varying in [0.09, 0.1]. On the contrary, for the triangular partitioning it varies from 0.54 to 0.49 because of different levels of intersection between the input Fact FS X_4 and the triangular FS "NONE" on the antecedent "Performer".

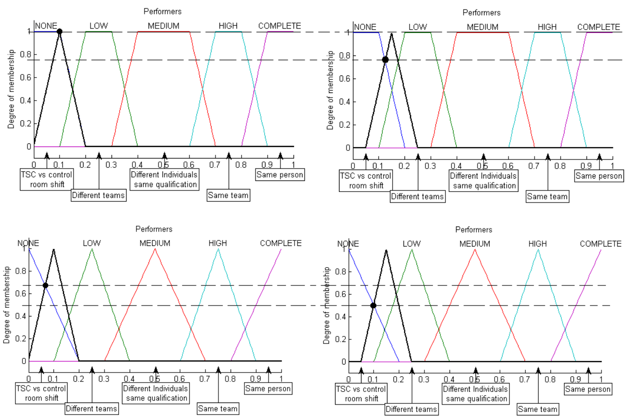


Figure 11. Examples of two contiguous triangular Performer input Facts in trapezoidal (top) input partitioning and in triangular (bottom) input partitioning. The circles represent the intersection of the input Fact with the “NONE” FS. The dot lines represent the corresponding degrees of membership with respect to the “NONE” FS.

In spite of this different absolute sensitivity of the two partitions, the relative differences of the activations of the dependence levels turn out to be less sensitive to the partitioning. *Figure* reports the activation of the dependence levels normalized to sum to 1 for any value of the center of the triangular Fact $X_4^{'}$ on [0,1]. The ‘normalized’ degrees of activation turn out to be very similar for both trapezoidal and triangular input UOD partitioning.

The results obtained confirm the robustness of the model with respect to the two different shapes of the input partitioning FSs here tested. This is quite important, considering that partitioning is chosen by the expert as basis of the dependence model whereas the analysts only interface with the anchored scale of the input variables and the supports of their linguistic labels.

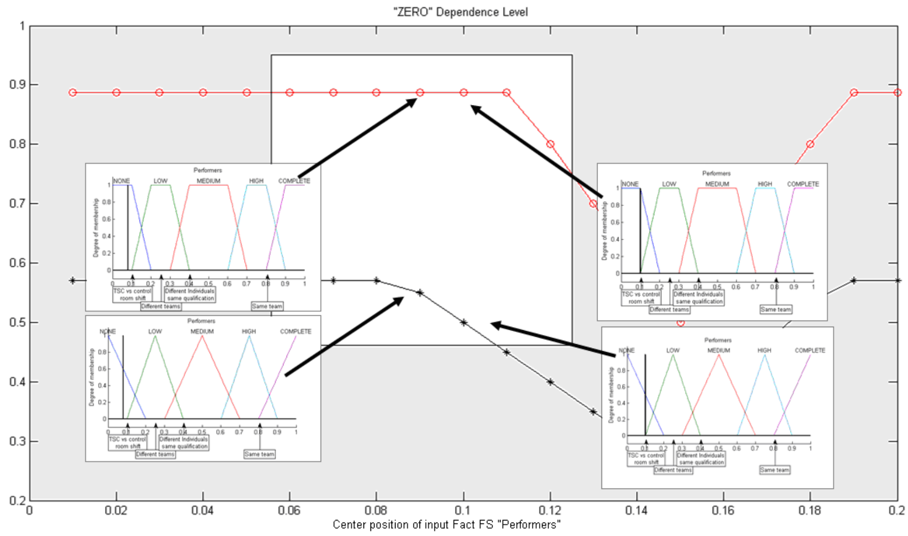


Figure 12. Degree of activation of the dependence level “ZERO” as a function of the singleton Fact “Performers”. Circles: trapezoidal input partitioning. Asterisks: triangular input partitioning. The small Figures show the intersection of the singleton “Performers” Fact (at 0.09, left and at 0.1, right) with trapezoidal (top) and triangular (bottom) partitioning of the corresponding UOD.

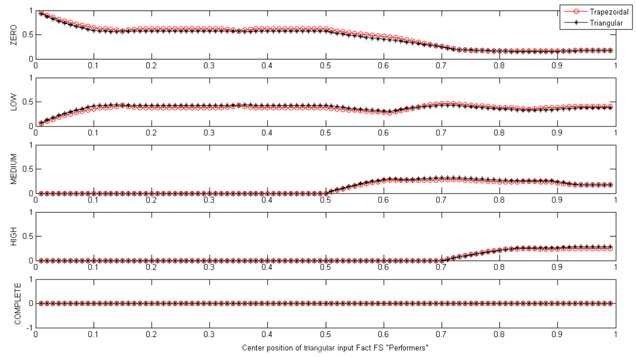


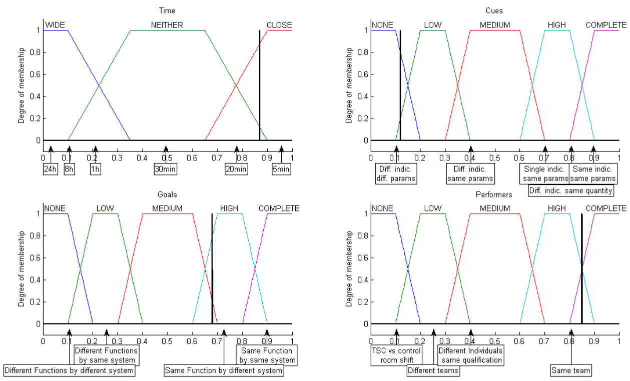
Figure 13. Normalized degree of activation of the dependence levels “ZERO”, “LOW”, “MEDIUM”, “HIGH” and “COMPLETE” as a function of the position of the center of the triangular Fact “Performers” FS. Circles: trapezoidal input partitioning. Asterisks: triangular input partitioning.

6. Model sensitivity to different input Fact FSs

Once the dependence model is fixed, its output depends on the input Fact judgment provided by the analyst. The uncertainty associated to this judgment is represented by the width of the interval supporting the fuzzy MF of the analyst input Fact assessment.

The extreme case of a point estimate judgment, i.e. with no associated ambiguity, leads to the results shown in *Figure 14* and *Figure 15*. The most activated dependence level is still “LOW”, as with triangular input Fact FSs (see *Figure 6 – Figure 7*), thus confirming the robustness of the model. Furthermore, the output “LOW” is relatively more pronounced with respect to the other dependence levels, as expected in this less ambiguous assessment by the analyst.

On the contrary, *Figure 16* and *Figure 17* show the effect of a large ambiguity in the analyst assessment, centered at the same point estimates as the previous case analyzed. This ambiguity is clearly propagated to the output which shows almost equally distributed activation of all the dependence levels.



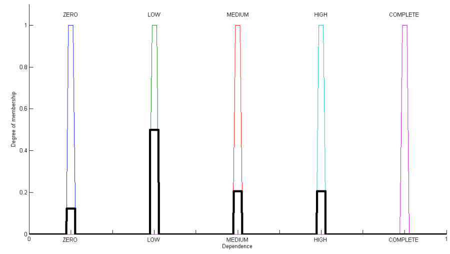


Figure 14. Output discrete FS (right) in correspondence of singleton input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning.

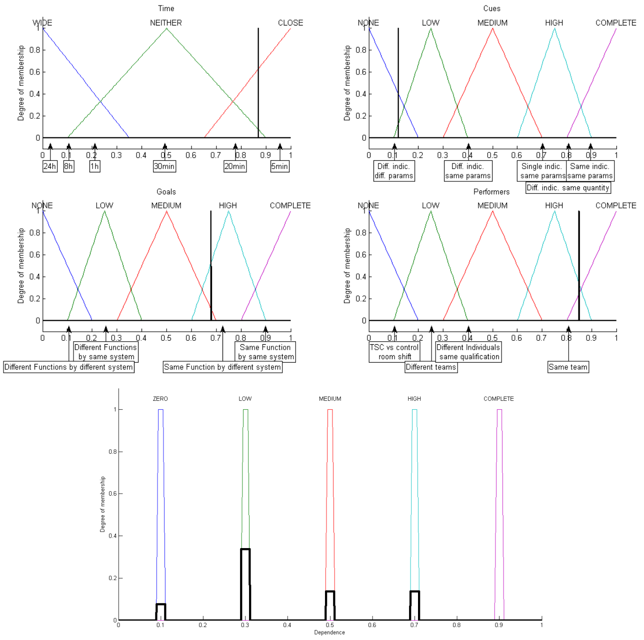


Figure 15. Output discrete FS (right) in correspondence of singleton input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning

Finally, *Figure 18* and *Figure 19* show a case in which the analyst provides only the range where the input Fact may lie, with an equal degree of belief for any points in the range. The support is assumed to be the same of the triangle input Fact FSs used in Section 5 (*Figure 6 – Figure 7*). For this reason, the discrete output FS presents the same number of activated dependence levels as in the case of triangular Fact FSs with the same support.

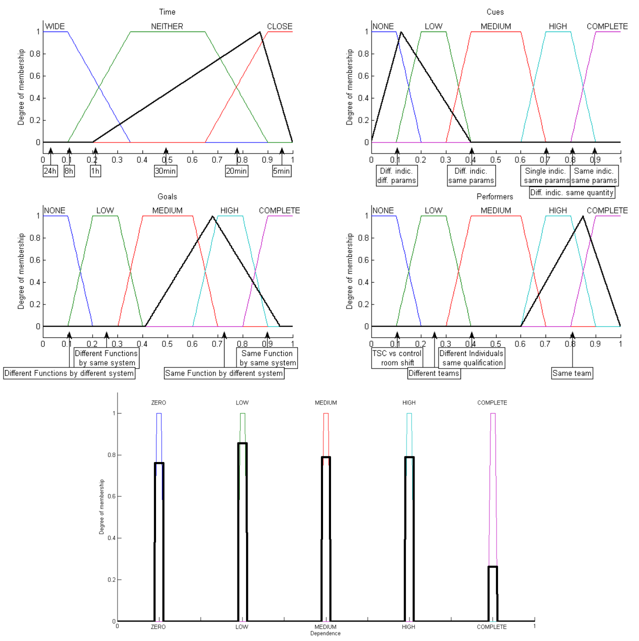


Figure 16. Output discrete FS (right) in correspondence of wide triangle input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning

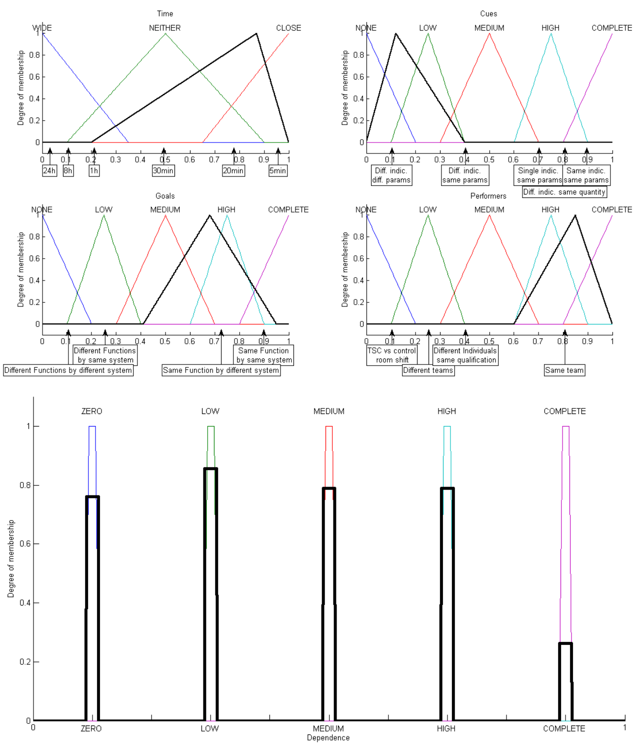


Figure 17. Output discrete FS (right) in correspondence of wide triangle input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning

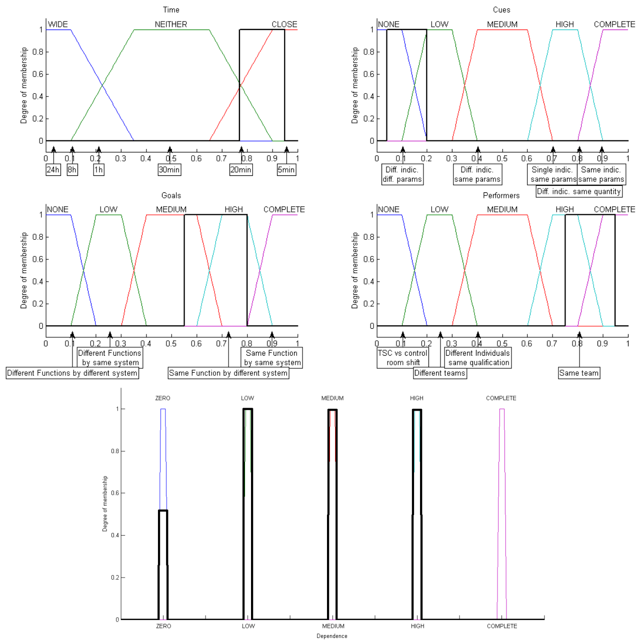


Figure 18. Output discrete FS (right) in correspondence of rectangular input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning

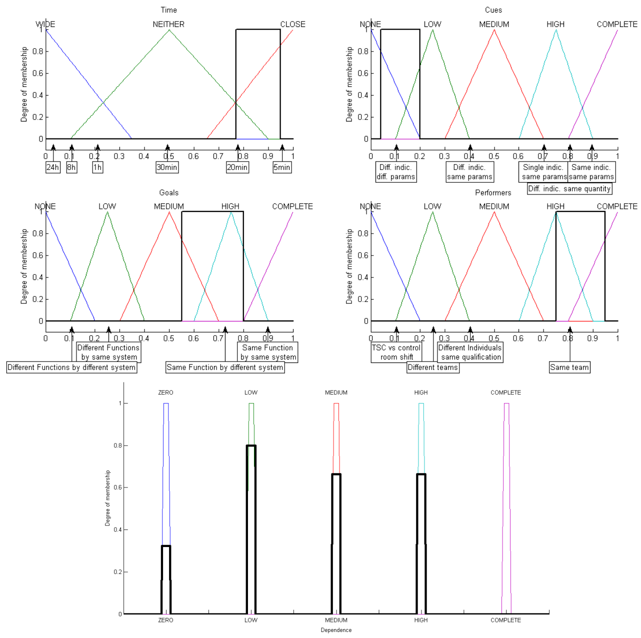


Figure 19. Output discrete FS (right) in correspondence of rectangular input Fact FS (left). Top: trapezoid UODs partitioning. Bottom: Triangle UODs partitioning.

7. Conclusion

In this paper, a fuzzy expert system for the evaluation of the dependence level between operator tasks in an emergency procedure has been considered. The design of the fuzzy expert system rests on an elicitation procedure for the identification of the main relationships between the input factors and the dependence of two successive tasks in correspondence of prototype conditions called anchor points. Then, an interpolation method is used to complete the logical rules necessary for the dependence assessment.

A sensitivity analysis has been performed to investigate the variability of the results obtained with respect to the choice of the input factors UOD partitioning, on a case study regarding the control of the reactor vessel level after the ADS failure in a nuclear reactor. The analysis has shown the robustness and stability of the inferred dependence level in the case considered. A further analysis of the sensitivity with respect to different fuzzy input evaluations by the analyst has been performed. The analyst uncertainty turns out to be properly propagated into the inferred outputs.

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