PREDICTING MICRO-LEVEL INNOVATION POTENTIAL WITH NEUROFUZZY HYBRID MODELING – A MODEL FRAMEWORK

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ABSTRACT

In this recent article I am intent on showing the findings of my model building process. The aims of my model is as follows: forecast/estimate the innovation performance of a corporation; solve statistical and methodological problems such as stability – plasticity, interpretablitiy - precision - significancy using linguistic variables; offer solution for information granulation; avoid significant loss of information observed at hard statistic methods; able to adapt to varying environment. Nevertheless, it may exploit and algorithmize the benefits of the everyday human thinking (soft calculation – fuzzy logic) and the learning and adapatation abilities of the neural systems – the synergy between the mathematized everyday human thinking and classical mathematics. Innovation management sets the economical base of my research, which is indisputably a current issue nowadays. Fuzzy technologies have become a magic word in engineering, logistics or even in medical sciences, however, it is scarcely used in the fields of social sciences. In contrast to hard calculations – where accuracy, assurance and rigidity are the primary points of view – this soft calculation method returns to the stochastic reality, which is characterized by the tolerance to inaccuracy and some doubtfulness, thus creating effective synergy between casual linguistic and classical analytical modeling.

INTRODUCTION

In my research the positivist paradigm plays the main role of the specific coherent practices of the standards of academic pragmatics (laws, theories, adaptations, tools of researches, models). This is accounted for by the peculiarity of the subject, on the other part the predominance of available positivist literature against the interpretative.

The positivist approximation can be decolonized from any ethical considerations, normative verdicts (Friedman 1953): according to Keynes it deals with what exists and not what must exist. This approach contains a system of generalizations which makes possible to describe correctly the effects of the environmental changes with such performance which depends exclusively on accuracy, scope and correspondence with the facts of the prognosis - creating an objective system like they occur in natural science (Friedman 1953). According to the positivists a theory which is unable to describe reality with numbers is inappropriate and not well reasoned (McCloskey 1986). The goal of science for the positivist research workers is to reveal the scientific regularities whereby the phenomena under investigation will be explicable and at the same time predictable (Alvesson 2000). The goal of research is to reveal the objective verity with the collation of the effects of the research worker's personality, the chosen research method and the influential factors (McCloskey 1986). Hence the analytic confines of the research is predefined and universal, the analytic model is class-based (problem granulation), the process of the research is convergent, logically traceable an objective. According to Friedman's theory (1953) the positivist science is just as objective (or transposable) as any other natural sciences. Nevertheless the fact that social sciences deal with connections between people and organizations, the researcher oneself is a part of the research - in a more direct way than in natural sciences - makes significantly difficult to reach objectivity.

Accordingly there are two potential ways offering themselves. One of them is loosening the objectivity postulations set up by positivism. This way it can be reasonable to consider how much is the greatest permissible subjectivity which is still able to grant the objectivity of the natural scientific positivist approach.

The other available way is to prepare the applied methodology to cope with handling "fuzzy", subjective, often inaccurate and noisy dataset by objective, solid mathematical laws.

And the research worker must choose from the two possible ways, hence according to Friedman's to this very day still standing thesis (1953) every economical deduction necessarily - even genuinely or impliedly - is based on a positivist prediction telling us the consequences of doing rather this instead of that: providing information about the consequences of a given series of actions and not determining normative verdicts.

In the course of my research I will choose the second way: try to set up such modeling methodology into economics which based on the positivism's logical basics is able to take into the object of research also subjective and inert factors beside the expected objectivity (without yielding it). These factors are either forced to be precise (along with a high bias) by the classic methodologies or easing the positivist objectivism.

METHODOLOGICAL DIFFICULTIES OF MODELING MANAGEMENT ISSUES

Natural sciences as positivist sciences contain conditionally approved, generalizations related to social/economical phenomena. With these generalizations the effects of variations which occur in the case maps can be predicted. The extension of generalization, the accuracy of approximations, the confidence level of them and the enhancement of the predictions' accuracy are discouraged not only by the boundaries of the researcher's all-time capabilities, but such circumstances as well which occur vigorously in social sciences, especially in economics - however this is not their obligate idiosyncrasy (Friedman 1953). In economics inevitably we better rely on non-controlled experiences than on controlled experiments, hence it is exceptionally hard to provide clear and unambiguous evidence to verify hypothesizes correctly.

A hypothesis can only be tested with its conclusions, predictions and realism whether it can be verified or not. This is what disturbs our methodological principles, making difficulties in testing hypothesizes and verifying them. Ergo the social scientist has to be fully aware of his methodological principles, more than others and must strictly stick to their restrictive case maps, not allowing rejecting each or more of them. In this manner a social scientist has to adapt to those few of the deductible conclusions.

Considering the above being fully aware of restrictive assumptions is elementary during the phase when we are building our model. It is also indispensable to have the wide knowledge about techniques of testing the restrictive assumptions, being familiar with the standard system of requirements of social science's models.

Modeling requirements

The essential requirements of modeling in social sciences - just like in mathematics - are **accuracy**, **significance** and **strictness**. The consistency originates in that tract of the science philosophy of mathematics in the XIX century which is called the "Revolution of strictness". The naming originates itself from Imre Lakatos, Hungarian mathematics and science philosopher (positive heuristics, the critique of naive falsificationism). Since that time we know the very precise and exact standardization which was taken over into the classic (hard) modeling of social science. Herewith arithmetization and standardization of modeling has been started. During arithmetization it was tried to reconduct the elusive terms of analysis and the theory of real numbers to the certain conception of natural numbers. Standardization meant the method of strict verification analysis.

The second group of requirements was conceived by Lotfi Zadeh - professor of mathematics at Berkeley University - in his "Fuzzy systems" theory. The first paradox states that increasing the complexity of a model (system) causes the decrease of the ability to make precise and significant conclusions. Moreover at a margin we realize that **exactitude** (arithmetical formalism) and **significance** became two criteria of the system which are respectively baring out each other.

The stability/plasticity dilemma means also a similar problem: how could we build such a model which is **plastic** enough to bear with its fast changing environment but at the same time it is also **stable** enough to reserve the previously acquired knowledge (coherence).

Similar contradiction turns up in case of interpretability - exactitude and interpretability - significance concept pairs.

Restrictive requirements

Beside the requirements above the research worker must face several restrictive requirements during the procedure of model building. The classic modeling techniques viz. often are not prepared for such problems like for instance issued by the extreme complexity of target function: what should be done when we cannot formulate the function which is analyzed for optimum (or any other known point). Perhaps if the high statistical error couples with low significance level or we can draw only approximate inference.

Subjective system information: Applying quantitative criteria is a common assumption of classic system modeling techniques. However in social science these so objective quantitative criteria are often not given for the researcher. In these cases the established custom is to transform the qualitative criteria to quantitatives but does this ensure objectivity? Are these transformations effective? The fact social science's - especially economics' - system information are subjective is widely admitted since all of our experiences are inevitably subjective. There are no exceptions to this rule (Babbie 2001). Accordingly it can be questioned whether a scientist could be such objective as the positivist ideal assumes. Now if our system information are subjective and the applied techniques require objectivity - just like the felt desire for positivism which seems invincible - then we must force the subjective information to precise or we must chose such methodology which is able to handle system information based on subjective value judgment.

Linearity: The cogency of congruity to the requirements of linearity is very strong since in most of the cases social scientists use linear regression in modeling. Most of the economic correspondences are nonlinear either by their variables or by their parameters. The research worker must transform the nonlinear model to linear - often with high bias - since during the estimation of parameters the case maps is near insatiable. In these cases the variables must be redefined.

Homoscedasticity: Must apply to every each probability variable of the regression model, so every variable must have the same finite σ^2 variance. Ergo each probability distribution has the same standard deviation with the target variable irrespectively of explanatory variables. Therefore the covariance matrix of the deviation variables is such a scalar matrix, which has the same σ^2 values in the main diagonal. For testing homoscedasticity the Goldfeld-Quandt, the Breusch-Pagan and the White tests are appropriate.

Independency: The explanatory variables of the model must be independent of each other: none of them can be reproduced by the linear combination of others. It is reasonable how difficult it is to find an example of such a system in reality organized in pursuance of stochastic principles where belonging to each of the criteria does not necessarily exclude the chance of belonging to another. It has an effect on that but besides there are other criteria which have effect on affiliation. In addition certainly there are lots of restrictive criteria the researcher must count on and which are well detailed in the most of statistics related books.

INTELLIGENT SYSTEMS

By the end of the 20th century the conventional system modeling techniques are more and more crowded out from scientific modeling by methods based on symbolic systems and artificial intelligence. These methods were used in same context with such expressions like interpretation and arguing by the end of the 90's. It was realized that systems based on these principles proved themselves to be efficient in solving such problems which could not be solved at all or only with defining lots of notations by traditional techniques like: analysis, statistics, precise and deterministic techniques of decision support and regulation, linear programming which can be perfect when dealing with simple problems. In more complicated cases certainly I mean the non-linear or dynamic programming techniques. The case maps of these techniques are increasingly insatiable. Let us take the simple regression model where the basic notation is the linearity of the variables and the disallowance of multicollinearity. However thinking through how hard it is to measure up to these expectations in such world where everything is coherent, connected: it is hard to identify every single effect and cause, making a big distinction between them.

Thus in very few cases the traditional techniques are not reliable and also not sure to be used. A problem can happen to be so complicated that we simply cannot formulate the function which is to be analyzed to find its optimum. It can also happen that the analysis could not provide a satisfying result, we get high statistical error with low significance level or we can only draw heuristic, approximate conclusions.

"Artificial intelligence based systems" is an umbrella term of such techniques and tools which handle problem solution by the human brain's functional analogies. The word "intelligence" alludes to the ability of efficient studying, adaptive response, making right decisions and the sophisticated way of lingual communication and comprehension. Hereby such models can be created which simulate the functioning of living organisms even the human brain's. These systems will be exceedingly appropriate for problem solution, pattern recognition, lingual processing, designing and forecasting more effectively and with less restrictions than the traditional models.

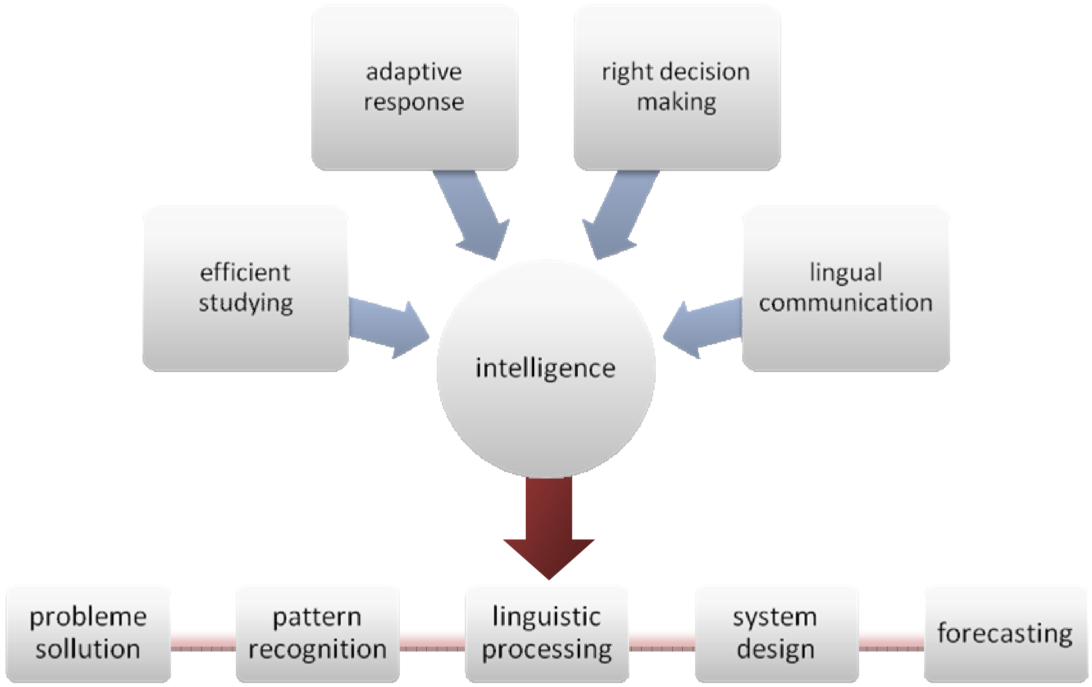

Figure 1: Intelligent systems (authors own edition)

ESTIMATION INNOVATION POTENTIAL

Modeling issues and performance objectives

Researchers tend to say that a model is not needed to develop a fuzzy controller, and this is the main advantage of the approach. However, will a proper understanding of the plant dynamics be obtained without trying to use first principles of physics to develop a mathematical model? And will a proper understanding of how to control the plant be obtained without simulation-based evaluations that also need a model? We always know roughly what process we are controlling (e.g., we know whether it is a vehicle or a nuclear reactor or a social model), and it is often possible to produce at least an approximate model. (Passino-Yurkovich, 1998) For a safety-critical application, if not a formal model is used, it is not possible to perform mathematical analysis or simulation-based evaluations. Is it wise to ignore these analytical approaches for such applications? Clearly, there will be some applications where you can simply "hack" together a controller, even fuzzy or conventional and go directly to implementation. In such a situation there is no need for a formal model of the process; however, is this type of control problem really so challenging that fuzzy control is even needed. Basically, the role of modeling in fuzzy control design is quite similar to its role in conventional control system design. In fuzzy control there is a more significant emphasis on the use of heuristics, but in many control approaches (e.g., PID control for process control) there is a similar emphasis. (Passino-Yurkovich, 1998) Basically, in fuzzy control there is a focus on the use of rules to represent how to control the plant rather than ordinary differential equations (ODE). This approach can offer some advantages in that the representation of knowledge in rules seems more lucid and natural to some people. For others, though, the use of differential equations is more clear and natural. Basically, there is simply a "language difference" between fuzzy and conventional control: ODEs are the language of conventional control, and rules are the language of fuzzy control. (Passino-Yurkovich, 1998)

Design of Controller module

According to Passino-Yurkovich fuzzy control system design essentially amounts to

- choosing the fuzzy controller inputs and outputs
- choosing the preprocessing that is needed for the controller inputs and possibly post-processing that is needed for the outputs
- designing each of the four components of the fuzzy controller

The fuzzy rule base is a central component of the fuzzy controller and it represents the "intelligence" in the fuzzy control algorithm. The rule-base is constructed so that it represents a human expert "in-the-loop." The information that we load into the rules in the rule-base may come from some human expert (this is the place where the designer's knowledge and experience must be correctly interpreted and organized into an appropriate set of rules). In some situations when there is no such human expert with many experiment, the control engineer will simply study the problem (perhaps using modeling and simulation) and write down a set of control rules that makes sense.

As an example, in the cruise control problem discussed above it is clear that anyone who has experience driving a car can practice regulating the speed about a desired set-point and load this information into a rule-base. For instance, one rule that a human driver may use is "If the speed is lower than the set-point, then press down further on the accelerator pedal." (Passino-Yurkovich, 1998) Every fuzzy rule can be divided into an antecedent part (IF...) and a consequent part (THEN...), with antecedent parts describing causes and consequent parts describing consequences relevant for control action. (Bouslama-Ichikawa, 1992). A rule that would represent even more detailed information about how to regulate the speed would be "If the speed is lower than the set-point AND the speed is approaching the set-point very fast, then release the accelerator pedal by a small amount". This second rule characterizes our knowledge about how to make sure that we do not overshoot our desired goal (the set-point speed). Generally speaking, if we load very detailed expertise into the rule-base, we enhance our chances of obtaining better performance. (Passino-Yurkovich, 1998)

Performance Evaluation

The basic reason for this is that a fuzzy controller is a nonlinear controller – so many conventional modeling, analysis (via mathematics, simulation, or experimentation), and design ideas apply directly. (Passino-Yurkovich, 1998) Since fuzzy control is a relatively new technology, it is often quite important to determine what value it has relative to conventional methods. Unfortunately, few have performed detailed comparative analyses between conventional and intelligent control that have taken into account a wide array of available conventional methods (linear, nonlinear, adaptive, etc.); fuzzy control methods (direct, adaptive, supervisory); theoretical, simulation, and experimental analyses; computational issues; and so on. Moreover, most work in fuzzy control to date has focused only on its advantages and has not taken a critical look at what possible disadvantages there could be to using it (hence the reader should be cautioned about this when reading the literature). For example, the following questions are cause for concern when you employ a strategy of gathering heuristic control knowledge.

- Will the behaviors that are observed by a human expert and used to construct the fuzzy controller include all situations that can occur due to disturbances, noise, or plant parameter variations?
- Can the human expert realistically and reliably foresee problems that could arise from closed-loop system instabilities or limit cycles?
- Will the human expert be able to effectively incorporate stability criteria and performance objectives (e.g., rise-time, overshoot, and tracking specifications) into a rule-base to ensure that reliable operation can be obtained? (Passino-Yurkovich, 1998)

These questions may seem even more troublesome (1) if the control problem involves a safety-critical environment where the failure of the control system to meet performance objectives could lead to loss of human life or an environmental disaster, or (2) if the human expert's knowledge implemented in the fuzzy controller is somewhat inferior to that of the very experienced specialist we would expect to design the control system (different designers have different levels of expertise). Clearly, then, for some applications there is a need for a methodology to develop, implement, and evaluate fuzzy controllers to ensure that they are reliable in meeting their performance specifications. (Passino-Yurkovich, 1998)

Architecture of fuzzy model

The architecture of my fuzzy controller or fuzzy logic controller (FLC) is shown below as a block diagram. This model is composed of four main elements:

- A fuzzy rule base (a set of IF-THEN rules) which has a fuzzy logic quantification of the expert's linguistic description of how to achieve a good control. It contains the knowledge in the form of a set or rules.
- An inference mechanism or inference engine (fuzzy inference module) which emulates the expert's judgment making in interpreting and applying knowledge about how to make predictions in desired fields.
- A fuzzification interface, which converts controller inputs into information that the inference mechanism can easily use to activate and apply rules.
- A defuzzification interface, which converts the conclusions of the interference mechanism into actual inputs of the process.

Basically we should view the fuzzy controller as an artificial decision maker that operates in a closed-loop system in real time. It gathers output data $y(t)$, compares it to the reference input $r(t)$ and then decides what the plant input $u(t)$ should be to ensure that the performance objectives will be met. (Passino-Yurkovich, 1998) To design the fuzzy controller, information must be gathered on how the artificial decision maker should act in the closed-loop system. Sometimes this information can come from a human decision maker who performs the control task, while at other times the control engineer can come to understand the dynamics of the system and write a set of rules about the forecast without outside help. These rules basically say "IF the innovation output and reference input are behaving in a certain manner, THEN the input should be some value" as mentioned above. A whole set of such "IF-THEN" rules is loaded into the rule-base, and an inference strategy is chosen, then the system is ready to be tested to see if the closed-loop specifications are met. (Passino-Yurkovich, 1998)

Fuzzy sets are used to quantify the information in the rule base, and the inference mechanism operates on fuzzy sets to produce fuzzy sets, so it must be specified, how the fuzzy system will convert its numeric inputs into linguistic outputs.

Let x (X be a linguistic variable and $T_i(x)$) be a fuzzy set associated with a linguistic value T_i. The conversion of a physical (numerical) value of x into a corresponding linguistic value by associating a membership degree, $x \rightarrow \mu T_i\,(x)$ is called fuzzification. The membership degree $\mu T_i\,(x)$ represents the fuzzy equivalent of the value of x. (Kovacic-Bogdan, 2006)

The inference mechanism has two basic tasks:

- determining the extent to which each rule is relevant to the current situation as characterized by the inputs u_i, $i = 1, 2, \ldots, n$ (this is task "matching")
- drawing conclusions using the current inputs ui and the information in the rule-base (we call this task an "inference step"). For matching note that $A_{j1} \times A_{k2} \times \cdots \times A_{ln}$ is the fuzzy set representing the premise of the ith rule $(j, k, \ldots, l; p, q)i$ (there may be more than one such rule with this premise). (Passino-Yurkovich, 1998)

The result of fuzzy inference is a fuzzy output set. On the other hand, every control task will imply the existence of crisp value at the fuzzy controller output. The procedure which extracts crisp output value from a fuzzy output set is called defuzzification.

Architecture of neural network

The neural network model is based on the following parameters which describe a neuron as shown on figure 2:

- Input connections (or inputs): $x_1, x_2, \ldots, x_n$. There are weights bound to the input connections: $w_1, w_2, \ldots, w_n$; one input to the neuron, called a bias, has a constant value of 1 and is usually represented as a separate input, say x_0.
- Input function f, calculates the aggregated net input signal to the neuron $u = f(x, w)$, where x and w are the input and weight vectors correspondingly; f is usually the summation function:
- An activation (signal) function s calculates the activation level of the neuron $a = s(u)$.

- An output function calculates the output signal value emitted through the output (the axon) of the neuron: $o = g(a)$; the output signal is usually assumed to be equal to the activation level of the neuron, that is, $o = a$. (Kasabov, 1998)

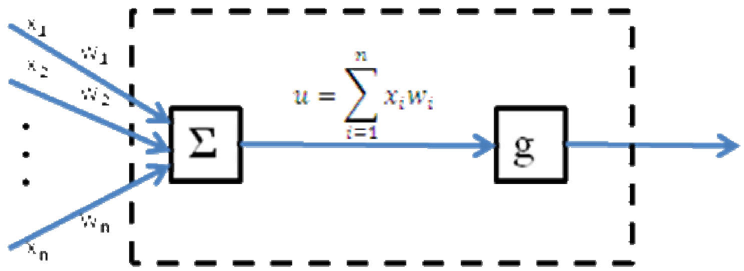

Figure 2: Artificial neuron (authors own edition)

An artificial neural network (or simply neural network) is a computational model defined by four parameters:

- Type of neurons (also called nodes, as a neural network resembles a graph)
- Connectionist architecture—the organization of the connections between neurons
- Learning algorithm
- Recall algorithm

The functioning of the neural network, when an input vector x is supplied, can be viewed as a mapping function $F: X \to Y$, where X is the input state space (domain) and Y is the output state space (range) of the network. The network simply maps input vectors $x \in X$ into output vectors $y \in Y$ through the "filter" of the weights, that is, $y = F (x = s (W, x)$, where W is the connection weight matrix. The functioning of a network is usually based on vector-matrix real-number calculations. The weight matrix represents the "knowledge", the long-term memory, of the system, while the activation of the neurons represents the current state, the short-term memory.

The most attractive characteristic of neural networks is their ability to learn. Learning makes possible modification of behavior in response to the environment. A neural network is trained so that application of a set X of input vectors produces the desired (or at least a consistent) set of output vectors Y, or the network learns about internal characteristics and structures of data from a set X. The set X used for training a network is called a training set. The elements x of this set X are called training examples. The training process is reflected in changing the connection weights of the network. During training, the network weights should gradually converge to values such that each input vector x from the set training data causes a desired output vector y produced by the network. Learning occurs if after supplying a training example, a change in at least one synaptic weight takes place. (Kasabov, 1998)

The training examples comprise input vectors x_i and the desired output vectors o_i. Training is performed until the neural network "learns" to associate each x_i input vector to its corresponding and desired output vector o_i. For example, a neural network can learn to approximate a function $y=f(x)$ represented by a set of training examples (x, y). It encodes the examples in its internal structure.

Hybrid modeling

The combined fuzzy-neuro system uses the advantages of both fuzzy model and neural network model. The output from the controlled process of the fuzzy controller is the input of the supervised neural network through the system's error detection mechanism. At the same time, the outputs of the neural network are the crisp inputs of the fuzzy controller. These inputs are modified by the feedback mechanism. In this sense there are two circles of the model: one for the neuro-fuzzy forecasting process mechanism, which produces outputs for the model, and the other feedback circle, intended to reduce the statistical errors of the weights of the neural network.

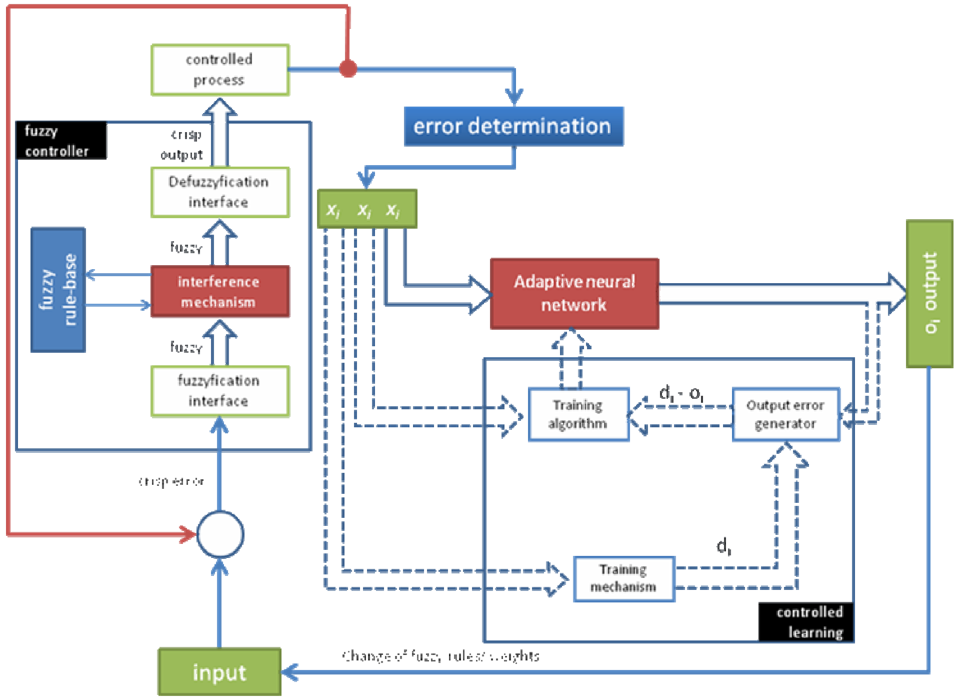

Figure 3: Block diagram of hybrid system (authors own edition)

ESTIMATION PARAMETERS

When defining the variables of the model we must separate them into two groups: on the one part the explanatory variables whereby we estimate and on the other hand the dependent (explained) variable which is estimated by the model. Each and every variable is a result of aggregation by factor analysis. The setup of each factor is done by the following variables:

F1a	Motivation	Creativity inspiration, Remuneration, Change seeking, Change adaptation	
F1b	Socialization	Group work, Innovation culture, Competitiveness, Communication, Ratio of experts, Age	
F1c	Action	Researches, Wide range of products, Modern products, improving quality, Adaptation of modern/efficient processes, Stepping to new markets, Increasing market share, Achieving higher elasticity in production, Improving work safety, Lowering the specific labor cost, Lowering the specific material cost, Meeting the rules, fulfilling standards	F1a-F1d: Organization
F1d	Adaptation	Problem solving, Brainstorming, Assimilation with tasks	
F2	Strategy	Long term company strategy, Market improvement strategy, Product improvement strategy, Innovation strategy, Reputation of strategies, Assimilation of strategies, Fitting of strategies	
F3	Diffusion	Company inside the group, Suppliers, Customers, Competitors, External experts, research centers, Universities, Outsourcing, Expositions, Conferences, Patent examination	
F4	Information	Efficiency of information, Effectiveness of information, Controlling, IT, Commercial sources, Marketing, Market leverage effect	
F5	Resources	Revenue, R & D expenses, Human resources, Creativity, Value added	
F6	Technology	Modernity, Incidence, Efficiency, Monitoring, Pushing effect, Adaptation of technologies, Supplier companies, Production-intensive company, Research-intensive company	

F7: Y Achievements	Amount of released publications, Number of protected patents, Number of know-hows, licenses, Marketization, Number of company innovations, Commitment, Competitiveness

SUMMARY

Hereby I schemed the reasonableness of necessarity of a neuralized fuzzy system in aspect of positivist scientific theory. I presented the procedure of building the system and the particularities of its operation. I have also defined the variables which can be used to estimate effectively the innovation potential at company level.

Although the data of the primary research are just being evaluated - so I cannot provide any consequences about the functioning of the model at this stage - but it is clear by now that the model is appropriate for solving scientific theoretical and methodological problems, thus describing reality more precisely.

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