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A Fuzzy Logic based Trend Impact Analysis method

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ABSTRACT

All Trend Impact Analysis (TIA) algorithms in literature conduct the analysis based on direct estimates provided by experts for the probability of occurrence of an unprecedented event as an input to the algorithm. In this paper, we propose an advanced mechanism to generate more justifiable estimates to the probability of occurrence of an unprecedented event as a function of time with different degrees of severity using Fuzzy Logic. We postulate that in some cases it is better not to estimate the probability of occurrence of an unprecedented event directly; but rather estimate it indirectly via its attributes, using Fuzzy Logic. The core idea of the paper is to customize the generic process of reasoning with Fuzzy Logic by adding the additional step of attributes simulation, as unprecedented events do not occur all of a sudden but rather their occurrence is affected by change in the values of a set of attributes, especially when they reach certain threshold values.

1. Introduction

Trend Impact Analysis (TIA) is a prominent hybrid method used in futures studies that combines qualitative and quantitative aspects to forecast the future. It is used to examine the effect of possible interruptions to a trend, namely unprecedented future events, that if would occur could cause deviation (negative or positive) from the surprise-free forecast [1]. As Gordon, the founder of the method puts it — "*TIA is a simple approach to forecasting in which a time series is modified to take into account experts' perceptions about how unprecedented future events may change extrapolations that would otherwise be surprise-free*" [2, p.3]. It permits extrapolations of historical trends to be modified in view of qualitative judgments about unprecedented events whose occurrence in the future could cause deviation from the surprise-free forecast. The method allows for systematic treatment of possible unprecedented future events, whether they are technological, political, social, economic or value-oriented. Expert judgments are sought about the probability of an event as a function of time and its expected impact on the trend under consideration. Events should be plausible, potentially powerful in impact and verifiable in retrospect [3]. The source of such a list might be for instance a Delphi study [4,5], some form of other informal consensus among experts or a literature search [6].

The principal steps of conducting a TIA as defined by its founder Gordon are:

1. "*A curve is fitted to historical data to calculate the future trend, given no unprecedented future events; and*
2. *Expert judgments are used to identify a set of future events that, if they were to occur, could cause deviations from the extrapolation of historical data. For each such event, experts judge the probability of occurrence as a function of time and its expected impact, should the event occur, on the future trend. An event with high impact is expected to swing the trend relatively far, in a positive or negative direction, from its un-impacted course*" [2, p.4].

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Using Monte-Carlo Simulation, the TIA algorithm then combines the impact and event probability judgments with results of the base-case scenario to generate a fan of possible future scenarios. Based on this fan, the median, 5th and 95th percentile scenarios can be computed to indicate three distinctive scenarios.

The framework of the basic TIA approach is outlined in Fig. 1.

In a recent research, Agami et al. [7] proposed an enhanced approach for TIA that takes into account the occurrence of an unprecedented future event given how severe the occurrence is. It allows the analyst to supply three levels of impact/probability pairs; where each pair is associated with one of three degrees of severity; low, medium and high.

The core steps of the enhanced approach for TIA (conducted for each scenario, for each year, for each event) are as follows:

1. Randomly generate the degree of severity 'D' (see Fig. 3 in [7]).
2. Accordingly (knowing the event and its degree), identify the corresponding event impact parameters: Maximum Impact, Steady-State Impact, Time to Maximum Impact and Time to Steady-State Impact. This is done by indexing the associated matrices.
3. Randomly generate the number of the month 'M' in the given year 'Y' on which the event would occur (assuming that an event can occur only once in a given year [7]).
4. Compute the Fractional Change Vector using the estimated event impact parameters (see Figs. 4–6 in [7]).
5. Update the current scenario (column) 'S' of the Scenarios Matrix accordingly.

This approach was then further enhanced by developing a dynamic forecasting mechanism using a neural network model to improve the prediction process of the original TIA algorithm instead of the static mechanism already applied [8].

All TIA algorithms documented in literature conduct the analysis based on direct estimates provided by experts for the probability of occurrence of an unprecedented event as an input to the algorithm. In this paper, we introduce an advanced mechanism to generate more justifiable estimates to the probability of occurrence of an unprecedented event as a function of time with different degrees of severity using Fuzzy Logic.

The rest of this paper is organized as follows: in Section 2, we discuss the problem addressed. In Section 3, we give an overview on Fuzzy Logic. Then in Section 4, we explain our proposed approach in details including the inputs, output and the algorithm itself. And in Section 5, we give a case study. Finally in Section 6, we conclude and suggest possible future work.

2. Problem addressed

To conduct a TIA, experts subjectively provide rough estimates of the event probability of occurrence as a function of time with varying degrees of severity based on educated guesses. However in reality – in some cases – unprecedented events do not occur without some early warning indicators, i.e. their occurrence is trigerred when the values of a set of attributes reach certain threshold values. For instance, the occurrence of a storm is usually affected by change in the values of temperature, humidity, etc.

We postulate that in some cases it is better not to estimate the probability of occurrence of an unprecedented event directly; but rather estimate it indirectly via its attributes. That is estimate the probability of occurrence for any future point in time as a function of the values of the associated set of attributes at the same point in time. The purpose is to generate more justifiable estimates. The scope of this study is limited to events whose occurrence and severity are influenced by some known attributes; in other words, it does not encompass "genuine" exogenous events. Our aim is to provide the analyst with a tool that must be used with discretion (i.e. in the appropriate cases only). Recall that "genuine" exogenous events are handled by previous studies [2,7,8].

We surveyed the literature and found that the usual practice to estimate the probability of occurrence of an event given different values of some other independent variables is done by employing Logistic Regression [9], Decision Trees [10], Bayesian Classification [11] and other similar models. However, these approaches need historical data in order to fit and estimate the model

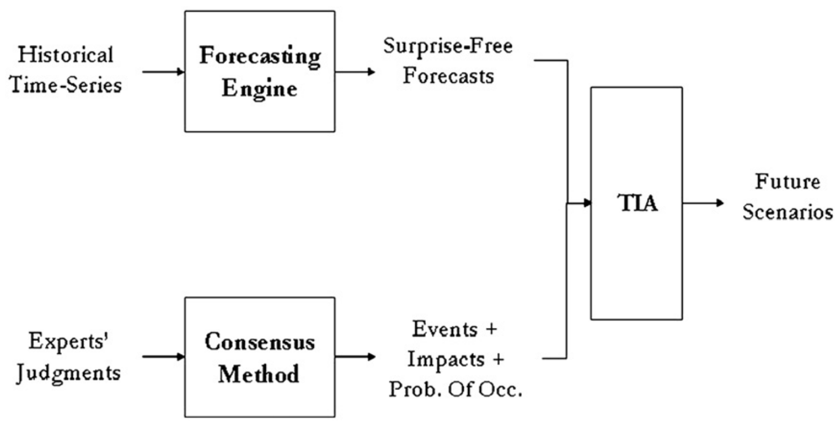

Fig. 1. Trend Impact Analysis framework.

parameters. Hence, they are not adequate to handle unprecedented events. Therefore, we propose an advanced mechanism to generate more justifiable estimates for the probability of occurrence over time using Fuzzy Logic. Our main hypothesis is that this advanced mechanism will properly and systematically address the problem explained above. The proposed approach will be discussed in details in Section 4. In the next section, we give a brief overview about Fuzzy Logic basics.

3. Fuzzy Logic — theoretical background

Fuzzy Logic (FL) was conceived and initiated by Lotfi A. Zadeh in 1965 — Professor of Computer Science at University of California in Berkley. It is generally defined as a multi-valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. [12,13]. The basic concept underlying FL is that of a linguistic variable — a variable whose values are words rather than numbers. This allows notions like ***rather*** tall or ***very*** fast to be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers.

Basically, FL is derived from fuzzy set theory dealing with reasoning which is approximate rather than precise. In the traditional set theory, an element either belongs to a set or it does not. However in FL, membership functions classify elements in the range [0, 1], with 0 and 1 being no and full inclusion respectively. Much of FL may be viewed as a methodology for computing with words rather than numbers. Although words are inherently less precise than numbers, their use is closer to human intuition [14]. The principal objective is to formalize the remarkable capability of humans to reason, solve problems and make decisions in an environment of uncertainty, imprecision, incompleteness of information and partiality of knowledge, truth and class membership [15].

Reasoning with FL consists of mainly 3 steps [16,17]: Fuzzification, Fuzzy Inference System and De-fuzzification respectively as illustrated in Fig. 2.

3.1. Fuzzification

Fuzzification is the process in which crisp quantities are converted to fuzzy ones. By identifying some of the uncertainties present in the crisp values, the fuzzy values are formed. The conversion to fuzzy values is represented by membership functions. A membership function is a graphical representation of the magnitude of participation of each input in a given set. It could be of any type such as Gaussian, Triangular, Trapezoidal, Singleton or many others [14,17]. The fuzzification process may involve assigning membership values for various sets to the given crisp quantities. There are various methods to assign the membership values or the membership functions to fuzzy variables. The assignment can be done by intuition (as shown in Fig. 3) or by using some algorithms or logical procedures.

3.2. Fuzzy Inference System

Fuzzy system is one which implements rule-based reasoning to determine an output response. It is a particular type of reasoning which uses IF–THEN rules. The inference engine evaluates all the rules to perform the reasoning process. Rules considered have to satisfy the following 4 properties: Completeness, Consistency, Continuity and Interaction. There are three relevant operators in the fuzzy set logic used to construct compound rules. These operators are: OR, AND and NOT.

3.3. De-fuzzification

De-fuzzification is the process of converting fuzzy to crisp values. The fuzzy results generated cannot be used as such; hence it is necessary to convert the fuzzy quantities into crisp ones for further processing. There are some famous methods used for de-fuzzification such as the Centroid method, Weighted Average method and the Maximum membership principle method.

There is no de-fuzzification method which is considered to be the best; instead it is context or problem dependent. There are 4 criteria against which to measure a method: Continuity, Disambiguity, Plausibility and Computational Simplicity.

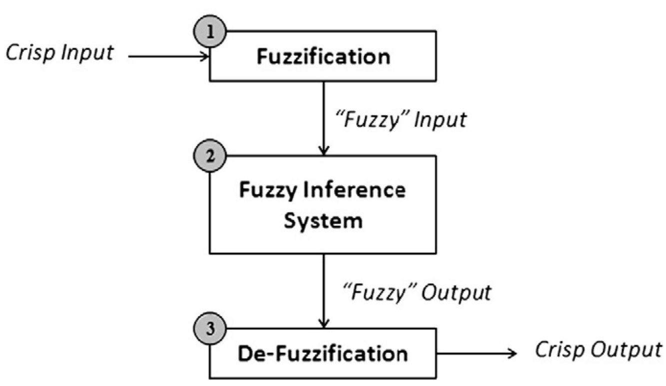

Fig. 2. Process of reasoning with Fuzzy Logic.

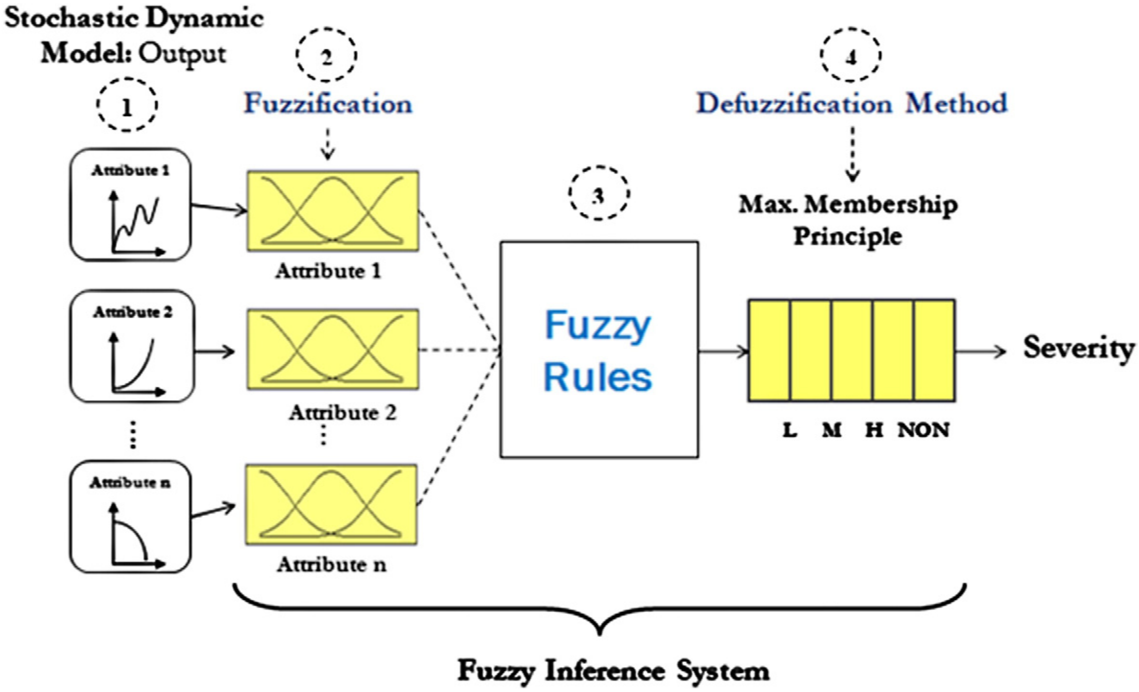

Fig. 3. Customized process of reasoning with Fuzzy Logic.

In this paper, for the sake of simplicity, we adopted the Maximum membership principle method. It is a straightforward method where we assume that the output membership function (for all sets) is Singleton [14,17].

4. Proposed approach

Our proposed approach uses the enhanced TIA [7] as the point of departure. We start by identifying a list of unprecedented events to be included in the analysis. For each such event we identify the set of associated attributes. Then for each attribute, we define the corresponding characteristics[1] and range of fuzzy values.

Now to tackle the research question of identifying the degree of severity of an event in a future point in time, we customize the generic process of reasoning with Fuzzy Logic (illustrated in Fig. 2) by adding the additional step of attributes simulation as outlined in Fig. 3:

Below we briefly explain each step in the above figure (and in the next section we will present a numerical example):

1. *Attributes simulation*: simulate the attributes values over time. This can be done using a stochastic dynamic model.
2. *Fuzzification*: converts the projected crisp values of attributes into fuzzy ones; i.e. membership values of different sets pre-defined by experts according to certain threshold values based on their subjective judgements or as found in literature.
3. *Inferencing*: evaluate all pre-defined rules to perform the reasoning process.
4. *De-fuzzification*: employ the maximum membership principle method to determine the degree of severity of the event, i.e. low (L), medium (M) or high or non-occurrence (NON).

In our approach, we chose Fuzzy Logic for the following reasons:

1. Provides a good solution to reasoning with uncertainty.
2. Can be built on top of the experience of experts.
3. Tolerant for imprecise information, i.e. expert judgements.
4. Does not need historical data because the output depends on the evaluation of a pre-defined (by experts) set of rules.
5. It's easy to generate fuzzy rules using survey data without much pre-processing (as illustrated in the next section).

All the assumptions, inputs and output of the enhanced TIA algorithm [7] hold true as shown in Tables 1 and 2. However, the Probability of Occurrence Matrix (ProbOccMx) (used in [7]) does not exist anymore because probabilities of occurrence are to be estimated dynamically for any future point in time using a Fuzzy Inference System.

[1] For example, the height attribute can have the following 3 characteristics: short, average and tall.

Table 1
Inputs.

Short name	Full name	Type	Dimensions
NumS	Number of scenarios	Scalar	–
NumY	Number of years	Scalar	–
NumE	Number of events	Scalar	–
BaseFrVect	Base forecast vector	Vector	–
MaxImMx	Maximum impact matrix	2D-Matrix	(NumE, 3)
SSImMx	Steady-State Impact matrix	2D-Matrix	(NumE, 3)
TMaxMx	Time to Maximum Impact Matrix	2D-Matrix	(NumE, 3)
TSSMx	Time to Steady-State Impact matrix	2D-Matrix	(NumE, 3)

Table 2
Output.

Short name	Full name	Type	Dimensions
SrMx	Scenarios Matrix	2D-Matrix	(NumM, NumS)

4.1. Inputs

The following table lists the inputs used in our proposed algorithm:

Besides, for every event we must identify as an input the attributes set. And for each attribute, we specify the membership function and its associated thresholds to define the fuzzy ranges.

4.2. Output

The single output of the algorithm is the Scenarios Matrix shown in the table below:

4.3. Algorithm

Below we explain in details the main function of the proposed approach illustrated in the previous flow chart:

Fig. 4[2] outlines the ‘Main’ function of the proposed algorithm. Basically the function consists of a triple loops structure. The outer-loop is a counter on the number of scenarios to be generated ($S = 1,\ldots,$ NumSc). The intermediate loop is a counter on the number of years we wish to study ahead ($Y = 1,\ldots,$ NumY); while the inner loop is a counter on the number unprecedented events incorporated in the study ($E = 1,\ldots,$ NumE). Before entering the triple loops structure, the Scenarios Matrix (SrMx) is initialized such that each column is equivalent to the Base Forecast Vector (BaseFrVect) — i.e. the surprise-free scenario (generated via a quantitative forecasting method).

The inner most loop then carries out the following steps:

1. Randomly generates the month ‘M’ on which the event could occur (as explained in [7]).
2. Randomly generates a seed for the stochastic model. The idea is that in the case of using a stochastic dynamic model, we need a different seed to generate a different sequence of random numbers each time.
3. Runs the stochastic dynamic model to determine the attributes values at month ‘M’ in year ‘Y’ (by calling a function).
4. Determines the event degree of severity (or non-occurrence) using the Fuzzy Inference Engine (by calling a function).
5. Accordingly (knowing the event and its degree of severity), it identifies the corresponding event impact parameters: Maximum Impact (MaxImp), Steady-State Impact (SSImp), Time to Maximum Impact (TMax) and Time to Steady-State Impact (TSS). This is done by indexing the associated matrices.
6. Computes the Fractional Change Vector (by calling a function — see Figs. 4–6 in [7]).
7. Updates the current scenario (column) ‘S’ of the SrMx accordingly (as explained in [6]).

Note that the algorithm was implemented and tested using the MATLAB software. Moreover, a GUI was developed in such a way that enables it to be flexible in the number of scenarios, years and events according to the experts' point of view and the information available.[3] Currently we are developing a version of the algorithm using the R-Language.

2 Fuzzy data for each attribute includes the membership functions and the associated thresholds.
3 The reader interested in the code can e-mail the authors.

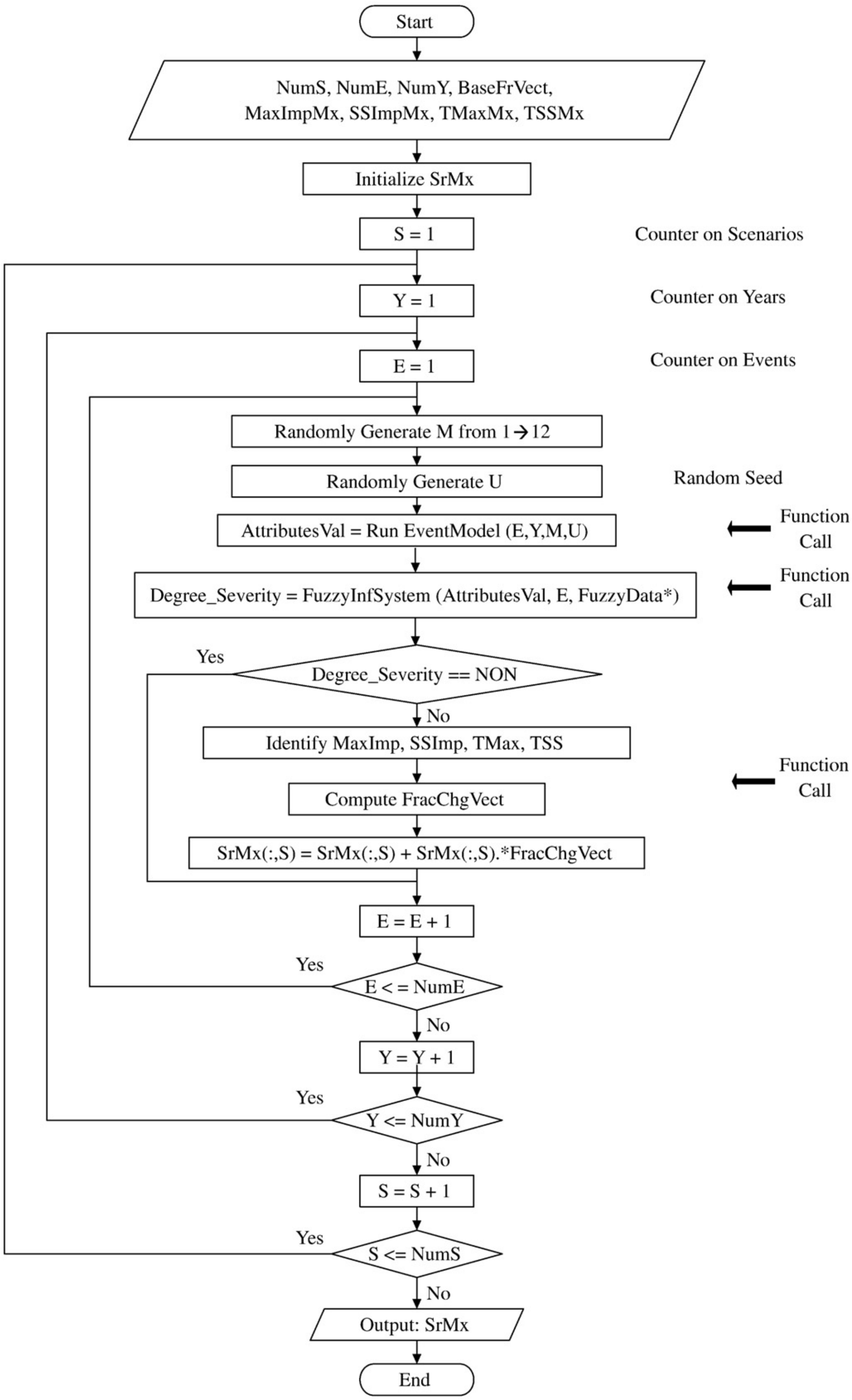

Fig. 4. Flow chart of the 'Main' function.

Table 3
MaxImpMx.

	High	Medium	Low
E1	−0.1875	−0.095	−0.0725

5. Case study

The following example illustrates the use and implementation of the new approach:

Assume that we need to study how would a possible '*Drought at a River Basin*' (unprecedented event) affect the annual flow of water into a certain lake. Thus for simplicity, one event (NumE = 1) is incorporated in the study. If it occurs, it has a negative impact. However, the algorithm can be directly applied to more general cases with possibly large number of events.

In our analysis, 100,000 scenarios are generated (NumS = 100,000) and the study is for fifteen years ahead (NumY = 15), i.e. from 2010 to 2025. Assume that surprise-free values (BaseFrVect) for fifteen years ahead, i.e. 180 months, are available. The data associated with the event (estimated by experts) is listed below.

A. Maximum Impact Matrix (MaxImpMx) (Table 3)
B. Steady-State Impact Matrix (SSImpMx) (Table 4)
C. Time *(in months)* to Maximum Impact Matrix (TMaxMx) (Table 5)
D. Time *(in months)* to Steady-State Impact Matrix (TSSMx) (Table 6)

From Tables 4 and 5, it is clear that the expected impact associated with the high degree of severity is greater than that associated with medium degree of severity which is greater than the one associated with low degree of severity.

The stochastic dynamic model we applied – in this specific case study – is a demo model inspired by Lorenz's (chaotic) model of weather prediction [18], which exhibits the phenomenon of the butterfly effect (i.e. sensitive dependence on initial conditions). The only element of stochasticity introduced to this model is a small perturbation in the initial condition of a certain stock (state variable). These very small perturbations in the initial condition produce large variations in the (long term) behaviour of the model.

The probability of occurrence of the event is assumed to be affected by change in the values of two attributes:

1. *Average temperature* — for which three characteristics are defined: low, medium and high. And;
2. *Average humidity* — for which two characteristics are defined: wet and dry.

To generate the set of fuzzy rules, we elicit the experts' knowledge. Table 7 illustrates a survey form for generating fuzzy rules in our case.

We assume that the majority of expert responses are the ones shaded in grey. Therefore, the fuzzy rules are accordingly defined as follows:

1. IF average temperature is low and average humidity is wet THEN severity is NON.
2. IF average temperature is low and average humidity is dry THEN severity is low.
3. IF average temperature is medium and average humidity is wet THEN severity is NON.
4. IF average temperature is medium and average humidity is dry THEN severity is medium.
5. IF average temperature is high and average humidity is wet THEN severity is NON.
6. IF average temperature is high and average humidity is dry THEN severity is high.

Rules 1, 3 and 5 can be combined into a single rule and hence only four rules exist. The modified rule is: IF average humidity is wet THEN severity is NON.

To illustrate how the inference process works, Fig. 5 shows detailed rules of evaluation process of a given scenario at a future point in time where the value of the average temperature is 30 and the value of the average humidity is 20. For each rule, we take the minimum value as a result of using the 'AND' operator [13,17]. And as mentioned before, we adopt the Maximum membership principle de-fuzzification method which corresponds to taking the largest value among those generated from the rules evaluation. As indicated by the figure, for this specific scenario in this point in time, the result is that the event 'Doesn't Occur', i.e. severity degree 'NON'.

After running the MATLAB program, we obtain 100,000 scenarios which differ based on the event timing and severity of occurrence. We cannot plot all the 100,000 scenarios and thus, we present three representative scenarios as illustrated in Fig. 6: the 90th percentile representing the best case, the 50th percentile (median) representing the most likely to happen and the 10th percentile representing the worst case.

The figure above shows that the three representative scenarios have lower values than the base forecast and thus proves logical since the unprecedented event incorporated in the analysis (drought at a river basin) has a negative impact. It also shows that the event effect started to take place after around four months from the present point[4] which is the average Time to Maximum Impact illustrated in Table 5. One can easily notice that the forecasted time series has an expanding oscillatory behaviour, with a period of

[4] Note that the historical data plotted in Fig. 6 are for only 3 years, i.e. 36 months.

Table 4
SSImpMx.

	High	Medium	Low
E1	−0.1	−0.05	−0.0375

Table 5
TMaxMx.

	High	Medium	Low
E1	2	4	6

Table 6
TSSMx.

	High	Medium	Low
E1	6	10	12

oscillation around forty months. The average flow values are approximately 5.25, 5.1, 4.85 and 4.7 (million cubic meter) for the base forecast, 90th percentile, median and 10th percentile scenarios respectively.

We have run several experiments to further validate the developed algorithm. The conducted experiments included incrementally changing the impact values for each degree of severity. By visually inspecting the figures of future scenarios associated with these experiments, we can verify that the algorithm works logically and responds to changes in a systematic way.

6. Conclusion and future work

Trend Impact Analysis (TIA) is an advanced forecasting tool used in futures studies for identifying, understanding and analyzing the consequences of unprecedented events on future trends. In some cases, unprecedented events do not occur without some early warning indicators that is; their occurrence is triggered when the values of a set of attributes reach certain threshold values. Therefore in such cases, it is better not to estimate the probability of occurrence of an unprecedented event directly; but rather estimate it indirectly via its attributes. Fuzzy Logic is a powerful approach for reasoning with uncertainty which is tolerant for imprecise information. Hence in this paper, we proposed a Fuzzy Logic based TIA approach that allows for generating more justifiable estimates for an event probability of occurrence as a function of the projected values of its associated attributes. The

Table 7
Survey form for generating fuzzy rules.

Rule	Attribute 1 (average temperature)	Attribute 2 (average humidity)	Event severity	
Rule #1	Low	Wet	Low	□
			Medium	□
			High	□
			NON	■
Rule #2	Low	Dry	Low	■
			Medium	□
			High	□
			NON	□
Rule #3	Medium	Wet	Low	□
			Medium	□
			High	□
			NON	■
Rule #4	Medium	Dry	Low	□
			Medium	■
			High	□
			NON	□
Rule #5	High	Wet	Low	□
			Medium	□
			High	□
			NON	■
Rule #6	High	Dry	Low	□
			Medium	□
			High	■
			NON	□

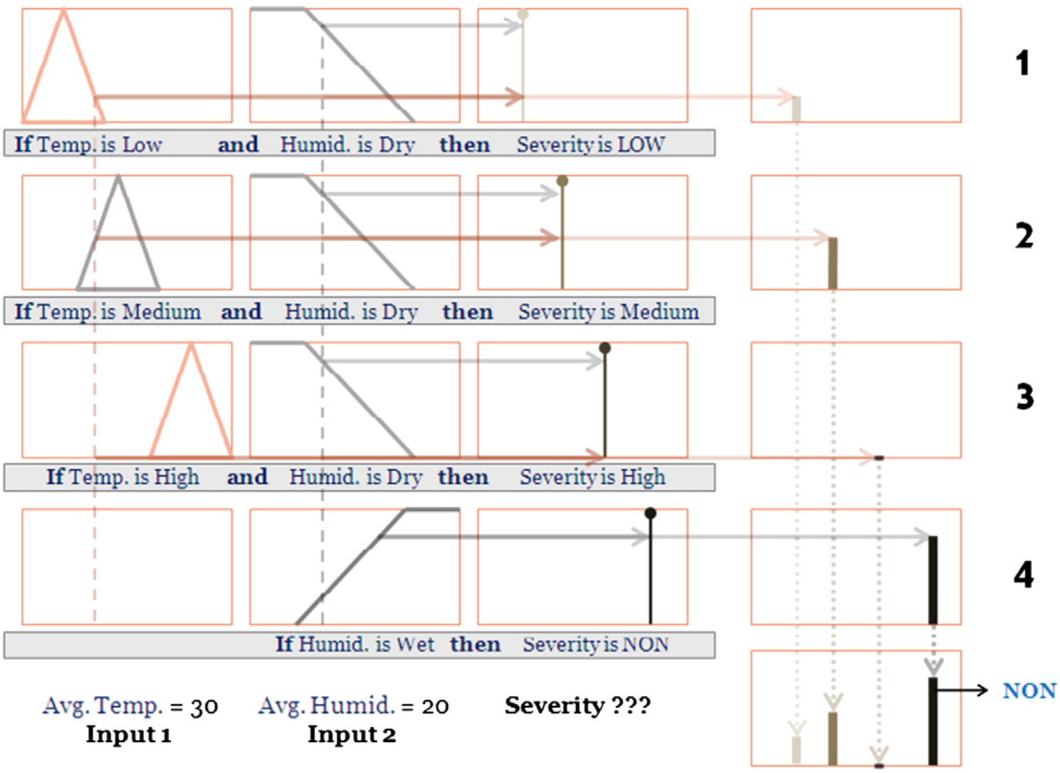

Fig. 5. Fuzzy inference mechanism.

proposed approach can be considered an efficient decision support tool that can give early indication of the timing and severity of unprecedented events.

To summarize, in this paper, we describe an extension of the Trend Impact Analysis (TIA) that avoids the usual expert estimation of event parameters by using trigger variables. A fuzzy approach is used to identify the occurrence and severity of an event, depending on the values of its trigger attributes. The trigger attributes can be calculated by a stochastic dynamic model; then different scenarios are generated using Monte-Carlo simulation. To illustrate the proposed method, a simple example is provided concerning the impact of river basin drought on the annual flow of water into a lake.

In a future research, this work could be extended by integrating the proposed approach with the Neural Network based TIA [8] – i.e. a developing a *Neuro–Fuzzy* approach. Moreover, this work could also be modified to take into account the inter-

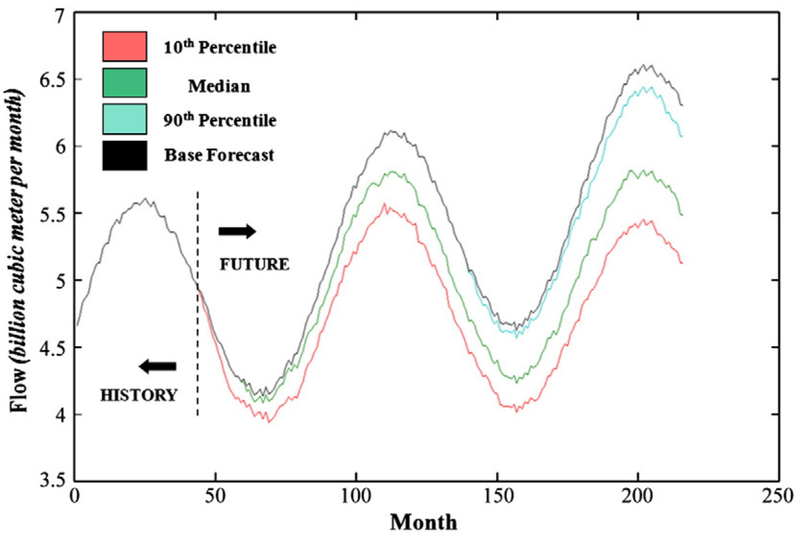

Fig. 6. Future scenarios generated.

dependencies between the occurrences of events and how would this affect their estimated probabilities — i.e. conducting a Cross Impact Study, as suggested by Gordon [2].

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