Time Manufacturing Prediction: Preprocess Model in Neuro Fuzzy Expert System

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ABSTRACT: It is well known that an efficient time manufacturing prevision is a key-factor in today's global market. In particular, the growing interest in job-shop model arises from the need of an efficient management of Mixed Model Assembly Cell and Flexible Manufacturing System. Due to the complexity of prevision problems, a neuro-fuzzy Expert System has been widely proposed.
Recently the hybridisation of Fuzzy Logic with self-learning procedure have received concrete performance increase by the continuos increasing of the computational power of available computers, but the difficulties connecting whit high number of entries still exist.
This paper presents a pre-learning procedure to overpass the complexity of entries domain. In particular the model is tested in a mechanical manufacturing operative contest.

KEYWORD: Time manufacturing, Flexible Manufacturing System, Neuro-Fuzzy Expert System

INTRODUCTION

The development of Fuzzy Inference System characterised by a large number of input variables (more than five or six), appears very difficult especially in knowledge engineering in order to specify the real input variables, the relative relations, such as the consequent complexity of the knowledge base. [1][3][4]
As matter of fact, the absence of standard methods for transforming human experience in knowledge base (rules and database) of Expert System and effective methods for tuning the membership functions such as minimising the output error measure or maximising performance index, influences the results of Fuzzy System. [3][6÷8]
Particularly, many difficulties appear during the knowledge building the system if skilled people and experts are not available. Lot of rules correspondent to the number of input variables and to the fuzzy set used, that involves the definition of rules often redundant and sometimes impossible combinations of fuzzy set from the logical and physical point of view. Then low system precision and long times of elaboration.
The problem is simplified cashiering the opportune rules or combinations, but in this case is necessary the availability and the collaboration of an expert with consequent expansion of the times for a correct development. Generally, the discrimination among the rules, renders hard maintenance of knowledge base system. In fact, the adjournment performed from different planners, often involves the writing of rules that could be redundant or in contrast with the previous rules.
In any case, also arranging experienced people, in operational very booming contexts characterised by an elevated numbers of variables, times and results of fuzzy inference process appear unlikely prevision. [6÷9]
In addition the Neural Networks of classical types, results complex to develop when they are processing a large number of signals related to the high numbers of variables. The main problem is the complexity of hidden layer that result in a high number of examples strictly depending from variables, layers and nodes. Especially if an adequate capability of generalisation is needed. [2][12][13]

In this situation, the phase of learning will be realised by adequate numbers of examples and by number of varying and from the number of levels and nodes.
Unfortunately, in industrial activity, the main difficulty is the availability of information, often incomplete or discriminating, and in each case times of development, relative to an optimal realisation of the neural structure will be elevated
The small number of examples, the choice of the self-learning algorithm and the determination of the architecture, affect the abilities of generalisation of the net, and the utilisation of pure neural networks, in the operational context appears particularly binding. [2][12][13]
The present work proposes a hybrid procedure that get from the effect synergy of the previous techniques a sensible increase of the throughputs of Expert System.
The proposed methodology, overpassing the difficulties to manage an elevated number of variables, answers to the characteristics of simplicity, objectivity and flexibility of the system, and also a small time of development and realisation. This model is based on a technique of pre-processing the input vector.

PROPOSED METHODOLOGY

When the fuzzy inference system is supported by the self-learning algorithm it achieves a hybrid mode to the definition of the if-then rules, also in absence of experts about the problem domain. [12÷18][20]
In fact, showing the patterns of data, and using the adequate instructions, the net can identify the fuzzy set and tuning the membership functions, and using the opportune defuzzification model allows the self-organisation of the neural structure prearranging the hidden layers, generally composed of fixed nodes characterised by weights and known connections. [12÷18][20]
The methodology presents itself particularly proper to the rebuilding of bonds in phenomena characterised from strongly non-linear bonds when information or experts are not available.
Additionally, the knowledge base of the Expert System is corporate from database and being separate from the inference system, it is easy the adjournment of the system using new data without break into the inferential ability of the algorithm. [12÷18][20]
The automatic generation of the rules, could realise, in case of high numbers of entries, complex if-then structures, and therefore would miss the simplicity and objectivity of the hybrid system. The proposed methodology is originated from some concepts of the Mathematical Analysis.
Human reasoning, consists of modelling across the expert system, the functional links existing between the input variables domain and the output one. (Figure 1). Particularly considering the functional link y= F (P) that correlates the input vector $P(x_1,x_2,..,x_N)$ defined in entering domain X^N, with the domain of the only output variableY (see Fig.1)

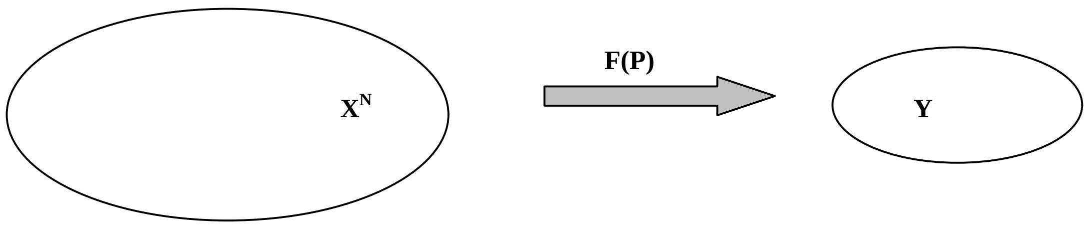

Fig.1

In order to reconsider the function F(P) utilising Composite Functions Theorem the function F(P) could be written as F(P)= g[f(P)], [19] reducing the problem of the determination of the only function unknown F, to the determination of the two functions components; respectively internal component function f and external component function g. (Figure 2).

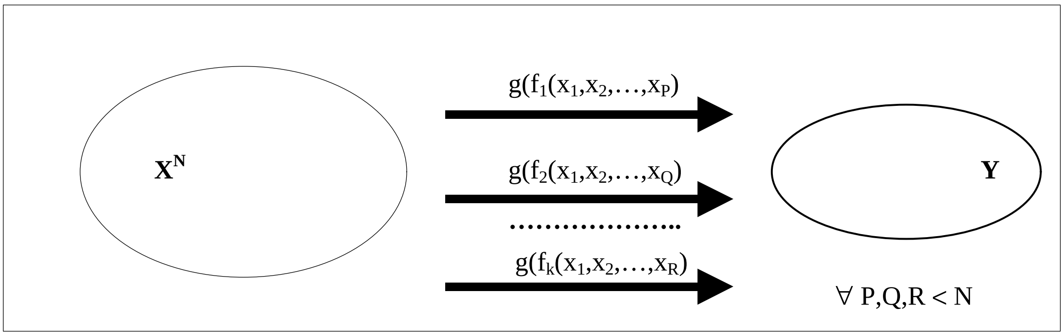

Fig.2 - Composite Functions Theorem

Successively, using human experience to approximate the internal components such as number, form, etc, ANFIS (Adaptive Network based Fuzzy Inference System) will provide to adapt the proposed link and adjust the error done using the human approximation. [12][13]

This pre-processing model allows starting from N input variables, trough the Composite Functions Theorem, to have K< N input variables, where K is the new number of internal components fixed in number and form. (Fig.2 – Fig.3)

The present paper proposes a fast methodology to design, develop and implement an expert system with many inputs which presents acceptable processing-data times through neuro-fuzzy principles. The proposed methodology has been tested in designing, developing and implementing an expert system for fast estimate of *processing times* on lathes of mechanical components.

CASE STUDY

The pre-processing methodology has been tested in an important Italian firm that, using flexible production cells, produces aeronautical and auto components on order.
Generally, in the operational context of a firm that manufactures batches of mechanical products, is very important the ability of estimate the production costs of components, parts and complex apparels with industrial reliability, in quickly times and with criterions of objective evaluations.

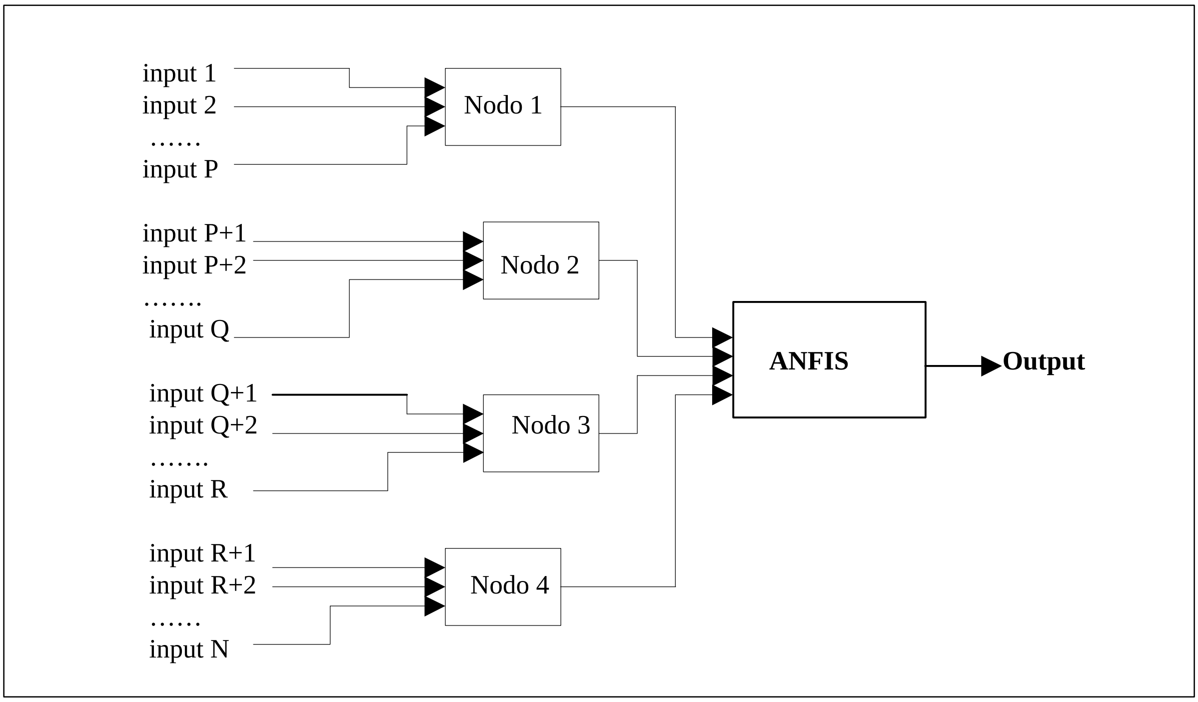

Fig.3 – *Pre-processing* model

The timeliness and reliability in the respect of the costs of production are actually the key of the success in the acquisition of new programs of production.
At this time the characteristics of timeliness, reliability and objectivity, are not achievable in an acceptable way using the usual operational based on the evaluation of "experience." We tend often to privilege the timeliness, but we obtain a reliability loss. In other cases, if we aim to the reliability of the estimation that involves an analytical rigid evaluation, in addiction of congruent times of answer. One of the most evident limits of the estimation process, it is the "subjectivity" of the analysis tied to the specific experience of the analyst, that makes not transferable and perishable the evaluation.
This research proposes an Expert System (ES) of estimation and the comparison with the "conventional" model, to the purpose of audit the implementation, in terms of availability, precision and objectivity of the evaluation, that they could be achieve using these systems.
This study consists of the evaluation of lathes process in circular symmetry pieces, noted that in the field of the removals processing, lathes constitutes the more frequent operation and the processing time represents the principal share of the time cycle in the modern flexible cell.
The logic of evaluation follows from the experience of the analyst, and consists to analyse the problem not considering simultaneously all the variables, but clustering variables group according to the reasoning structured showed in figure 4.
First, the expert analyses the homogeneous groups of entry variables, then esteems the value of the intermediary correspondent variables basing himself on experience rules, and afterward, correlates the intermediary variables up to arrive at to the last level of aggregation that furnishes the exit variable. The input variables are from the indicators that originate from the exterior of the process (tailored to the customer) and from the inland (state and availability of the resources).

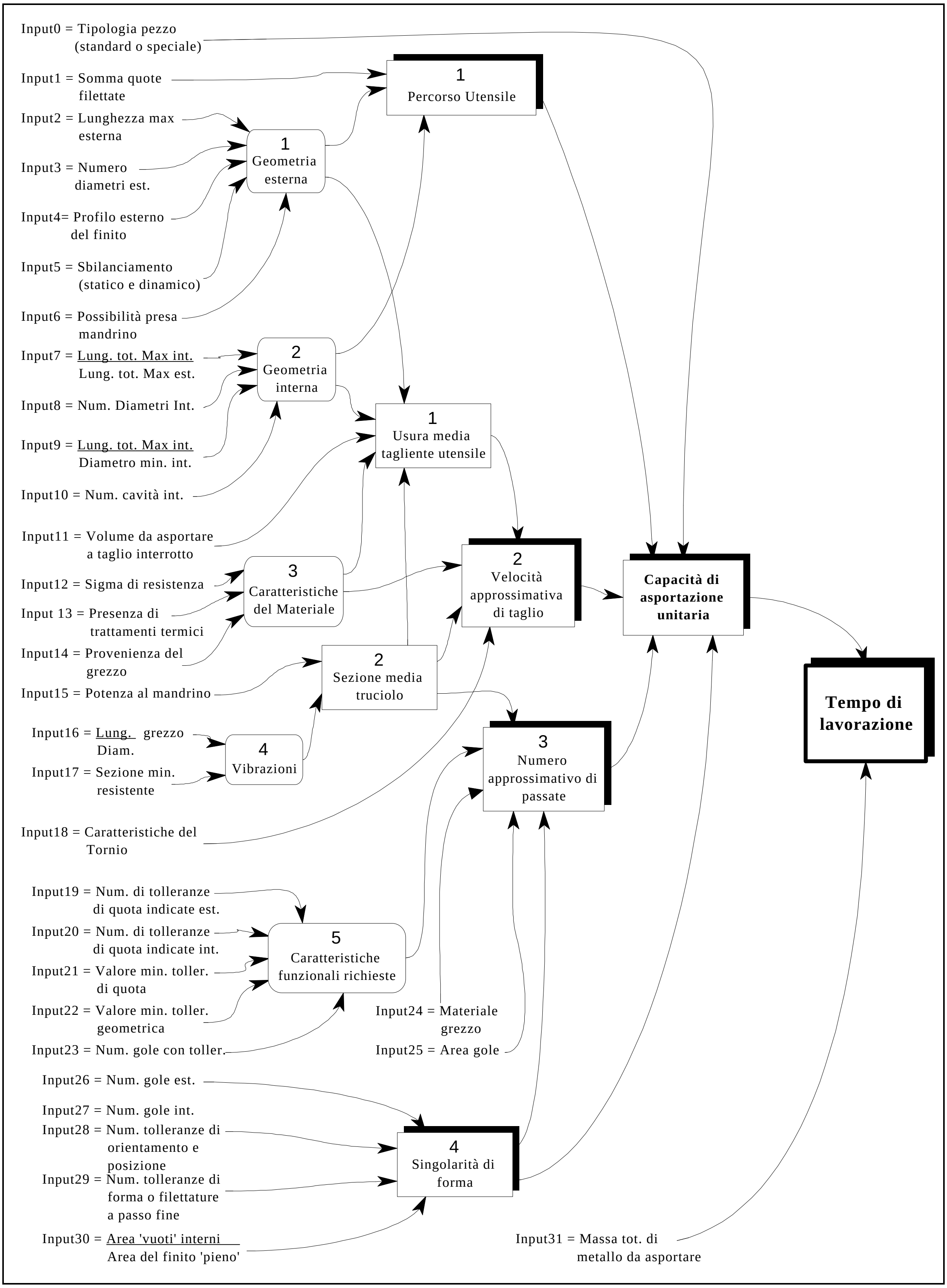

Fig 4 – Flow-chart of the human expert's knowledge

These parameters are called *direct variables*, respondent to specific applications of peculiarity, simplicity and objectivity. The following level, is corporate from the opportune aggregation of the *direct variables* and it has been decided level of the *secondary quantities*. The following level of the united variables is called the *primary quantities.* (Fig.4)
The passage from the *direct variables* to the *primary quantities,* is a phase strongly subjective because tied to the intimate patrimony of experience and chord of the experienced technologist. Schematically the modes of aggregation implicate:

- The evaluation of the applications to which the piece has destined, to recognise the parts that necessitate of more precise processing dilating the time manufacturing.
- The evaluation of the processing difficulties of the peculiar form or material of the piece, and then use it of distinctive devices, facility or methodology of work that satisfy the technical and economic requisite of the process.
- The graphic analysis of the component and morphological comparison of the product pieces with already realised to show the similarities that facilitate evaluation

Then, only a strongly subjective comparison and optimisation process of the indicators, we can find the *primary quantities* (*path tool, cutting speed, number of passing, removal bulk*). After reckoning these quantities we will furnish the quantity of removal material for hour (ability of hourly removal), and dividing the bulk of removal material with this quantities we will furnish the processing time.
The purpose to develop the Expert System, using the pre-processing methodology, we make some technological opportune hypotheses, that the problem dominion answers to the hypotheses of composed functions Theorem. [19] At first, to the goal of audit the definition hypotheses, and then consider the *direct variables* domain constituted from disjointed subsets whose union constitutes the dominion of the input variables (Fig.4- Fig.5), is necessary free from the strictly dependence of the technological indicators of processing.
On first step, using the firm experiences, chosen only four formal entry variables (*path tool, cutting speed, number of passing, removal bulk*), that will represent the real variable "handled" by the model, correspondent to the four functions [fk]. That represents a vector with 31 relative components related to the 31 *direct variables* (Fig 2- Fig.5 ÷Fig.7).

After we have characterised the subsets to correlate these parameters to the exit domain (time processing), the following passage is the way to determine the internal component functions ([fk]) that complete the pre-learning phase. In other words it consents, *"suggesting" bonds between the input variables, to restrict the number of the elaborate variable across the neuro-fuzzy structure.*

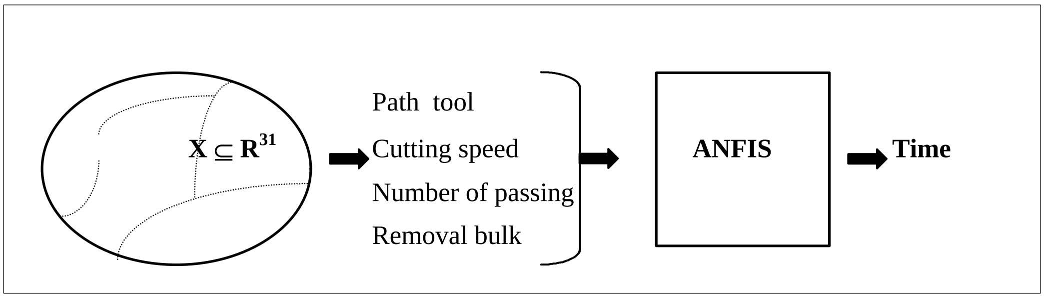

Fig.5- Transforming *31 direct variables* to *4 formal entries*

The functional dependence ([fk]), between the formal entering variables (*path tool, cutting speed, number of passing, removal bulk)* and the real entering variables (*direct variables*) have been formulate hypothesising a bond "simply" linear with coefficients +1 or- 1, depending on effect of the advised variable on the formal [fk], respectively of the increasing or decreasing type. In analytical terms, the described phase has characterised from a matrixes product whose execution is automated by a formal layer of fixed nodes, up stream of the input layer, called *pre-learning* layer (Fig.6). The matrixes are corporate from digital data representative of the values engaged from the *direct variables* in about 110 orders realised from the firm. Relatively to each order have been recorded the correspondent time processing also, to asses the result of the mode across the comparison between the values esteemed from the model (result of the learning) and the real correspondent values.

Summarising the hypotheses of ES is:

- Setting interdependence of some technological ties, formulating a simplified corporate model only from some lathes time prevision indicators (path tool, cutting speed, number of passing, removal bulk)
- Correlate these indicators between *direct variables* by means of simple relations ([fk]) that with the opportune coefficients point out the effects (increase-decrease), then place on top the functional bonds.

Also if determining the functional links without any experimental check could appear a substantial forcing, in the phase of engineering the input domain using firm experiences and the quality of result, legitimate the reasoning of the pre-processing mode.

$$f_1(X_1) = f_1(x_1,x_2,x_3,x_4,x_5,x_6,x_7,x_8,x_9,x_{10}) = \mathbf{+1x_1+1x_2+1x_3+1x_4+1x_5+1x_6+1x_7+1x_8+1x_9+1x_{10}}$$

$$f_2(X_2) = f_2(x_{11},x_{12},x_{13},x_{14},x_{15},x_{16},x_{17},x_{18}) = \mathbf{-1x_{11}-1x_{12}-1x_{13}-1x_{14}+1x_{15}-16x_{16}-1x_{17}+1x_{18}}$$

$$f_3(X_3) = f_3(x_{19},x_{20},x_{21},x_{22},x_{23},x_{24},x_{25},x_{26},x_{27},x_{28},x_{29},x_{30},) =$$

$$\mathbf{+1x_{19}+1x_{20}+1x_{21}+1x_{22}+1x_{23}+1x_{24}+1x_{25}+1x_{26}+1x_{27}+1x_{28}+1x_{29}+1x_{30}}$$

$$f_4(X_4) = f_4(x_{31}) = \mathbf{+1x_{31}}$$

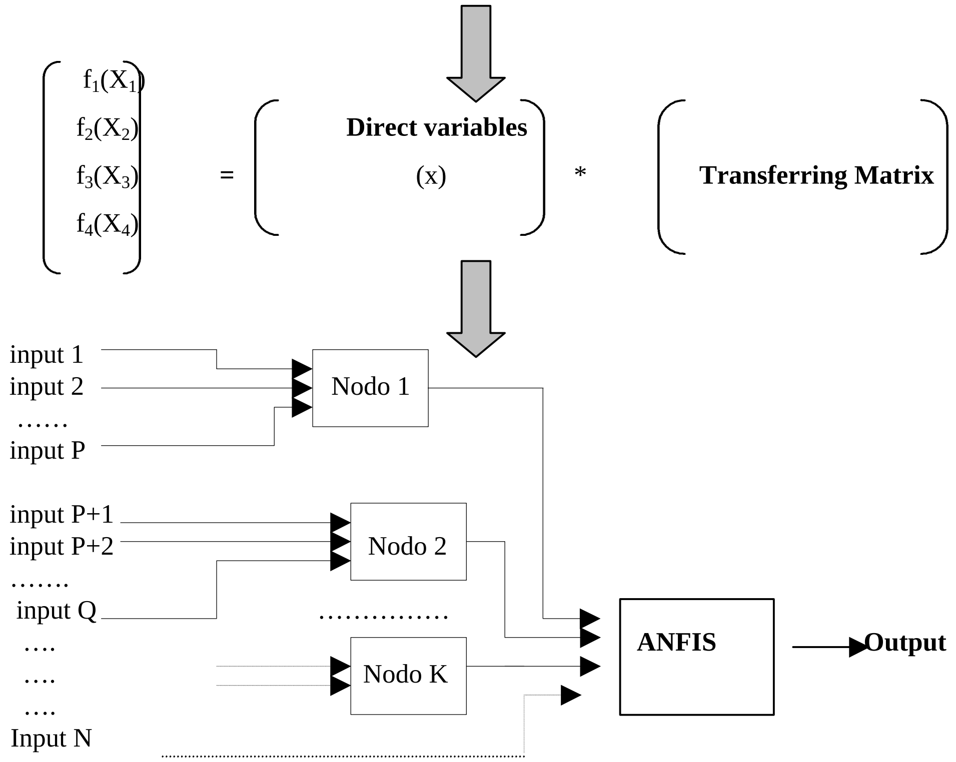

Fig.6 – Automatic pre-learning

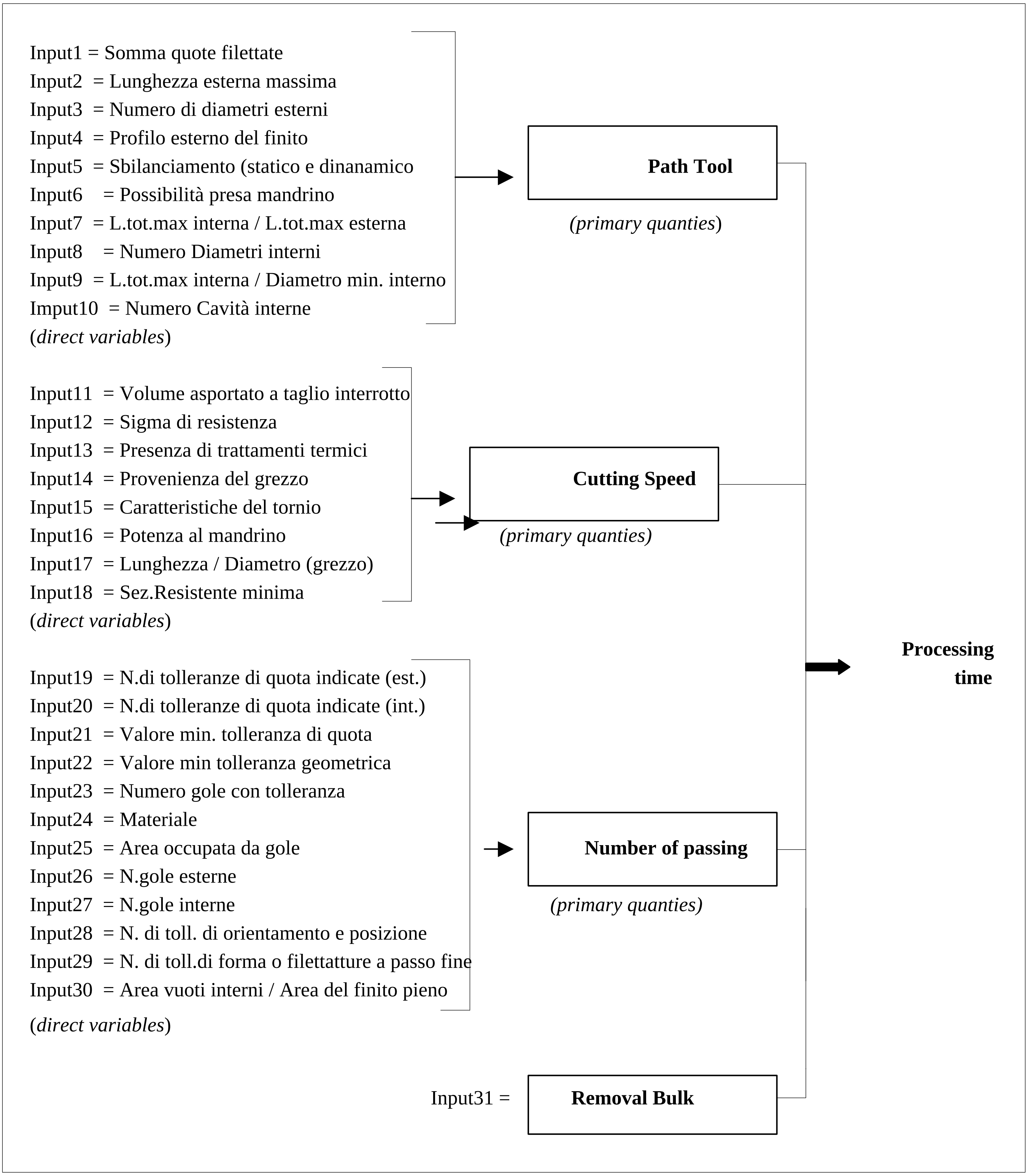

Fig.7 – Flow chart of "SE" knowledge

In order to understand the new methodology of aggregation and optimisation of input variables, showed in figure 7, it is necessary an example.

Referring, for simplicity, to the *path tool* to implement, it has seen like the morphological characteristics of the piece that also contributes to the determination of the *cutting speed*, but the experiences of the firm have highlighted that often in high precision mechanics, not being necessary distinctive attention to contain flickers and unbalance of the pieces, is possible to refer only to right indicators in the determination of the *path tool*, extrapolating that is from the *direct variables* domain articulate subsets of elements. Then, to realise the opportune partitions of the entry, dominion, the training data set has been built given to the neural network only commodities that they don't necessitate of complexes tighten tools. These elements have been characterised and represented in the groups of indicators showed in figure 7

Next step in pre-processing, for example, determinated entering domain of *path tool*, referring to input2 (fig.7), the practical experience allowed to approximate linear function link between this input and path tool, then we assign proportional constant to 1.

For other groups of indicators, for example Input12 (Sigma di resistenza- Fig.7), this observation arises in lathes operation, if increase the mechanical properties of the piece we need often to reduce cutting speed than we assign constant to -1. Using these reasonings conduct to the definition of a matrix (Fig.8) called of "transferring" where each row vectors is composed of the prevoius selected linear constants and that realise the metamorphosis from the 31 entering variables to the 4 real entering variables. Practically the four internal functions are representative of the four constituent equations the linear system of fig.6 (see also the figure 2), and comes realised across the pre-learning layer. The parameters of the fixed nodes of this layer represents the linear relative constants to the elaborate function, and all the mode has been automated by the MatLab system. The training matrix elaboration originates from this initial layer and it also generates the checking data set. The results of the elaboration have presented in next figure.

CONCLUSION

The listing of the Matlab program that realises the exposed mode is:

```
%*******CARICA DATI DI INGRESSO***********************
load dati;
load tempi;
load mas;
load cost;
% ******ATTIVA NEURONE  FORMALE DI INGRESSO**********
inform = cost*dati;
in = [inform mas];
in1 = (1:90,:);
in2 = (91,109,:);
tempi1 = (1:90,:);
tempi2 = (91,109,:);
trnData = [in1 tempi1]
chkData = [in2 tempi2]
NumMFs = 3;
MfType = ' gbellmf ';
%*****GENERA MATRICE ANFIS***************************
Fismat = genfis1(trnData,NumMFs,MfType);
[Fismat1, trnError, StepSize, Fismat2, chkError] = ...
    anfis(trnData, Fismat, [250;0;0.1;0.9;1.1], [], chkData);
%*****GENERA ANFIS OUTPUT******************************
trnOut = evalfis(in1, Fismat1);
```

Use of MatLab, for this algorithm, is justified from the capability of realising the analytical operations connected with the pre-learning phase and afterward it uses the ANFIS modes (Adaptive Network [based] Fuzzy Inference System) contained in the toolbox Fuzzy Logic and Neural Network, in an only environment, avoiding complex handling and transfers of the data.

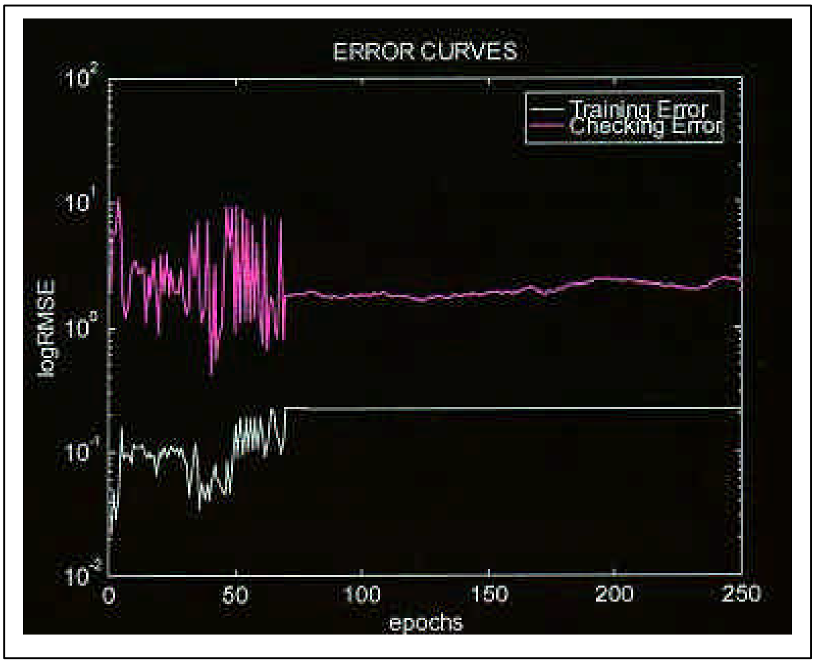

Fig.8

The operation of the program has been set on 90 training drawing of piece already produced by the firm and checked with 20 drawing piece. The answers of the Root Mean Square Error is showed in Fig.8 and we have compared it to the effective processing time to the ANFIS output in Fig.9. In terms of the mean error (deliberate like average of the error percent in each of the 110 examples) a mean error has been obtained, on the training time about of the 5% while on the checking data about of the 24%. This result, legitimate the operational capability of the pre-process reasoning and can be acceptable for some kinds of order, or for reference budgets, because the use of such kind of expert system doesn't require specialised manpower and we have had very small data processing.

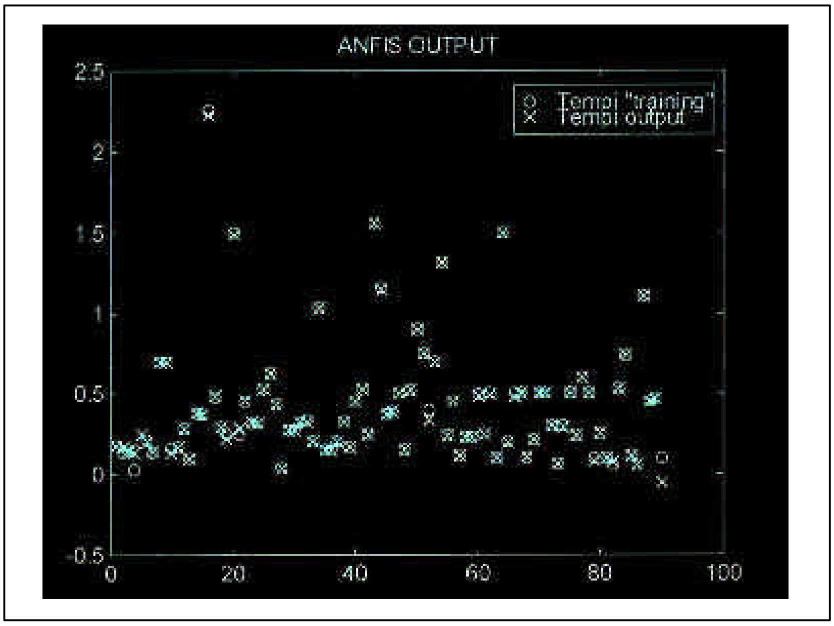

Fig.9

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