Application of Artificial Intelligence Approach for Optimizing Management of Road Traffic

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Abstract: An approach based on the artificial intelligence is proposed for the management of road traffic. By a fuzzy system, we are looking for purely numerical parametric characteristics and those that influence its structure. In fact, we use input and output data from a portion of the road traffic to identify a fuzzy model which makes possible the evaluation of the results of the estimated parameters obtained. This has been achievable through the combination of parametric and structural adjustment algorithms with the backpropagation algorithm. Consequently, the obtained results show that adaptive models are successfully used in the analysis and the management of road traffic through the efficiency of this combination.

1 INTRODUCTION

Overall, we will deal with the problem of identifying fuzzy models from input-output data. Sometimes we need to have the parameters of a system without knowing all the members. Through an example we demonstrate this fuzzy identification (RASTEGAR and al., 2011). With the fuzzy modeling formalism of systems focusing particularly on the Takagi-Sugeno model (CHEN and XIAO, 1999) , we represent the non-linear behavior of a system by a composition of "If . . . Then" rules, concatenating a set of sub-models locally linear. In what follows, the fuzzy model has been identified for a signal based on data in autoregressive way. This method is simple and allowed us to generate data without other variables in addition. The model is capable to predict other data on the process being studied once the optimization phase is over.

To build such models, we approach the application of a competitive agglomeration method : the algorithm of Gustafson and Kessel (PALACIO, 2007), (WU and al., 2018), which belongs to fuzzy clustering methods based on the minimization of an objective function. Finally, after having considered the general methodology for the construction of the Takagi-Sugeno fuzzy model from data, we will comment on what we will obtain as results.

This paper is organised as follows. Section 2 develops Takagi-Sugeno's fuzy model and discusses the types of adjustments made to fuzzy systems. Section 3 concisely discusses about achievements in scientific research related to the subject. And Sect. 4 explains the approaches adopted and the results of the simulations are established in Sect. 5. Finally, we conclude this paper in Sect. 6.

For all our simulations, we carried out fuzzy clustering simulations for the structural adjustment, parametric adjustment simulations with the GLS and WLS algorithms (OLSSON and al., 2000) combined with the backpropagation (ELMZABI, 2005) algorithm simultaneously. They give Root Mean Square Error (RMSE) on the validation set between the predicted values and measured data.

2 TAKAGI-SUGENO'S (TS) FUZZY MODELS

Developing an artificial intelligence to process a large amount of data is therefore an excellent idea. Today, the practical advantages of artificial intelligence are in fairly pragmatic operations. A fuzzy system is a system that integrates human expertise and aims to emulate the reasoning of human experts in complex systems. It is an important part of artificial intelligence.

In fuzzy systems, the basic idea is to model processes as would the human being (BOUZID and S.BENMERIEM, 2013). The relationships between input and output variables are explicitly represen-

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ted in the form of "*If ... Then ...*" rules, ie : **If** HYPOTHESIS (antecedent part) **Then** CONCLUSION (consequent part) (ISHIBUSHI and al., 1995). The above form allows to interpret the results and to determine the action of each rule and express an inference (MILAN and al., 2018) mechanism such that if a fact (hypothesis) is known, then another fact (conclusion) can be inferred. The Takagi-Sugeno fuzzy model (RASTEGAR and al., 2011) uses linear functions in the consequent part : for i rule and j output, we have : $y_j^i = f_j^i(x)$.

So, it can be seen as a combination (TOMAR and al., 2018) of the linguistic model and the mathematical regression (TOMAR and al., 2018) model in the sense that the antecedents describe fuzzy regions in the input space in which the consequent functions are valid. Basically, this model can encode the expertise, either directly from the prior knowledge of the problem, or indirectly from a set of learning data. It is very easy to identify because the conclusion of each rule is linear and its parameters can be estimated from the numerical data using optimization (MILAN and al., 2018) methods such as least squares algorithms.

We will use more particularly these models because they allow to approach non-linear systems by a combination (TOMAR and al., 2018) of several linear and simple local models. They are written as follows (IQDOUR, 2006) :

$$R_i : If\ x_t\ is\ A_i\ Then\ \widehat{y}_{t,i} = \beta_{0i} + x_t^T \beta_i \qquad (1)$$

R_i $(i = 1,2,...,c)$ indicates the i^{th} fuzzy rule, x_t $(t = 1,2,...,N)$ is the input variable $(x_t \in R^n)$, $\widehat{y}_{t,i}$ is the output of the i^{th} rule relative to the input x_t , A_i a fuzzy set (YANG and HU, 2018) and $\beta_i = (\beta_1, \beta_2, ..., \beta_n)^T$.

2.1 Structural Adjustment

Structural adjustement is about determining the correct number of rules to use in a fuzzy system (DASS and SRIVASTAVA, 2018), (KASHANI and MOHAYMANY, 2011). The structure to be searched for will have to be rich enough to allow for optimal learning, but not too much to avoid noise modeling in the data.

2.2 Parametric Adjustment

Once the number of rules determined, it is necessary to estimate the parameters (β_i) for each conclusion of the rules. If we have :

$$W_i = \begin{pmatrix} \mu_{i1} & 0 & \cdots & 0 \\ 0 & \mu_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mu_{iN} \end{pmatrix} \qquad (2)$$

$$X = \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix}, y = \begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix} \qquad (3)$$

And if we have :

$$X_e = [1\ X],\ \widetilde{X} = \left[W_1 X_e\ W_2 X_e\ \ldots\ W_c X_e\right].$$

2.2.1 Weighted Least Square (WLS)

The localized linearization method causes the resolution of c independent optimization problems. Linear parameters obtained do not depend on how the rules are aggregated. The criterion to be minimized is :

$$J = \sum_{i=1}^{c} \sum_{t=1}^{N} w_i \left(\hat{y}_t - x_t^T \beta_i\right)^2 \qquad (4)$$

The determination of the linear parameters β_i passes by the minimization of the criteria of each local model. This amounts to solving c independent weighted least squares problems whose solution is :

$$\beta_i = \left(X_e^T W_i X_e\right)^{-1} X_e^T W_i y \qquad (5)$$

2.2.2 Global Least Square (GLS)

The global system resulting from this method (IQDOUR, 2006), approximates the database with more perfection. But nothing tells us that the linear models thus obtained are optimal in their areas of expertise. Linear parameters are obtained by solving the equation :

$$\widetilde{X}\beta = y\ or\ \left(\widetilde{X}^T \widetilde{X}\right)\beta = \widetilde{X}^T y \qquad (6)$$

The criterion to be minimized for GLS is :

$$J = \frac{1}{2} \sum_{t=1}^{N} \left(\hat{y}_t - y_t\right)^2 \qquad (7)$$

3 A STATE OF THE ART

Accurate data from accident and road databases can be essential for modeling, mapping, identifying hazardous road segments and other studies to make decisions in a road network. Researches relating to the problems that are in the databases of road traffic and which propose solutions exist and bring a plus. Among them, we have :

C. Yixin and X. Deyun (CHEN and XIAO, 1999) represent an extension of the Takagi-Sugeno-Kang model (ETSK). Its analytic expression has been delivered and an algorithm to identify such a model has been proposed. TSK with variable weight

(VWTSK) was made to present the fuzzy controller algorithm of the ETSK model even definition of fuzzy rules since they are roughly equivalent. The simulation of this algorithmshows that the ETSK model can give more precision on the long-term predictions and the control algorithmcan reach a better controlmore efficient that Proportional-Integral- Derivative fuzzy regulation (PID). Furthermore, an adaptive control identification or method for a system based on FCM-KNN (Fast Fuzzy C-Means—K-Nearest Neighbors) and PSO (Particle Swarm Optimization) has been proposed by Rastegar et al. (RASTEGAR and al., 2011). The model identify the structure and parameters of the nonlinear model : the fuzzy set and the number of rules, and the location of the membership functions are automatically pulled from the system data. In comparison with other identification methods, larger values corresponding to a lower number of fuzzy rules have been achieved. Thus, their results showed that the proposed control model can control the process just by using a database of the TS Adaptive Fuzzy Model initialization process. On the other hand, C. N. Babu and B. E. Reddy (BABU and REDDY, 2015), for the prediction of time-based internet traffic that is very volatile in nature, have explored the applicability of various forecasting models. They considered during their study ARIMA (AutoRegressive Integrated Moving Average), ANN (Artificial Neural Network), Zhang's ARIMA-ANN hybrid model, Khashei and Bijari's ARIMA-ANN hybrid model, the ARIMA-ANN multiplicative model, MA (Moving Average Filter) filter based on the ARIMA-ANN hybrid model. One-step and/or multi-step predictions have been made. The measures of the error performance, MAE (Mean Absolute Error) and RMSE (RootMean Squared Error) are used to evaluate accuracy (BOVEIRI and ELHOSENY, 2018), (HAIDI and al., 2018), (CHEN and al., 2018). The results of the forecast in both cases showed that the MA filter based on the ARIMA-ANN hybrid model outperformed all the others models, both in terms of MAE and RMSE and is therefore suitable for more accurate prediction of internet traffic data.

4 APPROACHES

At first, we generate (ISHIBUSHI and al., 1997) fuzzy rules of the TS model. We use classification (KASHANI and MOHAYMANY, 2011), (MURUGAN and al., 2019), (SHANKAR and al., 2018) , (MUHAMMAD and al., 2019) , (HURRAH and al., 2019) algorithm (Gustafson Kessel : GK (BABUSKA and al., 2002) to estimate the number and initial positions of cluster centers where each one allows us to determine a fuzzy relationship between inputs and outputs by checking their similarity. Then we adopt fuzzy generation algorithms to predict fuzzy output. Even though there is no indication of this kind of problem, the GK algorithm (WU and al., 2018) makes it possible by giving the state or the quality of the road traffic taken as example from the output of the fuzzy model.

Secondly, we generate fuzzy rules from a base of examples where we want to classify the outputs into a set of predefined fuzzy classes. Then we use the first approach for fuzzy rule generation, we apply a weighted or generalized least squares fit to compare the fuzzy and predefined outputs of our model (Fig. 1).

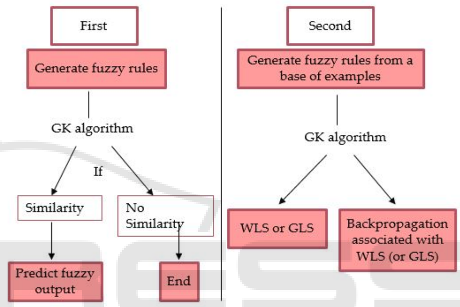

Figure 1: Approaches.

5 RESULTS

5.1 First Simulation

In Figs. 2 and 3, we represent the results after a simulation realized on matlab R2017a. There are the membership functions, the linear β_i and nonlinear parameters that are estimated with the WLS or GLS algorithms.

And in the following tables, Tables 1 and 2, we present the results on different values of the set of input in order to capture the sensitivity and the effects of these two methods on our example.

5.2 Second Simulation

In order to estimate road traffic (IHUEZE and ONWURAH, 2018) parameters, we use a database consisting of daily measured values for January 2012. These values were taken in the Gironde region, a french department located in the south-west of the

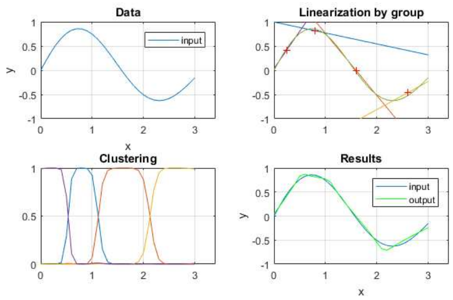

Figure 2: For 31 values with WLS algorithm.

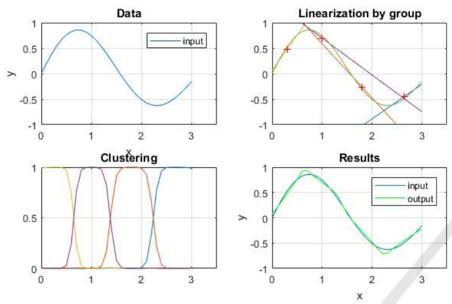

Figure 3: For 31 values with GLS algorithm.

Table 1: Results obtained with WLS algorithm.

Values	Clusters	RMSE	Errors
11	4	0.0076	6.3315×10^{-4}
21	4	0.0217	0.0099
31	4	0.0467	0.0676
51	4	0.0580	0.1717
71	6	0.0498	0.1763
151	8	0.0494	0.3678
501	26	0.0226	0.2554

Table 2: Results obtained with GLS algorithm.

Values	Clusters	RMSE	Errors
11	4	0.0074	6.0077×10^{-4}
21	4	0.0213	0.0095
31	4	0.0460	0.0655
51	4	0.0582	0.1730
71	6	0.0498	0.1758
151	8	0.0446	0.2997
501	28	0.0185	0.1709

country in the New Aquitaine region. You should know that a very simple autonomous car is only a categorization in real time to identify all objects on the road and define the behavior to adopt.

The performance criterion chosen remains the root mean squared error. We chose to sort three complete classes of the database that normally contains several classes (see Tables 3 and 4). We want to estimate the ratio between the length and speed provided. This is indeed an important data that characterizes the portion of the road taken into consideration.

Table 3: Results for WLS algorithm.

Class	Clusters	RMSE	Errors
CL1 :	4	0.0324	0.0326
CL2 :	4	1.3714×10^{-4}	5.8305×10^{-7}
CL3 :	4	5.3609×10^{-4}	8.9092×10^{-6}

Table 4: Results for GLS algorithm.

Class	Clusters	RMSE	Errors
CL1 :	4	0.0313	0.0304
CL2 :	4	1.3724×10^{-4}	5.8389×10^{-7}
CL3 :	4	5.3909×10^{-4}	9.0088×10^{-6}

A better approximation is an added value for prediction which is very useful in applications because it allows to generate traffic data for localities where measurements are not available. When the linear function is bounded and the activation function is derivable, it is possible to use powerful learning algorithms based on the search for a minimum of the error function, in particular the backpropagation (WANG and MENDEL, 1992) of the gradient which includes hidden layers. So, to update the connection weight within a network so that it succeeds in the task that is asked of it, and thus apply our example to artificial intelligence (JOHNSON and al., 2018), we used the method of backpropagation (HASSABIS and al., 2017).

Table 5: Results for WLS & Backpropagation algorithm.

Class	Clusters	RMSE	Errors
CL1 :	4	0.0311	0.0299
CL2 :	4	1.3712×10^{-4}	5.8284×10^{-7}
CL3 :	4	5.3922×10^{-4}	9.0137×10^{-6}

Table 6: Results for GLS & Backpropagation algorithm.

Class	Clusters	RMSE	Errors
CL1 :	4	0.0298	0.0276
CL2 :	4	1.3723×10^{-4}	5.8380×10^{-7}
CL3 :	4	5.3864×10^{-4}	8.9941×10^{-6}

5.3 Comments

The results obtained in Figs. (2) and (3) show that whatever the WLS or GLS algorithm we can have a good estimate justified by the mean squared error not by the graph. We can note that the choice of the number of clusters in the algorithm depends on how much data appears to us. It is important to find a number of clusters that best estimate the input. In statistics, generalized least squares are techniques for estimating parameters unknows in a linear regression model. Indeed, GLS is used to perform a linear regression when there is some degree of correlation between values in a model. In this case, the classical weighted least square method can be statistically ineffective or even give misleading inferences.

In accordance with previous results (in Tables 5 and 5), the results show that backpropagation associated with GLS, under conditions of poor specification, provides realistic indices of model implementation and less biased parameter values for paths that overlap with the real model. However, despite the recommendations of the literature that WLS should be used when data is not distributed normally, we find that under no circumstances is the WLS method better than the other two methods of estimating parameters in terms of bias and implementation. In fact, only for large sample and for implementation indices close to those obtained for backpropagation and the GLS method. In addition for wrongly specified models, WLS gives low estimates reliable and overly optimistic values of fit.

With simulations performed with WLS / GLS methods associated with backpropagation simultaneously, if we increase the number of iterations there is noise added because it takes more time during the simulation. It will be the same if we increase the number of hidden layers where a certain amount of information will be lost. It is advisable to consider few layers hidden to avoid noise and a number of reasonable iterations that best justifies the convergence of the error towards zero. Then the class CL1 is the best estimated by the GLS associated with backpropagation method which is more confident and is likely to help us make a decision.

6 CONCLUSION

In this work the fuzzy model TS has been identified for our example and for a signal of the road traffic studied based on data in an autoregressive way. This method is simple and allowed us to generate data without the need to use other variables in addition. Moreover, once the optimization phase is over, the model is capable to predict other data on the process being studied. We used design methods based on a learning that allows to iteratively define the best set of parameters : the optimization of fuzzy rules (WLS, GLS) and the optimization of membership functions. We also have proposed one of the WLS or GLS optimization models with backpropagation to test the convergence of the error. The results obtained show that even with a non linear we can hope to obtain quite satisfactory performance.

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