AN EXPERT SYSTEM BASED ON SOFT COMPUTING TECHNIQUES FOR MONITORING MULTIPHASE FLOWS

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1. The problem of the multiphase flow rate estimation

The knowledge and the forecast of the parameters which rule the downflow models in oil extraction and transport are today of paramount importance. In particular the extracted oil is mixed with water and gas in rates which differ not only from different wells, but also on the same well during its life. The main problems involved with the measurement of the flow rates are : well exhaustion, critical flow pattern prevision and pipeline leak detection.
Today the production of several wells is carried, with short pipelines, to a manifold from which, with a single long pipeline, the total production is carried to the oil centre. In this situation the information concerning the single well is lost so that the main oil industries require monitoring systems which can indicate the individual well flow rates.
So far general measurement systems don't exist and one of the main goals is the development of an instrumentation tool for the mass flow rate measurement of three phase flows (oil-gas-water). Building a single model for the whole range is very difficult because of the high non-linearity effects due to the variation of flow patterns, liquid viscosity and density and therefore different models for the data analysis, based on different approaches corresponding to different fluidynamic hypothesis, have been developed.
In this context building up an effective expert system for monitoring oil fields is a very hard challenge for the main oil companies and research institutes.

2. Current state of the art

At present the most utilised approach to solve the problem of the multiphase flow rate estimation in oil extraction and transport processes is to compare all available models and techniques, select the one which behaves better than the others and then use it in all conditions. In particular the main effort of the scientists of this area is the study of new physical models and new advanced techniques, as artificial neural networks, and to select the best one. In particular the neural approach has been already applied by several oil companies and research institutes.
So far data fusion between different models based on fuzzy control has not been applied to solve this problem. In the literature the most famous models for fuzzy control are the Mamdani [10] and the Takagi-Sugeno [11] models and for this problem the second one has been applied.
Moreover we'll see that the architecture we propose combines fluidynamic models, neural networks and fuzzy logic; it is a hybrid architecture which shall not be confused with the traditional hybrid systems [3] and in particular with the NeuroFuzzy ones (ANFIS architecture) [7].

3. The expert system and the data fusion problem

In this paper we propose an innovative expert system for monitoring multiphase oil flows. This work is placed within the C.E. Thermie project OG/143/94/IT "Monitoring and diagnostic system, based on expert system technology, for multiphase transportation processes" , leader: ENEA, partners: AGIP, Rome 1st University, Gammatom.
The expert system has been developed by using the G2 Gensym expert system shell and it has been installed on the AGIP oil field placed in Trecate(Novara - Italy).
The functional architecture of such system is composed by several modules.

At the head of each well different sensors and data processing modules are installed. In particular the main instruments are the Multiphase Expert Flowmeter (MEF) and the Choke Valve Analizers. Such redudancy proposes a data fusion problem and to solve it a specific module, which is core of the system, has been developed.
The flow line is simulated by a suitable code (the D-spice module) which takes as input the final results provided by the data fusion module.
At the end of the line the Flow Pattern Analizer is installed. This module is based on non linear dinamic techniques (chaos theory) and its task is that of slug detection.
Moreover the system is provided with a graphical user interface to allow the user to interact with the system.

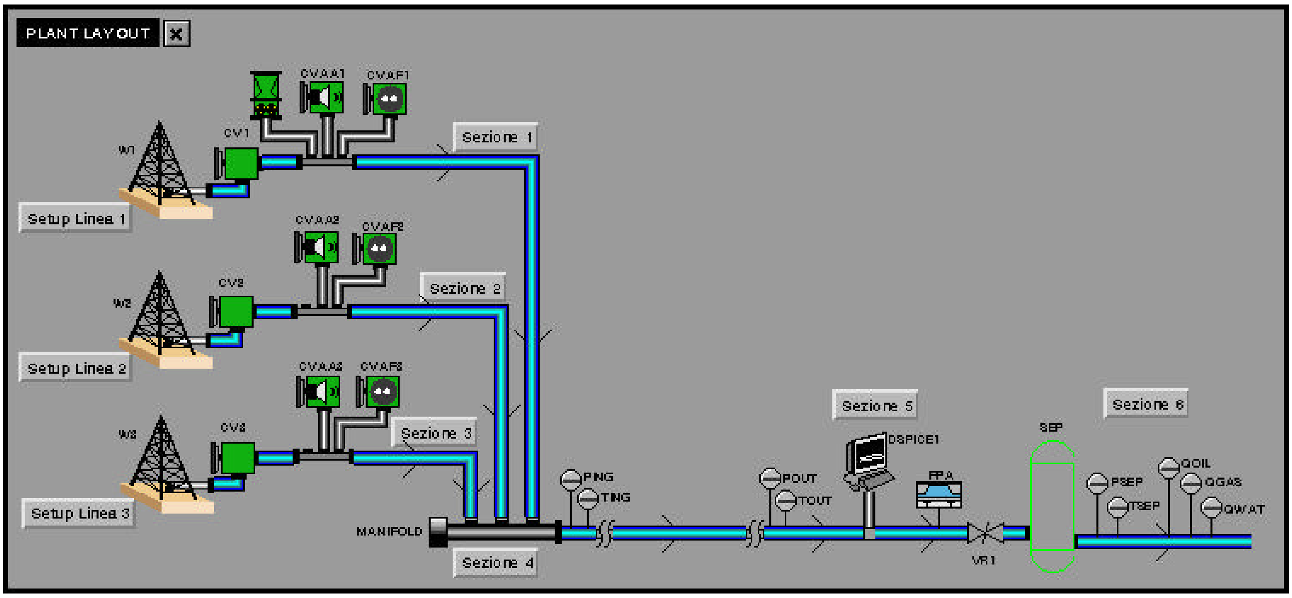

Figure 1 : Expert system implementation

What we are going to describe now is the implementation of the core of the system : the data fusion module.
The key idea to resolve the data fusion problem is inspired on an innovative principle of theoretical physics known as Bootstrap Theory [4]. Such approach proposes the integration of all different models building up a co-operative system able to get the best features of the models in all different conditions. The goal of such approach is reaching a system which performs better than the best available model. In this way it is clear that the attention of research moves from the study of the models to the relationship among the models.
What we are going to describe is how we applied the 'Co-operative Bootstrap Approach' to develop an expert system based on a fuzzy data fusion module which performs the integration of fluidynamic and neural models.

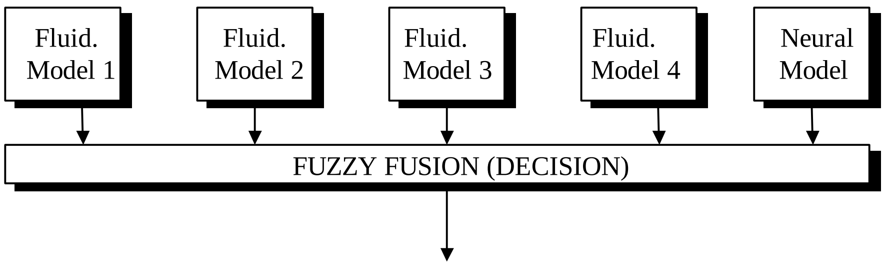

Figure 2. Co-operative approach

In the proposed architecture (figure 1) a set of modules provides the results to the decision maker which performs the data fusion step. In this way each module can be viewed as a virtual sensor so that the proposed architecture can be generalised to all measurement systems. In particular in this application the modules are four fluidynamic models and one neural model. The decision maker is a fuzzy logic based system which gives as output the final flow rates estimation; its core is the suitable definition of measure reliability based on opportune fuzzy rules. The criteria, on which these rules are based are the error estimation measure and the neighbourhood to the training conditions. The second criterion is very useful because in conditions far from the training ones, the fluidynamic model, which is more scaleable than the neural network, must be more reliable than the neural network which is not scaleable out of the training set. This is important because scaleability is one of the main requirements of the system. The final choice will favour more the most reliable measure and less the other ones. Such a system has been tested on real data and the final results provide very low final errors for the flow rates estimation showing a remarkably improvement in such estimations and thus a considerable error decrease.

3.1 The fuzzy decision maker

To implement the decision maker previously described it is needed to define the opportune fuzzy rules and the suitable fuzzy sets and for this purpose we defined the following knowledge base in the Takagi-Sugeno model.

IF x_i has low error AND x_i is in training conditions AND the sensors are working THEN $y_i = x_i$

where x_i are estimations provided by a model for i = 1, ... , num. models
In this way to implement this KB the following fuzzy sets have been defined.

A = ‘Estimations with *low* errors ’
B = ‘Estimations in training conditions ’
C = ‘ The sensors are working ’

The last of these is a fuzzy diagnostic parameter provided by the expert system, in which the presented work is inserted, which detects sensors’ failures. In this way the KB can be rewritten as

IF x_i ? A AND x_i ? B AND x_i ? C THEN $y_i = x_i$

for i = 1, ... , num. models
In terms of fuzzy sets this is equivalent to the definition of the measurement reliability as

R = A ? B ? C

The resulting output is then obtained by applying the centre of gravity method.
The described procedure has to be applied to all the quantity, water cut, liquid flow rate and gas flow rate, to be estimated.

3.2 Membership functions and decision models

When building up a fuzzy system the key feature to produce an effective system is the definition of opportune fuzzy sets and rules. These aspects have been described in the previous paragraph, but when a fuzzy set is defined we have to formalise its membership function. This step is very critical and considerably affects the performance of the whole system.
In the following part we describe how we defined the opportune membership functions of the fuzzy sets previously defined.
To define the membership function of the fuzzy set A = “Estimations with low errors” the following conditions have been taken :

1. $?_A(x)$ takes as argument an error estimation
2. $?_A(0) = 1$
3. $?_A(x)$ has to be monotonically decreasing
4. $?_A(x)$? 0 , for x? ?
5. $?_A(x)$ has to satisfy a decision model

The last heuristic is very important because it is essential to define the membership function, so we formulated the following criteria to which correspond different membership functions.

(a) “Consider the measure with the lowest error”
(b) “Consider the average of all measures”

(c) “If errors are different then consider the measure with the lowest error else consider the average of all measures”
(d) “If one measure has a low error then consider this one else consider the average of the measures”

A few considerations about the proposed criteria can be done.
The main feature of the first criterion is that it guarantees a result which is never worse than the best one, so if errors have the same sign then this criterion is surely the best because in this situation each kind of average can produce a worse result. However if errors have opposite sign then by performing an average between the measures we may obtain a result with an error lower than the best one because of the effect of possible compensation.
Criterion (b) has features which are exactly the opposite than the ones of the previous criterion.
The third criterion arises from the consideration of reducing the drawback of the arithmetic average, which is that of getting a much worse result if measures have the error with the same sign, by applying the average only in the case that the errors are similar, so that we get a result with an error close to zero if the errors are discordant, else the result will have an error a little worse than the best one.
The last criterion arises from the consideration that also in the previous one is not always true that measures with opposite sign provide a better measure when average is made. In particular this is the case when one of the measures has a low error. In this way it is clear that average has to be made when measures have errors with opposite sign and high values.
From these considerations it is clear that when measures have errors with the same sign then criterion (a) is the best one, otherwise the best is (d). Moreover by a numerical simulation we demonstrated that the fourth criterion is on average the most performing one and it is also possible to demonstrate that the membership function corresponding to such model is

$$?_{A}(x) = \frac{A}{A \, ? \, x}$$

Where the value of the parameter A has been set in order to minimise the prediction error of the criterion.
To determine the membership function of the fuzzy set B = ‘Estimations *near* to the training conditions’ we proceeded in the following way. We divided the data set in two complementary parts, the training set and the testing set, in such a way that the training set was composed by the data included around the medium value and the testing set was composed by the remaining data which are those included in the initial and final parts of the range of the data set. Successively the neural module has been trained and tested on the formed sets and the error committed by the network on the testing data has been studied in function of the distance of these from the training set. The results of such exercise demonstrated that points far from the training set are estimated with high errors. This fact has led us to define trapezoidal membership functions which provides low reliability to the results out of the training range and reliability one for all the results falling in training conditions.
When the estimation is provided by a fluidynamic module the trapezoidal membership function extends also outside the extreme points of the training range and decreases more smoothly than the neural one because mathematical models are more scaleable.

3.3 The neural networks

The neural module of the proposed architecture is a set of supervised neural networks.
In particular this module is composed by three different feed forward networks, one dedicated to estimate water cut, the second liquid flow rate and last gas flow rate.
In our implementation this module gets as input the results of the first fluidynamic model, the most effective one, so that it can be viewed also as a correcting filter.
In such way the three neural networks composing this module have the same input and one output. They differ in the number of hidden nodes and in the transfer functions utilised.
Moreover neural networks have been utilised inside of each of the five modules to provide an unsigned estimation of the error committed.
All the neural networks have been developed with the Semeion Research Centre. For details about the neural networks utilised see [14].

4. Experimental results

In order to test the capability of the proposed ‘Co-operative Bootstrap Approach’, whose task is to reduce the average measurement errors, we have performed several tests on real data. To ungroup the results we have computed the medium (unsigned) error for the main quantities for each fluidynamic model and for the neural model and then we have computed the final error after the fuzzy fusion.
In table 1 experimental results are shown. In particular the results of the best models are compared to the final results obtained using the real errors, theoretical case, and the neural estimations of the errors (real case).
It is clear that the accuracy increase is very high comparing the results of the single modules to the final one. In the theoretical case the average error reduction is about 2 times with respect to the neural model which is the best one.
Also in the real case a slight improvement over the best module, about 10-30% error decrease, is performed.

	BEST FLUIDYNAMIC MODEL	BEST MODEL (NEURAL)	TEORETHICAL RESULT	REAL RESULT
Liquid flow rate error	4.7%	4.2%	2.7%	3.3%
Gas flow rate error	11%	8%	4.9%	6.88%

Table 1. Experimental results

5. Conclusion

In this paper we proposed an innovative approach for multiphase flow rate estimation. Such approach is inspired by an approach of theoretical physics in which the co-operation of different models is proposed. In our work we built up a system in which mathematical models of multiphase flow rate estimation co-operate with neural networks by utilising a meta-decision maker based on fuzzy theory.
Neural networks have been adopted because they are able to catch the highly non linear features of the phenomenon giving the system high precision. Fluidynamic models have been utilised because they provide results scaleable to different conditions. In this way we are able to design a system which catches the best features of all models by combining them using opportune rules and functions. The result is a system which performs better than the best model. In fact from the experimental results it is easy to see that the final error is lower than the lowest error committed by all models. We want to notice that by using the classical approach of utilising only the best fluidynamic model we would have obtained a system which performs with a medium relative error of 4.7% for liquid estimation and 11% for gas estimation. With the proposed system we are able to obtain measurements with a very low medium relative error, with an error decrease which is about two times lower for liquid and gas estimations.
The co-operative approach has also allowed us to build a scaleable system. In fact with the opportune fuzzy rules it is possible to let the system work in condition far from the training ones and in conditions of sensors’ failures.
Finally each module can be viewed as a virtual sensor so the proposed architecture can be generalised to an arbitrary number of different measurement systems making it possible to simulate and experiment new sensors without having them physically installed.

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