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Invited Survey Paper

Fuzzy inductive reasoning: a consolidated approach to data-driven construction of complex dynamical systems

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Fuzzy inductive reasoning (FIR) is a modelling and simulation methodology derived from the General Systems Problem Solver. It compares favourably with other soft computing methodologies, such as neural networks, genetic or neuro-fuzzy systems, and with hard computing methodologies, such as AR, ARIMA, or NARMAX, when it is used to predict future behaviour of different kinds of systems. This paper contains an overview of the FIR methodology, its historical background, and its evolution.

Keywords: fuzzy inductive reasoning; General Systems Problem Solver; complex dynamical systems; fault detection and diagnostic systems; decision support systems

1. Introduction

Fuzzy inductive reasoning (FIR), based on General Systems Problem Solver (GSPS; Klir 1985), is a methodological tool for data-driven construction of dynamical systems and for studying their conceptual modes of behaviour. FIR performs induction starting from raw data to build qualitative models. Some of the main advantages of this methodology are the following:

- The methodology can be applied to any application domain. It is fully pattern based, with no need for assuming any internal structure of the constructed system. In this respect, it is similar to neural networks.
- FIR allows the otherwise qualitative models to treat time as a continuous (quantitative) variable. This is of primary importance when dealing with mixed quantitative/qualitative systems (Cellier, Nebot, Mugica and de Albornoz 1992). In this respect, other qualitative approaches, such as the Qualitative Physics of Forbus (1984) or the QSIM of Kuipers (1986), are not adequate in this case.
- The methodology contains an inherent model validation mechanism that prevents reaching conclusions that are not justifiable on the basis of available facts. In this respect, FIR is similar to knowledge-based systems.
- Inductive reasoning operates in a qualitative fashion just like the knowledge-based reasoning. Although it is not able to offer a complete trace back of the full reasoning process, as expert systems do, it does provide information about the subset of variables selected for the reasoning process, and it can at least provide a justification

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for the predicted output based on the qualitative states of the selected input variables. Somehow, the structure of the system that allows us to provide explanations underlay in the set of pattern rules generated by inductive reasoning. There are various ways of generalizing this structure, for example using linguistic or fuzzy rules, as is explained in Section 5.

We agree that 'in general, allowing more uncertainty tends to reduce complexity and increase credibility of the resulting model' (Klir and Yuan 1995). In fact, this principle has guided the development of FIR, with the aim of enlarging the class of problems that can be dealt with by FIR.

This paper is structured as follows: in Section 2, basic ideas of the GSPS are briefly outlined. Section 3 is an overview of the evolution of the FIR methodology since its emergence in 1979. The main characteristics of the methodology are presented in Section 4, and Section 5 is devoted to a discussion of relevant recent developments. Finally, conclusions of this study are given in Section 6.

2. General Systems Problem Solver

The term 'GSPS' has been used in the literature for some 50 years in the following two senses:

1. A broad conceptual framework for describing all conceivable systems at the most general level of abstraction, to categorize them into useful mathematical categories, and to formulate all possible systems problems that emanate from these categories.
2. A methodology for dealing with all systems problems that can be formulated in terms of the chosen categories of systems within the conceptual framework.

Since FIR is a direct methodological outgrowth of GSPS, we introduce in this section some key ideas regarding the categorization of systems within the GSPS conceptual framework that are essential for understanding our overview of FIR in Sections 3–5. The full coverage of GSPS is in the book by Klir (1985) and its expanded and reformatted second edition (Klir and Elias 2003). A personal account of the process through which the GSPS had developed is in an autobiographical article by Klir (1988).

The most fundamental categories of systems recognized within the GSPS framework are characterized by epistemological criteria. Hence, they are usually called epistemological categories of systems. These categories are partially ordered by their information content: a system in some category contains, according to this ordering, all information contained in comparable systems in any lower-level category, but contains some additional information. The ordering forms a semilattice, which is usually referred to as an epistemological hierarchy of systems.

The most primitive category, and the lowest one in the epistemological hierarchy, consists of systems that are now usually called experimental frames (in older publications, they were called source systems or primitive systems). Importance of experimental frames is that all systems in any other (i.e. higher) category area are based on them. Systems belonging to distinct categories are comparable when they are based on the same experimental frame. Each experimental frame consists of the following components:

1. A set of variables chosen on an object of interest for some purpose, such as prediction, retrodiction, prescription, diagnosis, control, decision making, and the like.
2. A set of states that are recognized for each chosen variable.

3. One or several supporting parameters (such as time, space, population, space-time, and so on), each associated with a set of instances, that represent an essential background for change of states of the variables involved. The overall set of instances for all supporting parameter is called a support set. However, FIR deals only with dynamical systems in which the supporting parameter is time.

It is important to realize that experimental frames do not contain any information about how the variables are constrained. Their role is solely to provide a framework within which systems at higher epistemological levels are described.

At the next (higher) epistemological level is a category of systems that are called data systems. Each of them consists of an experimental frame and data regarding states of variables involved within the support set specified in the experimental frame. In general, data are functions that map overall supporting sets to overall state sets of the variables.

At the next epistemological level is a category of systems in which a constraint (relation) among variables of the experimental frame is described in some support-invariant manner. This changeless description can be used for generating data within any given support set and any given initial or boundary conditions. Systems in this category are called generative systems.

Climbing further up the epistemological hierarchy involves two principles of integrating systems as components into larger systems. According to the first principle, several systems of one of the three introduced categories, which may share some variables or interact in some other way, are viewed as subsystems integrated into one overall system. Overall systems of this sort are called *structure systems*. The subsystems forming a structure system are often called its *elements*. When elements of a structure system are themselves structure systems, the overall system is called a *second-order structure system*. *Higher-order structure systems* are defined recursively in the same way.

According to the second integrating principle, an overall system is viewed as varying in the given support set and within a class of systems of any of the other categories. The change from one system to another within the delimited class is described by a replacement procedure that is *support-invariant*. Overall systems of this category are called *metasystems*. In principle, the replacement procedure of a metasystem may also change. Then, a support-invariant higher-level replacement procedure is needed to describe the change. Overall systems of this sort, with two levels of replacement procedures, are called *meta-metasystems* or *metasystems of second order*. *Higher-order metasystems* are defined recursively in the same way. Structure systems whose elements are metasystems are also acceptable, as well as metasystems defined in terms of structure systems.

It is significant that all the GSPS epistemological categories of systems are actually categories in the strong sense of the mathematical category theory (Klir and Rozehnal 1996).

Systems in each epistemological systems category are further classified by various methodological distinctions. These are relevant secondary distinguishing characteristics between systems in each epistemological category that are methodologically significant. That is, problems involving systems characterized by different methodological distinctions must be handled by different methods.

Methodological distinctions between experimental frames involve variables and their supporting parameters. Examples are distinctions between continuous and discrete variables, crisp and fuzzy variables, continuous and discrete time, and the like. See Klir and Elias (2003) for further details.

It was already mentioned that systems contained in some epistemological category entail all knowledge contained in comparable systems in epistemological categories at any lower level. Comparable systems are those that are based on the same experimental frame. Climbing up the ladder is the aim of inductive reasoning methodology.

To climb from an experimental frame to a data system requires some data gathering. Before climbing further up, to the category of generative systems, a suitable preprocessing of rough data obtained by observation, measurement, or in any other way, is often desirable. Details of this process within FIR are described in Section 3. Once data are represented in a suitable form, FIR methodology analyses the data with the aim of finding one or more time-invariant relations among variables of the experimental frame that are maximally useful in some specified sense. In any of the time-invariant relations, variables may be classified into input and output variables. If they are, then states of the input variables are usually viewed as being determined from outside the system and used as conditions for determining states of the output variable via the time-invariant relation. Such systems are called directed systems, whereas systems in which variables are not classified into input and output variables are called neutral systems.

A simplified hierarchy of epistemological categories of systems and its role in FIR is shown in Figure 1. Observe that FIR involves only the lowest three levels in the hierarchy.

3. FIR methodology

The FIR methodology, as described in Section 2, is located entirely at the hierarchical levels of experimental frames, data systems, and generative systems of the GSPS. It deals with transformations within each of data and generative levels and with transitions between the two levels. The FIR methodology is composed of four basic functions: fuzzification, qualitative modelling, qualitative simulation, and defuzzification, as can be seen in Figure 2, in which the main screen of the Visual-FIR platform is shown.

The fuzzification module (*Recode*) describes a transformation within the data level, namely from the quantitative (raw) data to its qualitative counterpart. The qualitative modelling module (*Optimal mask*) describes the next step up the ladder from the data

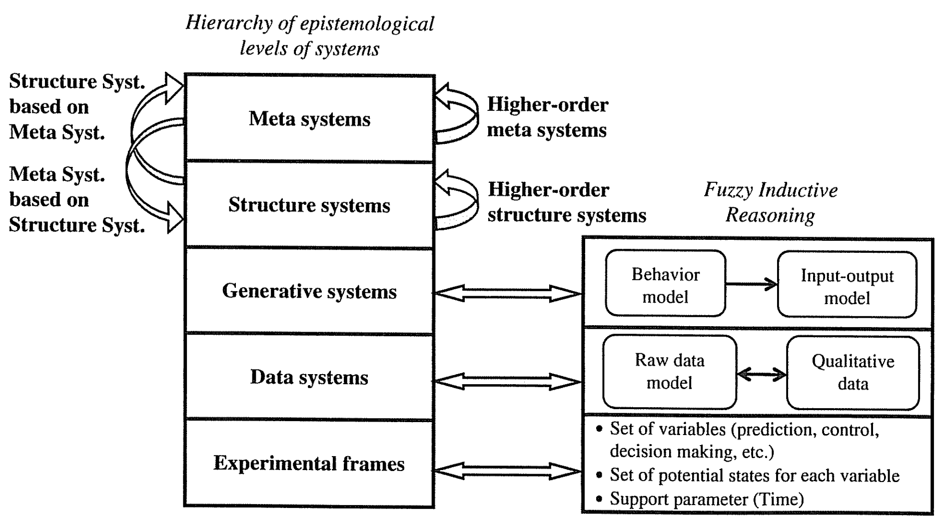


Figure 1. Simplified overview of the hierarchy of epistemological categories of systems and its role in FIR.

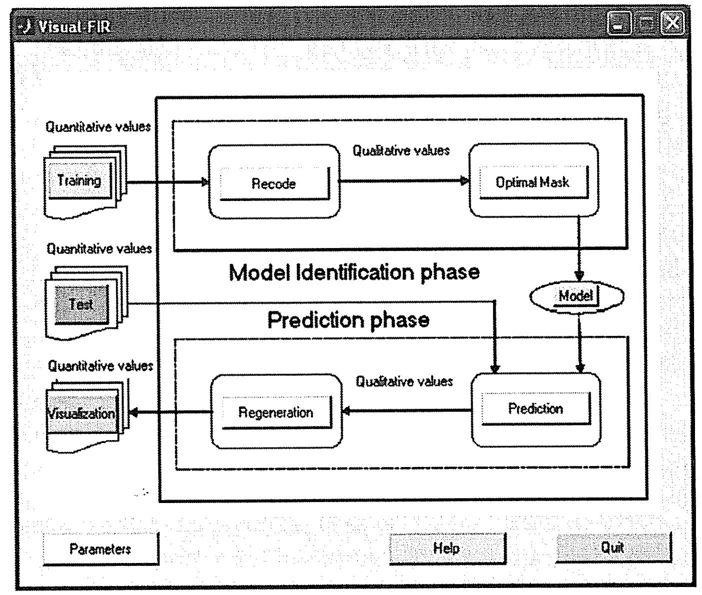


Figure 2. Visual-FIR main screen with the four main processes of FIR methodology, i.e. *Recode*, *Optimal mask*, *Prediction*, and *Regeneration*.

systems level to the generative systems level. This is accomplished by induction. The term induction is synonymous with climbing up the epistemological ladder, whereas deduction means descending it. The qualitative simulation module (*Prediction*) denotes the transition back down the ladder to the previous level, and the defuzzification module (*Regeneration*) performs another transformation at the data systems level.

3.1 *Fuzzification*

A transformation from quantitative values into qualitative values is very useful for the purpose of inductive modelling. Any data-fitting algorithm (and this is what inductive modelling is all about) invariably involves some sort of optimization procedure. Thus, inductive modelling applied to the original quantitative, i.e. real-valued, variables involves a search across an n-dimensional continuous search space. Such a search is invariably very time-consuming. By converting the quantitative values to qualitative values, the search is simplified dramatically, since the search space gets reduced to the n-dimensional discrete search space of the class values. Using this approach, the class values are used for a fairly coarse optimization, whereas the fuzzy membership values are then used for the fine interpolation between neighbouring class values, once the optimal class value has been found. In the FIR methodology, the fuzzification process is accomplished by means of the fuzzy recoding function. In most transformations from a quantitative to a qualitative space, some information is lost in the process. Obviously, a temperature value of 30°C contains more information than the value hot. The FIR recoding technique avoids this problem.

Figure 3 shows an example of fuzzy recoding of the variable temperature. For instance, a quantitative temperature value of 23°C is recoded into a qualitative class value of 'normal', with a fuzzy membership function value of 0.755 and a side function value of 'right' (since it is to the right of the maximum of the bell-shaped membership function that characterizes the class 'normal'). Thus, a single quantitative value is recoded into a

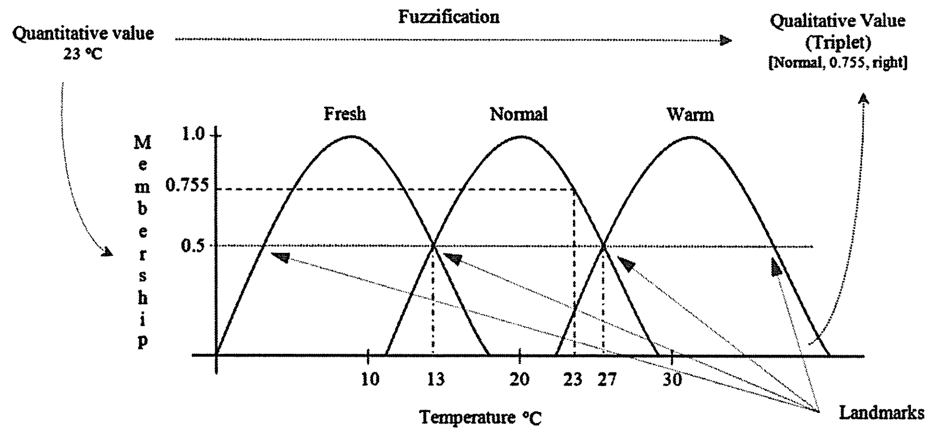


Figure 3. FIR recoding of a temperature value of 23°C.

qualitative triple that contains exactly the same information as the original quantitative value and it is thus possible to regenerate the quantitative value precisely.

In order to convert quantitative values to qualitative triples, it is necessary to specify to the recode function the number of classes into which the definition domain of each variable is going to be divided, as well as the landmarks that separate neighbouring classes from each other. Once this information is given, the recode engine of FIR automatically fuzzifies the quantitative data values. As will be explained later, genetic fuzzy systems have also been developed to learn the number of classes and landmarks.

3.2 *Qualitative modelling*

At this point, the continuous trajectory behaviour recorded from the system has been converted into episodic behaviour (a qualitative data stream) by means of the recode function. In the process of modelling, it is desired to discover causal relations among the variables that make the resulting state transition matrices as deterministic as possible. This is accomplished by means of the optimal mask function which is responsible for and temporal relations between variables that offer the best likelihood for being able to predict the future system behaviour from its own past, thereby obtaining the best model (composed by the mask and the pattern rule base in the FIR terminology) that represents the system. A mask represents a possible relation among the qualitative variables. Let us introduce the concept of a mask by means of a simple example composed of two inputs, u_1 and u_2, and one output, y. A possible mask for a system with two inputs and one output is shown in Figure 4.

The negative elements in the matrix of Figure 4 are referred to as *m*-inputs (mask inputs). They denote input arguments of the qualitative functional relationship. They can be

t \ x	u_1	u_2	y
$t-2\delta t$	-1	0	-2
$t-\delta t$	0	-3	0
t	-4	0	+1

Figure 4. Example of a mask for a system with two inputs (u_1 and u_2) and one output (y).

either inputs or outputs of the system to be modelled, and they can have different time stamps. The above example contains four *m*-inputs. The sequence in which they are enumerated is immaterial. The single positive value denotes the *m*-output and the zero elements represent unused connections. In the above example, the first *m*-input corresponds to the input variable u_1 two sampling intervals back, $u_1(t-2\delta t)$, whereas the second *m*-input refers to the output variable y two sampling intervals into the past, $y(t-2\delta t)$, etc.

A mask denotes a dynamic relationship among qualitative variables. It has a certain number of rows, i.e. the depth of the mask. It represents the temporal domain that can influence the output. Each row is delayed relative to its successor by a time interval of δt representing the time lapse between two consecutive samplings. How is a mask found that, within the framework of all allowable masks, represents the most deterministic state transition matrix? In the FIR methodology, the concept of a mask candidate matrix is introduced. A mask candidate matrix is an ensemble of all possible masks from which the best is chosen by a mechanism of exhaustive search. The optimal mask function searches through all legal masks of complexity two, i.e. all masks with a single *m*-input, and finds the best one; it then proceeds by searching through all legal masks of complexity three, i.e. all masks with two *m*-inputs, and finds the best of those; and it continues in the same manner until the maximum allowed complexity (a parameter) has been reached. In all practical examples, the quality of the masks will first grow with increasing complexity, then reach a maximum, and then decay rapidly. As will be mentioned later, other search strategies have been developed, i.e. variants of hill-climbing and genetic algorithms as well as statistical approaches based on cross-correlation and spectral coherence functions.

Each of the possible masks is compared to the others with respect to its potential merit. The optimality of the mask is evaluated with respect to the maximization of its forecasting power that is quantified by means of a quality measure, based mainly on Shannon entropy. Once the best mask has been identified, it can be applied to the qualitative data matrices that were previously obtained in the recoding process, resulting in a fuzzy pattern rule base that, in FIR terminology, is called the behaviour matrix. Figure 5 shows the process of constructing the pattern rule base. The left side of Figure 5 shows an excerpt of the class qualitative data matrix, one of the three matrices belonging to the qualitative data model. The dashed box symbolizes the mask that is shifted downwards along the class qualitative

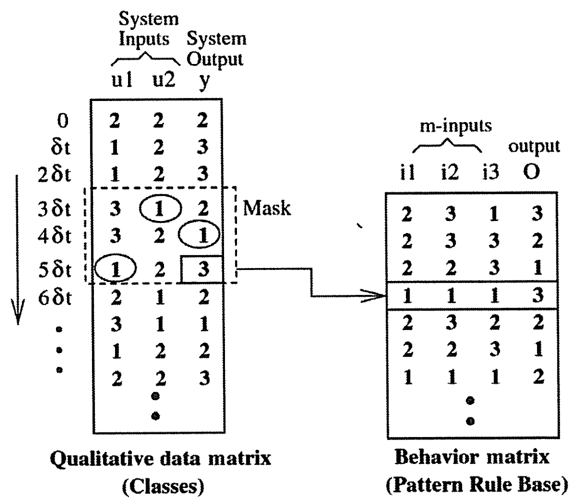


Figure 5. FIR pattern rule base construction.

data matrix. The round shaded 'holes' in the mask denote the positions of the m-inputs, whereas the square shaded 'hole' indicates the position of the output. The class values are read out from the class qualitative data matrix through the 'holes' of the mask and are placed next to each other in the behaviour matrix (pattern rule base) that is shown on the right side of the Figure 5. Each row of the behaviour matrix represents one pseudo-static qualitative state or qualitative rule. For example, the shaded rule of this figure can be read as follows: 'If the first m-input, $i1$, has a value of '1' (corresponding to 'low'), and the second and third m-inputs, $i2$ and $i3$, have also values of '1' (corresponding to 'low') then the output, o, assumes a value of '3' (corresponding to 'high')'.

3.3 *Qualitative simulation*

The FIR inference engine is based on a variant of the k-nearest neighbour rule. The five nearest neighbours (5NN) pattern-matching algorithm is the core of the FIR inferencing process. The forecast of the output variable is obtained as a weighted average of the potential conclusions that result from firing the five rules, whose antecedents best match the actual state. The prediction procedure is presented in the diagram of Figure 6 for an example containing three inputs and one output.

The optimal mask is placed on top of the qualitative data matrix in such a way that the m-output matches with the first element to be predicted. The values of the m-inputs are read out from the mask, and the behaviour matrix (pattern rule base) is used to determine the future value of the m-output, which can then be copied back into the qualitative data matrix. The mask is then shifted further down by one position to predict the next output value. This process is repeated until all desired values have been forecast. The qualitative simulation process predicts an entire qualitative triple, from which a quantitative variable can be obtained whenever needed. The prediction process works as follows.

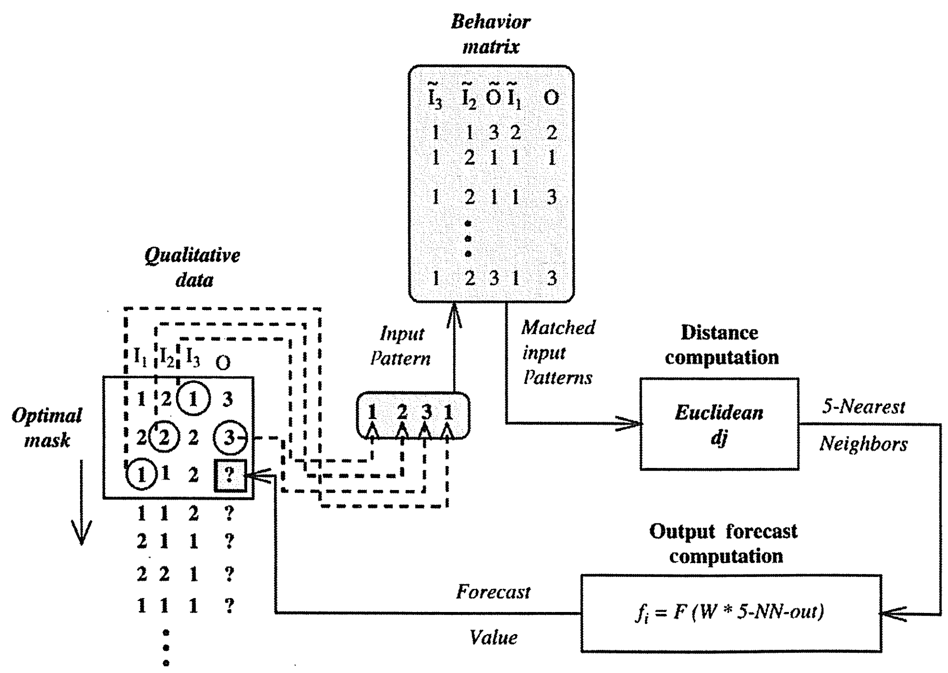


Figure 6. FIR forecasting process diagram.

The membership and side functions of the new input state (input pattern in Figure 6) are compared with those of all previous recordings of the same input state contained in the behaviour matrix.

For this purpose, a normalization function is computed for every element of the new input state, and a distance formula is used to select the 5NN, the neighbours with the smallest distances, that are used to forecast the new output state. Several normalization and distance functions are available in the implementation of the FIR methodology. The contribution of each neighbour to the estimation of the prediction of the new output state is a function of its proximity. This is expressed by giving a distance-weight to each neighbour, as shown in Figure 6. The new output state values can be computed as a weighted sum of the output states of the previously observed 5NN. Several enhancements, described in Section 4, have been introduced in the prediction module, i.e. the confidence measure that allows determining the reliability of predictions and the causal relevance concept that quantifies the importance of each m-input variable with respect to the output, improving the predictions obtained.

3.4 *Defuzzification*

Regeneration is the inverse function of recoding. It converts qualitative triples into quantitative values. As was mentioned earlier, no information is lost in the process of fuzzification. The qualitative triple contains exactly the same information as the original quantitative value, and it is thus possible to recover a unique quantitative value from the qualitative triple.

4. Evolution of the inductive reasoning methodology

In the late 1970s, a subset of the GSPS methodology that was well developed at that time was implemented under the name 'Systems Approach Problem Solver' (SAPS) by Uyttenhove (1979). The limited computer science tools available at that time prevented the development of a sufficiently flexible implementation of the GSPS concepts and, consequently, SAPS could never be used for anything but mere toy problems. In the mid-1980s, Cellier and some of his students reimplemented SAPS as a CTRL-C function library. The new implementation was called SAPS-II (Cellier and Yandell 1987). Fuzzy measures (Klir and Folger 1988; Wang and Klir 1992) or, according to current terminology, generalized measures (Wang and Klir 2009) were introduced into the GSPS methodology in the late 1980s, and some were incorporated into the SAPS-II toolkit (Li and Cellier 1990).

In the 1990s and the 2000s, it has been demonstrated that SAPS-II was an effective tool for dealing qualitatively with behaviours of highly complex non-linear technical systems (Cellier and Mugica 1992; de Albornoz and Cellier 1993, 1994; Mugica and Cellier 1994; López, Cembrano and Cellier 1996; Mirats, Cellier and Huber 2002), as well as biomedical and biological systems (Nebot and Cellier 1994; Nebot, Cellier and Linkens 1996; Jensen, Nebot, Caminal and Henneberg 1999; Nebot, Mugica and Gómez 2001; Nebot, Mugica, Cellier and Vallverdú 2003; Nebot, Cellier, Carvajal and Mugica 2009a). At that time, SAPS-II went through several methodological enhancements (explained later), and SAPS-II has become FIR. Some of the most interesting application areas in which the FIR methodology has been used are the following:

- *Control*: In this area, a method for a systematic design of fuzzy controllers that can be used to control any plant for which the inverse dynamics problem can be solved was

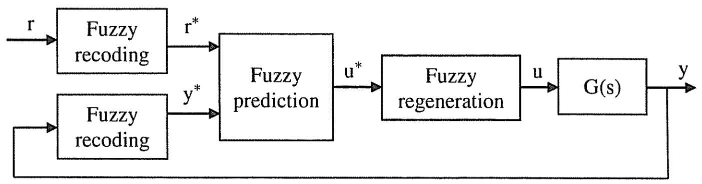


Figure 7. Fuzzy controller design.

developed via FIR methodology. The idea behind the design is summarized in Figure 7. It is based on the identification of a FIR model of the control system. Once obtained, the crisp input and output, r and y, are converted into fuzzy variables, $r*$ and $y*$, by means of fuzzy recoding. The FIR controller uses these two fuzzy variables to compute a fuzzy control input, $u*$, by means of fuzzy prediction, that is converted back to a crisp control signal, u, by means of fuzzy regeneration. This systematic way of designing fuzzy controllers has been used to design controllers for different problems, i.e. inverse pendulum, cargo ship steering, and amount of anaesthetic agent to be administered to patients among others (Mugica 1995; Nebot *et al.* 1996).

- *Ill-defined systems*: Quite a large number of ill-defined applications in the context of biological and biomedical systems have been addressed by means of the FIR methodology, i.e. anesthesiology, cardiology, shrimp farming, ozone concentration, etc. (Nebot *et al.* 1996, 2001, 2003, 2009a; Gómez *et al.* 2003). These kinds of systems suffer from particular problems such as the lack of information from the point of view of both quantity and quality, technical and ethical difficulties with obtaining information, diversity in patient behaviour, incomplete information, different sampling rates, different time constants, etc. Due to all these difficulties, coming up with decent models for such systems is usually a very difficult task. However, the FIR methodology has done a very good job when compared with modelling and prediction capabilities of other inductive methodologies, both quantitative and qualitative, such as NARMAX, long and short-term memory, neural network, multilayer perceptrons, Elman and modified Elman networks, as well as some genetic fuzzy rule base systems.
- *Time series*: The prediction of univariate time series poses, as it is the case of ill-defined systems, serious practical problems because of their intrinsic characteristics, i.e. lack of information available, non-stationary characteristics, time varying, etc. Therefore, it is also an interesting area for studying the usefulness of FIR modelling and prediction methodology. To this end, water demands series in different cities were modelled with FIR and compared with other methodologies largely used for predicting time series, e.g. AR, ARIMA, and NAR models, as well as a standard feed-forward neural network. The results showed that FIR models performed much better than the other methodologies for these applications (López 1999).

As was already mentioned, several relevant enhancements have been incorporated into the methodology over the years:

- Development of a technique that allows FIR to deal with missing values (Nebot 1994).
- Development of an evolutionary fuzzy system for learning the fuzzification parameters of FIR, i.e. the number of classes per variable (granularity) and the membership functions (landmarks) that define its semantics (Acosta 2006). This reduces the number of parameters that the user should determine.
- Development of qualitative confidence measures (based on similarity and proximity) for the estimation of the prediction error, without the necessity of knowing the true value of the system's output data. The proximity measure is based on a distance function, whereas the similarity measure is based on the similarity between fuzzy sets (López 1999).
- Development of prediction techniques that make use of these confidence measures, allowing selection, at every time instant, of the best qualitative prediction model. By dynamically changing the qualitative model, the prediction error can be reduced considerably in those systems that operate in multiple regimes (López 1999).
- Development of different approaches to deal with suboptimal mask search strategies:
  - Variants of hill-climbing and genetic algorithms (Jerez and Nebot 1997; Nebot and Jerez 1997; Mirats 2001).
  - Statistical approaches based on cross-correlation functions. One of them only looks at linear relationships between variables, and therefore often finds a suboptimal mask of highly inferior quality (de Albornoz 1996), although converges in polynomial time. Another is based on spectral coherence functions. It also converges in polynomial time but avoids the pitfall on relying on linear relationships only. Thus, it also is more likely to find a high-quality mask (Mirats 2001).
- Development of a method that allows the decomposition of the system into subsystems. This would allow obtaining a model of the system from its subsystems, which in turn reduces the computational time needed for the overall effort. Given a k-variable system, the cost of computing a unique k-variable model is much higher than computing a set of p models of $p < k$ variables. The task of decomposing a model into subsystems is done sequentially. First, linear static relations between variables are searched in order to form groups of variables that are linearly related. Afterwards, with the variables that do not form part of any of the founded groups, nonlinear relations are searched. Finally, time is added to the process in order to cope with the information contained in the time dependence between variables (Mirats 2001).
- Development of the causal relevance concept. The idea behind causal relevance is to quantify how much influence each system variable has, from the spatial and temporal points of view, on the prediction of the output. Quantify the importance of each variable with respect to the output allows to reduce uncertainty during the forecasting stage becoming easier to obtain good predictions. This concept is implemented in FIR methodology by weighting the distances between neighbours. Depending on the richness of the data available and the difference between the causal relevance of the variables, better neighbours are going to be selected due to the fact that it weighs the contribution of each variable (Nebot, Mugica and Castro 2009b).
- Development of a visual platform for the FIR methodology under the Matlab environment. The new tool, named Visual-FIR, provides a new interface to the FIR methodology, offering a user-friendly platform and a high-efficiency implementation. This platform presents a new vision of the methodology based on process blocks and adds new features, increasing the overall capabilities of the FIR methodology (Escobet, Nebot and Cellier 2008).

5. New developments

A FIR model is a qualitative, non-parametric, grey model based on fuzzy logic. FIR models are synthesized rather than trained, which speeds up the modelling phase in comparison with other inductive modelling techniques, such as NN. While NN uses the training data to approximate a function and afterwards the training data are discarded, FIR transforms the training data into pattern rules, being part of the prediction process. Therefore, while the neural network will always predict something, the fuzzy inductive reasoner will not predict anything that cannot be validated on the basis of the available data. In this manner, the technique guarantees that the model will not forecast behaviour for which the available data are insufficient to substantiate the prediction. We consider this intrinsic model validation mechanism a distinct and significant advantage in comparison with other modelling methodologies such as neural networks. However, this advantage can experience a drawback when the size of the pattern rule base obtained is quite large, i.e. when the number of data available from the system is huge. To deal with this problem, the Uncertainty with FIR (UN-FIR) approach has been developed in order to reduce the number of pattern rules stored while preserving as much of the information given by the data as possible.

On the other hand, although FIR models are grey models, and therefore are more comprehensible than black models, they are not clear enough to be useful for decision-makers. Therefore, another interesting goal is to allow FIR models to be useful also as decision support systems. With this idea in mind, the Linguistic rules in FIR (LR-FIR) approach has been developed. Finally, going one step further to the design of FIR controllers (see Section 4), a tool for developing fault detection and diagnosis systems (FDDS) based on FIR, named VisualBlock-FIR, has been created. Figure 8 synthesizes the evolution of the FIR methodology. This section describes the three new approaches: UN-FIR, LR-FIR, and VisualBlock-FIR.

5.1 *Uncertainty with FIR*

As said before, FIR methodology has an important drawback. The pattern rule base generated by the qualitative model identification process can be very large when working with large data sets. The number of generated rules can be almost as large as the number of observations. Therefore, when a large number of pattern rules exist in the rule base, the

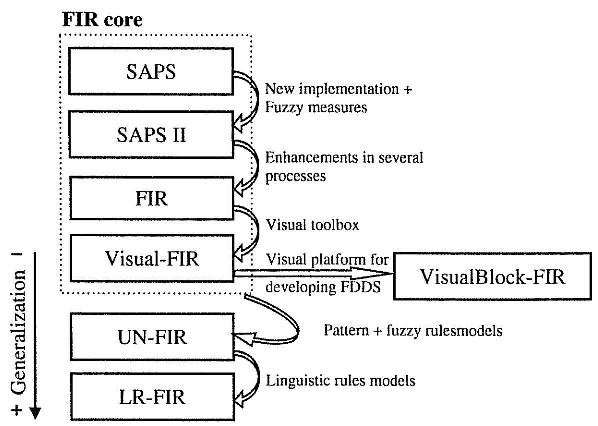


Figure 8. Evolution of the FIR methodology.

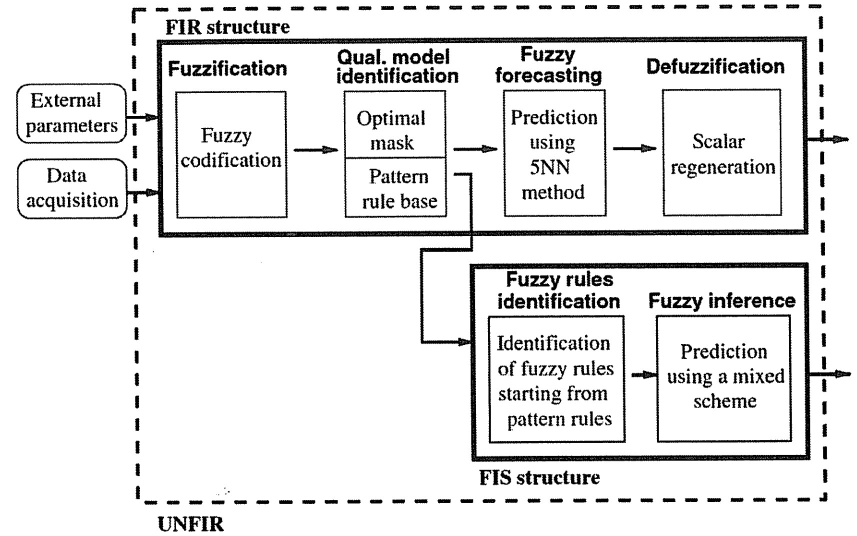


Figure 9. UN-FIR structure.

prediction of a new output value becomes tedious and slow. UN-FIR proposes an alternative for the last two processes of FIR methodology (fuzzy forecasting and defuzzification) that consists of a fuzzy inference system (FIS) that allows to compact the pattern rule base in a classical fuzzy rule base and to define a mixed scheme that affords the prediction of the future behaviour of the system. This is shown in the FIS structure box of Figure 9.

The additional structure does not pretend to substitute the fuzzy prediction and defuzzification processes but to increase the efficiency of FIR methodology. The extended methodology obtains a fuzzy rule base by means of the fuzzy rules identification process that preserves as much information contained in the pattern rule base as possible. Therefore, the former can be considered a generalization of the latter. In other words, the fuzzy rule base is a set of compacted rules that contains the knowledge of the pattern rule base. In this process, some precision is lost but the robustness is increased.

The idea behind the *fuzzy rules identification process* is to obtain fuzzy rules starting from pattern rules based on the spatial representation of both kinds of rules. The pattern rule base can be represented graphically in the input–output space. If the model identified by FIR is of high quality, then the pattern rules form a uniform thin surface in the input–output space. However, if the model obtained is not so good the spatial representation looks as a surface where the thickness of some parts is more significant than that of others. The thickness of the surface means that for a given input pattern (or a set of antecedents) the output variable (or consequent) can take different class values, i.e. the pattern rule base is not deterministic and has a high degree of uncertainty. As mentioned before, the quality of the model is computed by means of an entropy reduction measure that reflects the level of determinism of the state transition matrix associated with the mask and the behaviour matrix. A good model is characterized by a high level of determinism associated with its rules, and all physical behaviour patterns are represented in the model. The spatial representation of such a situation would be a uniform thin surface. A FIS generates a unique output value (consequent) for a set of antecedents. Therefore, the graphical representation looks always like a totally uniform surface or mesh in the input–output space. The tuning process consists on automatically adjusting the mesh built by the FIS to the surface obtained from the pattern rules. The tuning process is different if a Mamdani (Mamdani and Assilian 1975) or a Sugeno (Sugeno and Yasukawa 1993) FIS is going to be used in the prediction process.

The *fuzzy inference process* of UN-FIR methodology allows the prediction of systems behaviour by means of five different schemes. The first scheme corresponds to the classical fuzzy forecasting process of FIR methodology (only pattern rules). The second and third schemes correspond to purely Mamdani and Sugeno FISs, respectively (only classical fuzzy rules). Finally, the fourth and fifth are mixed schemes that allow the prediction of systems' output by using a combination of a purely FIS and pattern rules.

The mixed scheme is a combination of a fuzzy scheme and a set of pattern rules. The advantage of the pattern rules is that they are more accurate than the fuzzy rules in those areas where a large degree of uncertainty exists. In order to take advantage of this fact, the mixed scheme keeps a percentage of pattern rules that will allow the prediction of those system states with a high degree of uncertainty. The idea is to keep those pattern rules that are located outside of the multidimensional mesh generated by the FIS. In this way, the mixed scheme is integrated by the fuzzy scheme and a set of pattern rules that the fuzzy system is not able to capture due to its uncertainty level.

The integration strategy is defined by means of a function that is able to reduce the influence of the fuzzy scheme and to increase the influence of the pattern rule scheme or vice versa. When the antecedents of the system's state to be predicted and the antecedents of the closest pattern rule are very close or are exactly the same the mixed scheme will eliminate the influence of the fuzzy system and the prediction value is then obtained directly from the consequent of that pattern rule. When both antecedents are far away from each other (defined by a parameter), the prediction is obtained exclusively from the fuzzy system. Otherwise, the prediction process obtains, on the one hand, a prediction value by using the selected fuzzy scheme and, on the other hand, obtains the prediction value directly from the closest pattern rule available. The prediction obtained from the mixed scheme is a weighing of both values. The weighing between these two values is computed with respect to the distance between the antecedents of the system state to be predicted and the antecedents of the closest pattern rule. The mixed prediction schemes take advantage of the uncertainty inherent to the data. UN-FIR methodology has been used in several applications given very good results (Mugica and Nebot 2006).

5.2 *Linguistic rules with FIR*

The UN-FIR model composed by a set of classical fuzzy rules and a reduced subset of the pattern rule base is, still, quite large and complex enough to make it difficult to understand the systems' dynamics involved. Therefore, it is not a good tool for decision-makers. More comprehensible and simple models become indispensable when the goal is to construct decision support systems. This is accomplished by developing the LR-FIR approach. The main trait of LR-FIR is that it is able to compact the pattern rule base obtained by FIR into a significantly reduced set of linguistic rules, which contains the main aspects of system's behaviour. This is shown in the LR-FIR structure box of Figure 10.

Notice that, contrary to UN-FIR approach, the aim of LR-FIR is not, but an easy understanding of systems' behaviour. Therefore, the main goal of the proposed approach is to offer a useful tool for decision support. Figure 11 shows in a schematic way the main phases of the LR-FIR algorithm. The model can be summarized as a set of ordered steps:

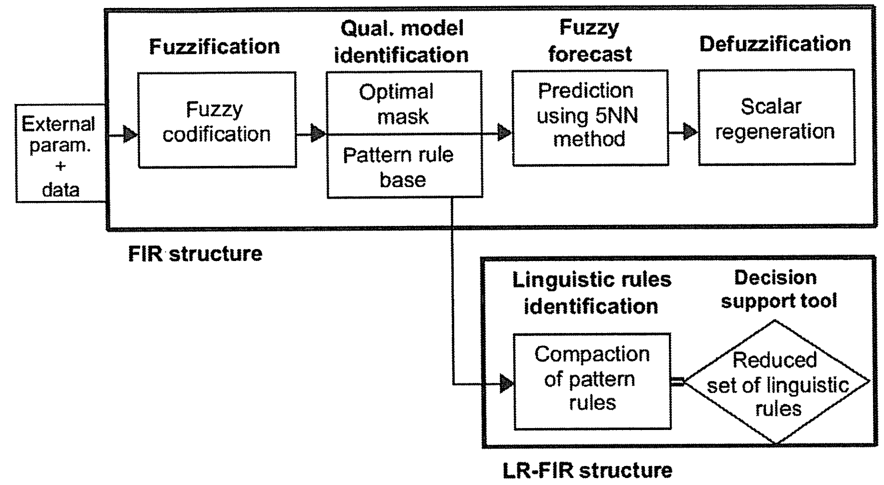


Figure 10. FIR and LR-FIR structures.

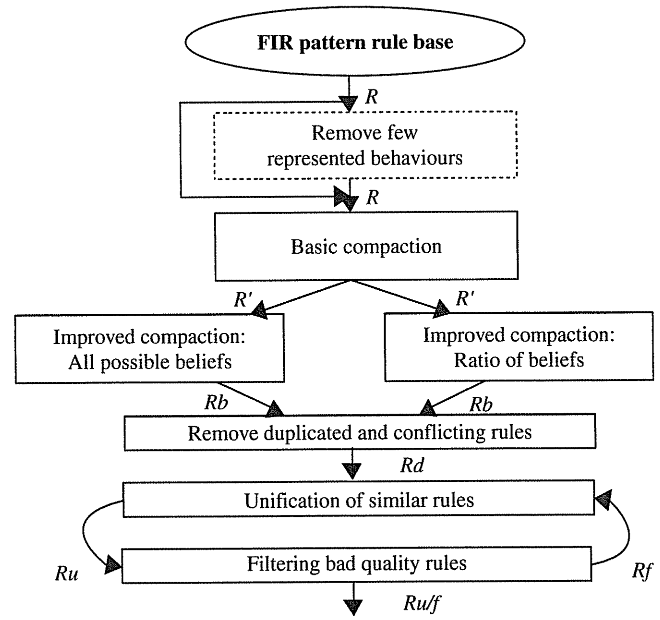


Figure 11. Ordered steps of the rule extraction method.

(1) *Basic compaction*. This is an iterative step that evaluates, one at a time, all the rules in a pattern rule base. The pattern rule base, R, is compacted on the basis of the 'knowledge' obtained by FIR. A subset of rules can be compacted in the form of a single rule, when all premises but one (P_a), as well as the consequence share the same values. Premises, in this context, represent the input features, whereas consequence is the output feature in a rule. If the subset contains all legal values of P_a, all these rules can be replaced by a single rule that has a value of -1 in the premise P_a. When more than one -1 value is present in a compacted rule, it is compulsory to evaluate the existence of conflicts. If conflicts exist, the compacted

rule is rejected, otherwise, it is accepted. Conflicts occur when one or more extended rules have the same values in all its premises but different values in the consequence.

(2) *Improved compaction.* Whereas the previous step only structures the available knowledge and represents it in a more compact form, the improved compaction step extends the knowledge base to cases that have not been previously used to build the model. Thus, whereas step 1 leads to a compacted data base that only contains knowledge, R', the enhanced algorithm contains undisputed knowledge and uncontested belief. Two options are developed: in the first one, from R' all input features (premises) are visited once more in all the rules that have non-negative vales (not compacted), and their values are replaced by -1. An expansion to all possible full sets of rules and their comparison with the original rules are carried out. If no conflicts are found, the compacted rule is accepted, and otherwise, rejected. The second option is an extension of the basic compaction, where a consistent and reasonable minimal ratio of the legal values should be present in the candidate subset, in order to compact it in the form of a single rule. This latter option seems more reasonable because the assumed beliefs are minimal and do not compromise the model previously identified by FIR.

The obtained set of rules is subjected to a number of refinement steps: removal of duplicate rules and conflicting rules; unification of similar rules; evaluation of the obtained rules; and the removal of rules with low specificity and sensitivity. These are standard metrics that assess the quality of the obtained rules. LR-FIR has been applied to different domains, such as e-learning global change temperature, and brain tumours diagnosis, where useful results were obtained (Castro, Nebot and Mugica 2011).

5.3 *Fault detection and diagnosis with FIR (VisualBlock-FIR)*

A FDDS is a monitoring system that is used to detect faults and diagnose their location and significance in a system (Chen and Patton 1999). It performs *fault detection*, *fault isolation*, and *fault identification* tasks. Fault detection determines when a fault occurs; fault isolation indicates the location of the fault; and fault identification estimates the size and nature of the fault (Bocaniala and Sá da Costa 2006). The VisualBlock-FIR FDDS performs these tasks in two processes: fault detection and fault isolation/identification. The detection task determines when the fault occurs and triggers an alarm. The isolation/identification task studies the new systems' behaviour and determines the fault that has occurred. Therefore, the information related to the specific fault, i.e. location, nature, and size, is obtained in the same process.

The fault detection process of VisualBlock-FIR is described in Figure 12. In this figure, the grey boxes represent FIR processes, whereas the white boxes constitute the fault detection procedure. The data measured from the system is converted into qualitative triples by means of the FIR fuzzification process. The fuzzy forecasting process predicts the next output value from the qualitative data using the FIR model that represents the current behaviour of the system. The fuzzy forecasting process computes also the enveloping interval that drives the detection process. The enveloping concept is based on the 5NN that are computed inside the FIR inference engine by means of the k-nearest neighbour technique. The enveloping is composed by an upper bound (maximum value of the 5NN) and a lower bound (minimum value of the 5NN) delimiting the space where the real output signal should be present.

It is important to notice that the enveloping bounds are obtained directly from the 5NN, and therefore the predicted signal is always in the range set by the two bounds. This is not

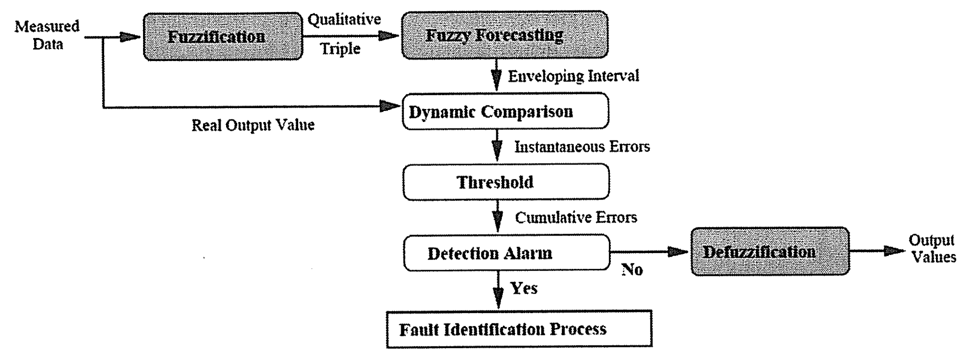


Figure 12. VisualBlock-FIR fault detection process.

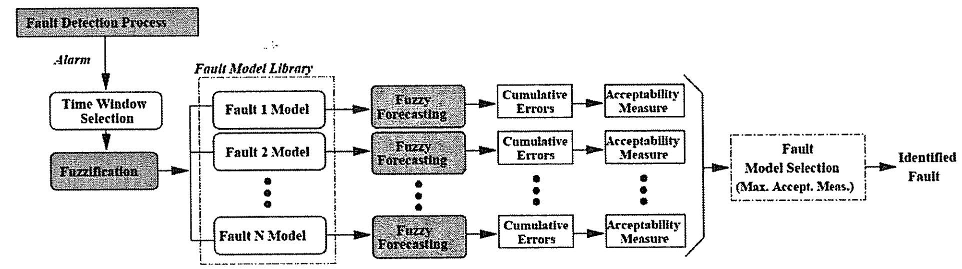


Figure 13. VisualBlock-FIR fault isolation/identification process.

the case of the real signal. If a real value falls outside the envelope, an instantaneous error occurs, meaning that the model used in the prediction does not correctly represent the system at that specific point. The instantaneous errors encountered inside a predetermined *detection* time window are accumulated over time. When the cumulative errors within the time window are greater than the threshold specified by the modeller, an alarm is issued, and it is then necessary to isolate/identify the fault that has occurred.

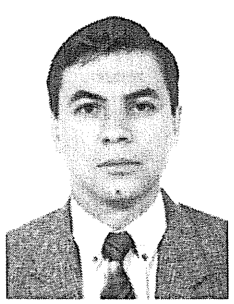
The fault isolation/identification process is presented in Figure 13. The grey boxes represent again FIR processes, whereas the white boxes constitute the fault isolation/identification procedure. Once an alarm has been triggered because abnormal behaviour has been detected, a *prediction* time window is selected. The size of the time window defines the number of prediction values that will be used in order to isolate/identify the fault that has been generated. Therefore, the prediction time window guides the prediction during the isolation/identification process. A small size of the time window is desired because it implies fast model identification. For each fault model stored in the fault model library, a prediction of the size of the time window takes place using the FIR fuzzy forecasting process. The prediction errors produced during each of the forecasting processes are accumulated. Therefore, each fault model stored in the library has associated a cumulative error. This error is used to compute the model acceptability measure, i.e. a relative index ranking the models in terms of their ability to predict the new behaviour of the system. This measure allows isolating and identifying the fault that has occurred in a reliable way. It also offers guidance when the identification process faces additional problems, e.g. when the produced fault is not a foreseen fault and, therefore, is not available in the fault model library, or when two different models can explain an observed fault. The model with the largest acceptability measure is selected as the one that best represents the new behaviour of the system, and therefore, the detected fault has been isolated/identified. VisualBlock-FIR performs detection and isolation/identification tasks by means of a user-friendly framework that runs under the Simulink platform. VisualBlock-FIR has not yet been applied to industrial plants in real time. However, its usefulness has been studied by means of two complex systems, the DAMADICS actuator benchmark (Escobet, Nebot and Cellier 2011a) and a fuel cell power system (Escobet, Nebot and Mugica 2011b), where the detection and identification times obtained by VisualBlock-FIR compares favourably with other FDDS such are the model-based fault diagnosis approach based on computing residuals (Escobet *et al.* 2009), the neuro-fuzzy multiple-model observer (Uppal, Patton and Witczak 2003), the extended unknown input observer with genetic programming and a qualitative reasoning coupled with fuzzy neural networks approaches (Calado, Sá da Costa, Bartyś and Korbicz 2006).

6. Conclusions

In this paper, an overview of the FIR methodology is presented. Successful results obtained in different types of applications when FIR is used to identify a model and simulate or predict its future behaviour has motivated the enhancement of the methodology over the years. Some of the more relevant enrichments are allowing FIR to work with missing values, reducing the amount of parameters that should be defined by the user by designing a genetic fuzzy system that learns the fuzzification parameters of FIR, the development of qualitative confidence measures which allow the estimation of the prediction error without knowing the system's real value, the development of different artificial intelligence and statistical strategies to enhance the mask search process or the definition of the causal relevancy concept that quantifies the importance of each variable already selected by the mask search. Currently, the FIR methodology is available to the user in the form of a visual tool, named Visual-FIR, which offers a user-friendly platform and a high-efficiency implementation.

Moreover, new approaches whose main objective is increasing the type of problems that FIR can deal with have been also developed in recent years. In this direction, the UN-FIR approach solves the problem of obtaining a big pattern rule base by allowing to compact the pattern rule base into a classical fuzzy rule base and a reduced set of pattern rules. It also defines a mixed pattern-fuzzy rules prediction scheme. On the other hand, the LR-FIR approach deals with the problem of identifying white FIR models, which is fundamental if the goal is to use FIR models as decision support systems. Finally, the VisualBlock-FIR tool allows the development of FDDS based on FIR to deal with real plants in a user-friendly manner.

Notes on contributors



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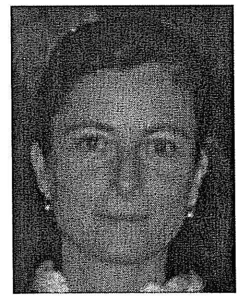

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