Fuzzy Inference Systems applied to LV Substation Load Estimation

Tatjana Konjic, Vladimiro Miranda, *Senior Member* and Izudin Kapetanovic

***Abstract* - This paper describes a system for estimating load curves at Low Voltage Substations. The system is built by the aggregation of individual Fuzzy Inference Systems of the Takagi-Sugeno type. The model was developed from actual measurements forming a base of raw data of consumer behavior. This database allowed one to build large test and training sets of simulated LV substations, which led to the development of the Fuzzy System. The results are compared in terms of accuracy with the ones obtained with a previous Artificial Neural Network approach, with better performance.**

Index Terms - **Fuzzy systems, load forecasting, power distribution**

I. Introduction

The ability to estimate 24-h load curves at Low Voltage Substations (LVS) is of great importance both in planning and operation of distribution systems.

A public Low Voltage Substation, in a European system concept, may supply a large number of Low Voltage consumers, plus public lighting, and typically there are no metering devices allowing the monitoring of power and energy consumption. Installing such devices is unrealistic due to the excessive cost involved. This also means that load prediction at a LVS cannot rely on past data series.

The expansion of DMS – Distribution Management Systems has put in evidence the need for good estimation for loads at the nodes of MV networks. With the implementation of real time procedures, some sort of State Estimation must be periodically run. However, utilities usually do not have devices installed at LV substations allowing them to monitor on line voltages or power consumptions – nor they plan to d it, because the expense would not be justified. Nevertheless, the emergence of distributed generation (based on co-generation or renewables) has made the operation of a distribution network far more complex than it used to be. Due to the lack of measurements and to run a State Estimation procedure, one needs to proceed to allocate to load nodes some form of pseudo-values. This estimation can be combined with actual measurement data, usually collected at an MV substation, on the lower voltage busbar (for voltage) and on each departing line (for current) to provide a load allocation and state estimation capacity to the Distribution Control Center, integrated in a SCADA/DMS environment. A model has been shown in [1] with the allocation of fuzzy loads and the development of a Fuzzy State Estimation procedure adapted for distribution systems. All this justifies the need for 24 h load curves when, in the past and in distribution systems, one had been mostly worried only with peak value prediction.

But the motivation for the work presented in this paper was found primarily in the need of EDP – Electricidade de Portugal S.A., the national distribution utility in Portugal, to translate into load values the economic forecasts for economic development, energy consumption and change in types of consumption. At distribution level, development plans for the territory strongly influence load because they may condition the types of consumption (residential, industrial, etc.) and their growth. 24 hour load curve predictions linked to the type of consump tion expected were the requirement of the utility, and a prediction for peak load was just not enough.

For this purpose, INESC Porto together with EDP have developed a successful model based on ANN – Artificial Neural Networks [2], with good results in predicting load curves for LV substations or for groups of consumers whose prediction came as a result of planning exercises.

This paper describes an alternative model using 1st order Takagi-Sugeno (TS) Fuzzy Inference Systems (FIS), for estimating 24-hour load curves at Low Voltage Substations (LVS). While the ANN model was based on a single neural network with multiple inputs for a number of consumption classes and 24 outputs to generate the prediction of a daily load curve, our model is based on a number of TS-FIS, each tuned for a particular class of consumption, and the LVS curve estimation derives form the aggregation of individual consumer class predictions.

The research reported in this paper aimed directly at reaching a model with a better performance than the ANN model used by EDP. First, it was hypothesized that models

T. Konjic. is with the University of Tuzla, Bosnia and Herzegovina (e-mail: tkonjic@inescporto.pt).

V.Miranda is with INESC Porto - Institute of Engineering in Systems and Computers of Porto, Portugal, and also with FEUP - Faculty of Engineering of the University of Porto (email: vmiranda@inescporto.pt).

I.Kapetanovic is with the University of Tuzla, Bosnia and Herzegovina.

developed for homogeneous classes of consumers would lead to higher accuracy than the ANN model, based on an aggregation of classes. Second, by using fuzzy rule systems one will have access to rules explaining the prediction results whose analysis may give insight into the prediction process and allow some form of new knowledge acquisition. This topic is not discussed in this paper, but is has a potential to be explored and should not be neglected.

The model development was based on the same data that had allowed the development of the ANN model and therefore the results are directly comparable. The data have been collected by EDP and have served to build an ANN prediction model used for planning purposes.

II. Related Work

This section is devoted to referencing a few significant or more recent works with relation to LV load prediction. There is no intention in making a thorough survey but only to highlight a diversity of tendencies and objectives in LV load estimation. We can distinguish among deterministic, probabilistic and fuzzy models and also between peak and whole load curve prediction. Another way to classify models is based on if they depart from individual consumers or even from appliances and build up an aggregated result or if they depart directly from aggregated load curves without specific information about the load components. In general, build-up models try to take advantage of billing information on clients, while aggregate models are based on actual power measurements at substation level.

Yet another way of looking at LV load prediction is the purpose of the prediction. Some objectives have been identified: annual peak prediction for equipment sizing; peak prediction for operation purposes; load curve estimation for expansion planning and for operation planning (switching); load curve estimation for branch loading prediction and state estimation; load estimation associated with energy loss.

The deterministic approach is the most classic one. It is usually based on the selection of typical or representative days, and in most cases it served basically to estimate peak load. As an example, associating load estimation to typical loads has been the option in [3].

In probabilistic models, an important historical reference is [4], for the prediction of load/current in network branches through the development of specific representations for the behavior of individual consumers. However, probabilistic models of this type are heavy and demand a high number of parameters to represent self and mutual correlation among consumers in a network. Furthermore, because of requirements for fine tuning, these kinds of models have difficulties in addressing the problem of integrating newcomers, i.e., new consumers added to the network for which no information exists.

An even more basic approach is building load profiles from guessing the use of domestic basic appliances. The work reported in [5] is a good example. However, the model has the objective of determining the peak load at LV substations (not the 24 hour curve); it is only dedicated to residential loads and based on a deterministic reasoning. In the same line of being mainly concerned with peak load is [6], with an application to MV substations. Another work concerning peak load is reported in [7], where a fuzzy model for uncertain data has been adopted coupled with a regression procedure. A classical option in [3] has been to anchor load estimation on typical loads in winter days. A classical aggregation of load profiles has also been the approach followed in [8].

With the emergence of computational intelligence tools and methods, new approaches have been proposed. In [9] we find a proposal based on the conversion of basic probabilistic models for individual consumers to fuzzy load profiles of consumer classes. In [10] the authors propose an hourly load curve estimation based on clustering techniques such as fuzzy c-means and ANN, with the purpose of serving the interest of an Energy Service Provider.

Some of these models have been adopted in practice. One example is the Artificial Neural Network (ANN) model proposed in [2], which has been developed by INESC Porto together with EDP-S.A., the Portuguese national utility, for planning purposes.

As far as the authors know, no model had so far been proposed based on Takagi-Sugeno Fuzzy Inference Systems and the work reported in this paper therefore contains a new approach based on Computational Intelligence tools.

III. Description of Data

A. *Data collection*

In order to build a comprehensive data sample on individual consumer behavior, EDP together with INESC Porto have prepared and launched a campaign of measurements to constitute a representative database.

The data collected were then related to the commercial data at the utility's files, because the objective was to build a prediction model that would allow the estimation of the influence in the load curve or newcomers, evaluated only on the basis of their billing record.

The data collected by the Portuguese electrical utility EDP – Electricidade de Portugal, refer to several low voltage substations - LVS, spread geographically in the north of Portugal. Consumers were randomly selected in the neighborhood of five different Portuguese towns and the power during sets of 24 hours was measured, for a sample of consumers of different types. Load diagrams in data consist of the power recorded at each hour of a day during the evaluation period, which was about 2 weeks. The data were filtered. Some patterns were abnormal, due to a diversity of factors interfering with data collection, and were removed from the original file and some missing patterns were completed using expert experience and knowledge about the observed consumers.

Examples of individual consumer curves from the database of collected data are represented in Fig. 1 to 3.

The available commercial file elements have been put together with actual power values collected during the campaigns of data gathering. The commercial data relate to:

hired or contracted power: in Portugal, as well as in many European countries, the monthly payment to the electrical supplier depends not only on the energy consumption but also on contracted or hired power. Contracted power represents the maximum power one has available in a given moment. In Portugal, the contracted power for residential consumers may be of 1.1, 3.3, ... , 19.8 kW.

type of consumers: in commercial files and for commercial purposes, EDP has traditionally defined a classification of consumers as follows:

- domestic (type 0)
- not domestic, commercial (type 1)
- building lighting in public buildings (type 2)
- kitchen and heating (type 3, a classification allocated only to special residential consumers)
- industrial (type 4),
- street lighting (type 5),
- farm, agricultural uses (type 6)
- other (type 7).

monthly energy consumption of LVS: usually, in Portugal, each MV/LV substation feeds about 60 to 120 consumers of a mix of types. The monthly energy consumption refers to the month in which the power values were measured at each consumer facility.

B. *LVS database building*

The set of collected data has allowed one to compose fictitious LV substations, by randomly sampling sets of consumers from the database. The fictitious LVS were generated to have a number of consumers of different types in the same range as actual substations. Notice that these fictitious LVS are built from real data and their adoption allows one to verify model behavior without generating any artificial data.

After a LVS having been formed, its consumers were classified by type and their load curves aggregated. With this the procedure, we have formed a LVS database with 1800 new LV substations, containing the following information:

- types of consumers (Ty)
- number of different types of consumer in the LV substation (NTyLVS)
- number of consumers in the LV substation (NCLVS)
- number of consumers in each type (NCTy)
- monthly consumption of the LV substation (MCLVS)
- monthly consumption of each type (MCTy)
- 24 hour load diagram of each type of consumers (LDTy).

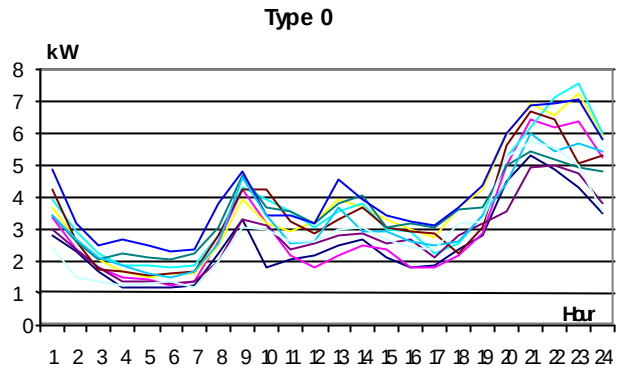

Fig. 1. Daily load curves for consumers of the domestic type

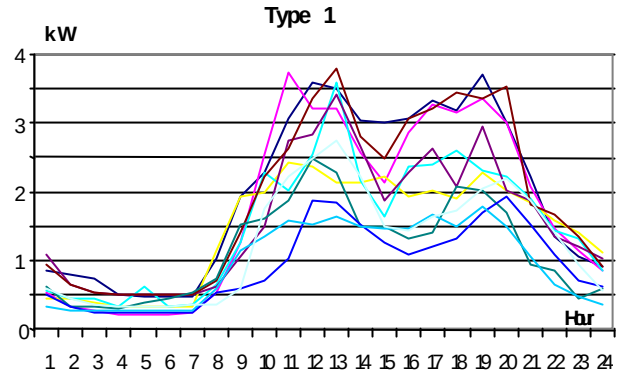

Fig. 2. Daily load curves for non-domestic (commercial) consumers

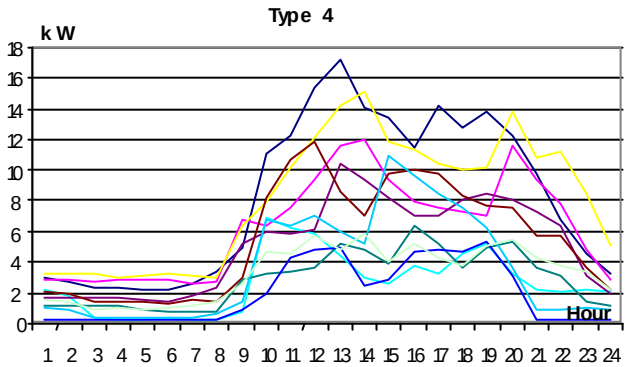

Fig. 3. Daily load curves for consumers of the industrial LV type

The sets of consumers and LVS were later divided in training and validation sets, according to the usual practice to train the Fuzzy Inference Systems. The curves were also divided according to seasonal criteria (Winter, Summer…) and to day of the week, Saturday Sunday or holiday.

As described in [2], the consumer diagrams were clustered, using the Fuzzy c-Means algorithm and also a Kohonen neural network, to confirm that the classes of consumption identified in the billing files were, in fact, matching actual load curve shapes. This allowed the identification of some "operating classes", represented in Fig. 4. This work is needed because, in a practical application, a new consumer must be counted into the model by means only of its billing file classification, as no measurement will be available.

The classes in Fig. 4 correspond to:

A. Domestic consumers with hired power $P_c \leq 6.6$kW and monthly energy consumption $E_c \leq 600$ kWh
B. Industrial consumers
C. Other non-nightly consumption
D. Nightly consumption (includes street lighting)

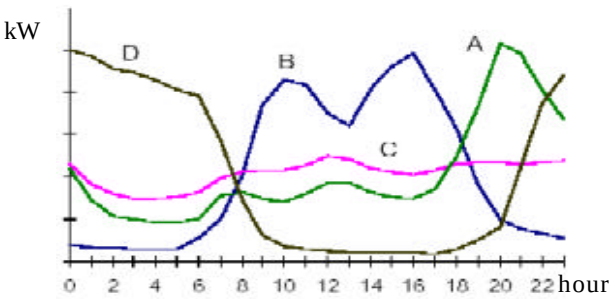

Fig. 4. 24 hour curve shapes for the four classes of consumption matching closely the classes represented in the billing files [2]

IV. THE ANN MODEL

The ANN model [2] is based on a single neural network as represented in Fig. 5. Its inputs refer to the number of consumers of each of the four classes (n_A, n_B, n_C, n_D) and their global monthly energy consumption (E_A, E_B, E_C, E_D), and its 24 outputs correspond to the LVS load at each hour of the day (p(0), p(1), …p(23)).

We may see that the ANN model performs an aggregation of classes of consumption. Furthermore, it provides in a single run 24 power values for the 24 hours. This means that the ANN must perform an interpolation in a complicated space representing several clusters of loads and several hours of the day.

In order to perform well on average, this ANN must reach some form of compromise and therefore the opportunity for a better model lies here.

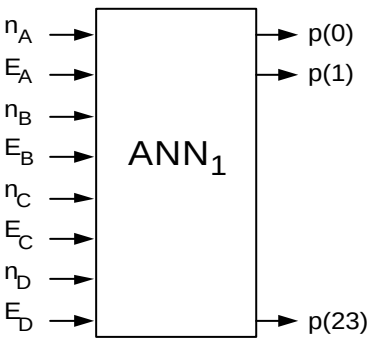

Fig. 5. ANN from [2] with inputs for number of consumers and monthly energy consumption for four classes and 24 outputs for global hourly load

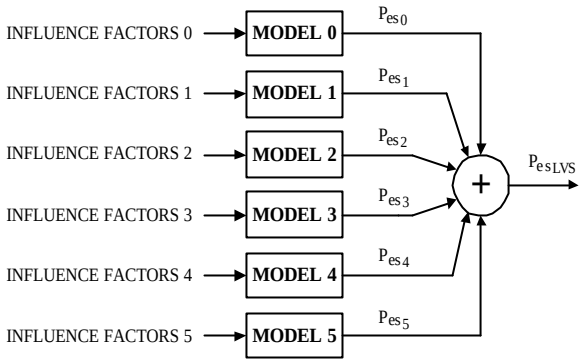

Fig. 6. Fuzzy inference model for the estimation a load curve of low voltage substation.

V. BUILDING THE FUZZY INFERENCE MODEL

Opposite to the ANN model, our idea was to make separate fuzzy inference models, each with its own rule base for each class of consumers. By relying in more homogeneous classes to perform inference, one (correctly) hoped to reach a higher level of accuracy in predictions.

The output of each model will be an estimated load for each class at a given hour. By successively inputting the 24 hours of the day, a model will generate a 24-hour sequence of loads forming a class load curve. The class load curves for all models will be aggregated (added) to obtain the estimated load curve for the Low Voltage substation. The inputs of the models will be influence factors, obtained form fuzzifying the range of data from the commercial database.

The general block diagram of the model is given in Fig. 6. Model 0 represents a FIS for domestic consumers (Type 0), Model 1 represents a FIS for non-domestic (commercial) consumers (Type 1), etc. Each FIS block produces a load prediction for a specific class and single hour, defined at the input vector. The summation of all classes gives the LVS load for the specified hour.

In this paper, we will pay attention to the model devoted to winter working days, the approach for other days being similar. The FIS for winter working days has the structure displayed in Fig. 7, for all models.

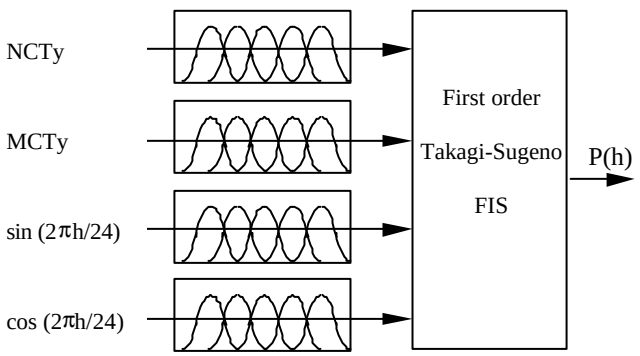

Fig. 7. Input-output structure for the WWD models

The influence factors adopted as inputs are:

- number of consumers in each type (NCTy) connected to the LVS,
- total monthly energy consumption of type (MCTy)
- hour of the day, represented by two sinusoidal functions $\sin\left(\frac{2\pi h}{24}\right)$ and $\cos\left(\frac{2\pi h}{24}\right)$, in order to faithfully represent the daily cycle; variable h represents the hour of the day (h=1, …, 24).

The input fuzzy variables are described by five Gaussian membership functions such as

$$m = f(x, \mu, \sigma) = e^{-\left(\frac{\mu - x}{\sigma}\right)^2}$$

where x – input defined in the universe of discourse

m – degree of membership

μ, σ - central value or offset and spread or width of the membership function

These membership functions are associated with the linguistic labels *Very Small*, *Small*, *Medium*, *Large* and *Very Large*, defined by Gaussian membership functions in the domain of each variable.

For each fuzzy model, we adopted the 1st order Takagi-Sugeno approach (TS-FIS) with fuzzy inputs and crisp output - the load at hour h. The model is organized in the form of rules. A rule k has the following format:

IF x_1 is A_{a1} AND x_2 is A_{b2} AND x_3 is A_{c3} AND x_4 is A_{d4}

$$\textbf{THEN} \quad f_k = \sum_{i=1}^{4} \omega_{ki} x_i + \omega_k$$

where x_i – crisp instantiation of variable i

$A_{(.)i}$ – fuzzy set describing input i

f_k – crisp output of rule k

ω_k, ω_{ki} – weights or parameters associated to rule k and input variables i

This is a 1st order TS-FIS definition. If all $\omega_{ki} = 0$ then we have a 0-order TS-FIS.

The antecedent part of a rule is formed by an AND operation. The output is obtained by an OR operation over the rule outputs. One may use any T-norm for the AND operation but it is usual to adopt the product T-norm, meaning that the membership value of the conjunction of two conditions is equal to the product of the membership values m_i of each term.

Therefore, for rule k with two antecedent terms numbered 1 and 2, the firing strength g_k is given by

$$g_k = m_1 . m_2$$

The FIS output is in most cases defined as

$$y = \frac{\sum_{j=1}^{NF} g_j f_j}{\sum_{j=1}^{NF} g_j}$$

or as a weighted sum of the firing strength f_k of each of the NF rules activated by the input. This formula is attractive because it is formally equivalent to a Center of Mass calculation. A different expression is just

$$y = \sum_{j=1}^{NF} \bar{g}_j f_j$$

if one normalizes the g values by having

$$\bar{g}_k = \frac{g_k}{\sum_{j=1}^{NF} g_j}$$

The problem of building up a TS-FIS is of finding the adequate values of parameters ω, μ and σ such that the FIS output y will represent an implicit function y = F(**x**) as approximate as possible to the relation T = F(**x**) desired, or observed in reality in a test or validation set. Usually, this is achieved by minimizing the quadratic error of the FIS output relative to target output.

For this purpose, we have adopted a hybrid algorithm [11]. It is based on half-iterations that use backward or back-propagation passes to update the μ and σ parameters, and then a Least-Squares forward pass to adjust the ω weights. As described in [12], we obtained more reliable results with this algorithm than simply with a classical back-propagation approach.

We have also trained the FIS without normalizing inputs, after realizing that FIS generated with normalized inputs would emulate interpolating functions giving negative outputs in some cases, especially at lightly loaded hours. This problem never happened with non-normalized inputs

The resulting TS-FIS, for each model, were systems with distinct number of rules. The rule base of the system consists of 1215 (=240+272+193+48+256+206) rules. The number of rules is distinct for each model because a rule is only generated if there are cases in the training set that require such rule. For instance, there are 240 rules in Model 0, but only 48 rules in Model 3.

VI. Some Results

Each model has been tested against series generated with real data, and the predictions have been very good. This result was not a total surprise, because the above mentioned ANN model had already suggested that such kind of estimation/interpolation was possible.

Fig. 8 to 11 show how close the predicted curves are from actual curves, for distinct "pure" sets of consumers all belonging to a single class. The accuracy of predictions for a LVS with a mix of consumers may also be appreciated in Fig. 12, where two distinct Low Voltage substations with a different mix of consumers have been simulated. In Fig. 13 we present two cases where the prediction does not match so accurately the actual result.

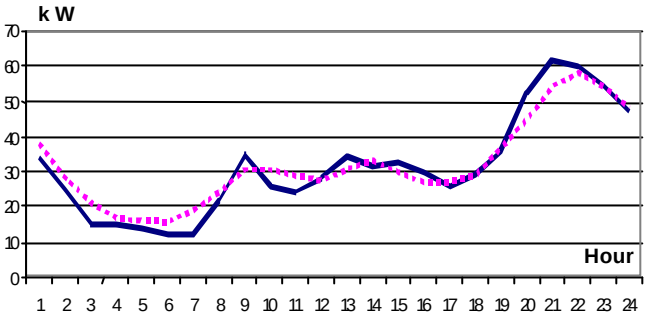

Fig. 8. Real curve (black line) and prediction (dashed line) for a set of domestic consumers (type 0)

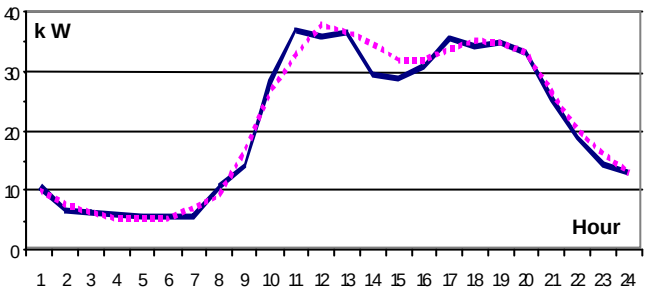

Fig. 9. Real curve (black line) and prediction (dashed line) for a set of non-domestic consumers (type 1)

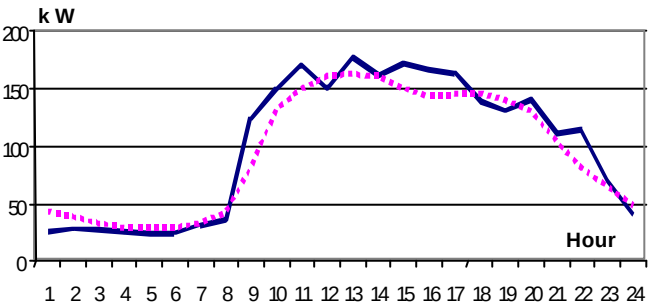

Fig. 10. Real curve (black line) and prediction (dashed line) for a set of industrial consumers (type 4)

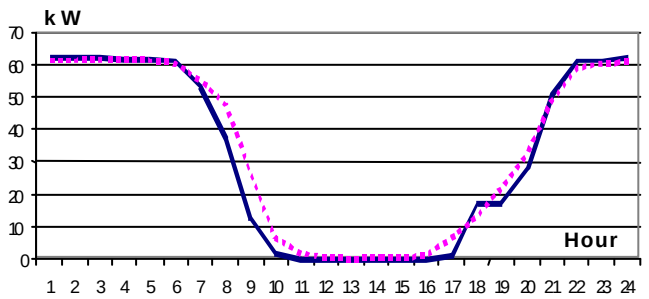

Fig. 11. Real curve (black line) and prediction (dashed line) for a set of street lighting consumers (type 5)

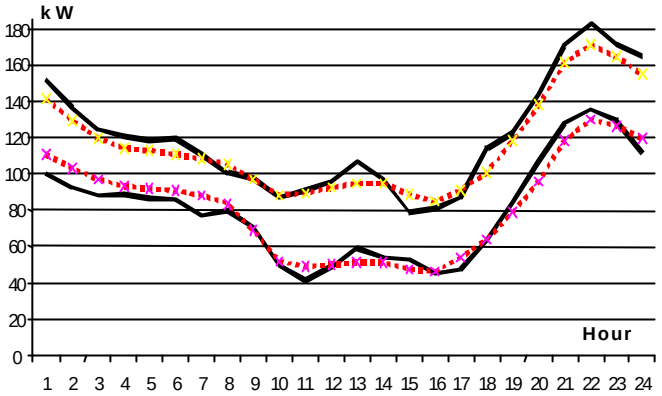

Fig. 12. Load curves of two LV substations with a mix of consumers. Black lines are actual cur ves while dashed lines are predicted curves.

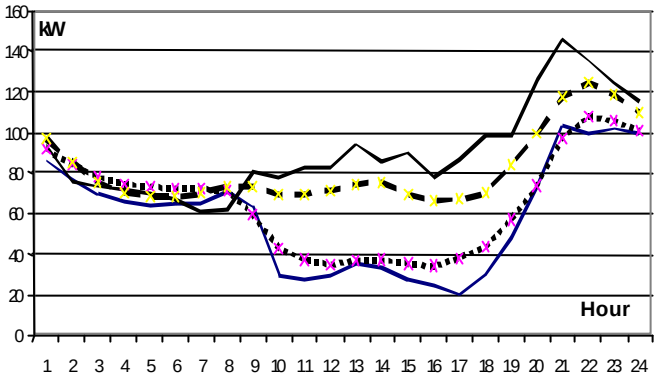

Fig. 13. Two cases of LV substations where the predicted curve does not match accurately the real curve.

VII. Confidence Intervals

One possible approach, which we have adopted, is to define a confidence band around the prediction curve - this confidence band is useful because the accuracy of predictions is not the same in all 24 hours.

Using both training and test sets, we could define the variance of deviations of predictions for each hour, and therefore calculate bandwidths of $P_{es}\pm\sigma$; $P_{es}\pm2\sigma$ and $P_{es}\pm3\sigma$.

Fig. 14 displays an example of confidence band for the case of industrial consumers (type 4).

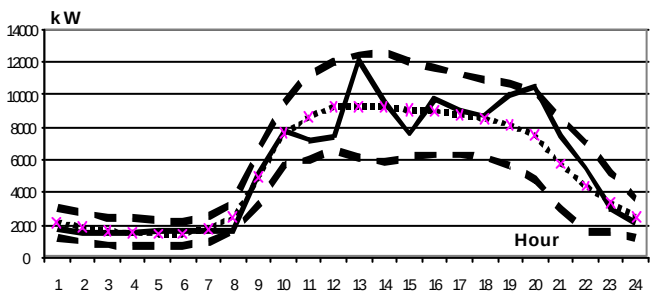

Fig. 14. Confidence band around the whole set of data associated with industrial consumers (type 4)

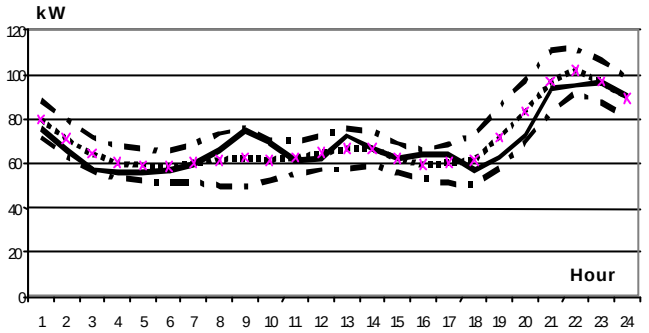

Fig. 15. Confidence band P±σ around actual and predicted curve for a substation simulated with real data

The load curve P_{es} for a LVS is calculated by summing up the load curve predictions P_k for each type,

$$P_{es} = P_0 + P_1 + P_2 + P_3 + P_4 + P_5$$

The standard deviation for the aggregate model, at each hour, will be given by

$$\sigma = \sqrt{\sigma_0^2 + \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_4^2 + \sigma_5^2}$$

Fig. 15 illustrates the application of the concept to a case of a LVS built with real data of mixed type consumers.

We have then verified in both the training and test sets how many substation load patterns would fall inside confidence bands of different breadths. Table I presents some results for bands of σ and 2σ of size at every hour.

TABLE I
PERCENTAGE OF LOAD CURVES THAT FALL INSIDE CONFIDENCE BANDS OF DIFFERENT BREADTHS, FOR THE TRAINING SET AND FOR THE TEST SET (IN BRACKETS)

	$P_{es} \pm s$ (%)	$P_{es} \pm 2s$ (%)
Model 0	67.18 (67.43)	95.92 (95.85)
Model 1	69.03 (69.14)	95.49 (95.25)
Model 2	72.33 (72.08)	95.46 (95.36)
Model 3	80.49 (83.17)	91.88 (96.72)
Model 4	69.92 (70.58)	95.36 (95.14)
Model 5	68.62 (68.81)	96.28 (96.17)

VIII. COMPARISON WITH THE ANN MODEL

There has been some interesting work on the definition of confidence intervals for predictions with ANN [13]. Based on the same raw data as used in the work reported in this paper, previous researchers have developed a successful Artificial Neural Network model [2], in use by the power distribution utility of Portugal for distribution planning purposes.

When comparing our new model with the previous model, we may state that we have achieved a certain degree of progress and improvement. The following points deserve attention:

a) *Knowledge extraction* - the ANNs are black boxes and give no explanation on how or why a prediction is generated. However, the architecture of the TS-FIS reveals a set of rules that may receive interpretation. It is out of the scope of this work to extensively analyze and provide interpretation for the rules generated in the process of creating the FIS predictors, but nevertheless the rules have been created and are available to examination.

b) *Knowledge separation* - the previous ANN model used a single neural network receiving as input the numbers of consumers in each type of consumption, plus the energies consumed and other data. This means that only an aggregate model was available, raising doubts whether the ANN would interpolate well if some classes of consumers would be absent. However, our FIS approach is composed of individual models for each class of consumption, each model having been trained for a specific type of consumption, allowing a flexible and adaptive architecture to be used according to the case under study or simulation.

c) *Accuracy* - the results for confidence intervals published for the ANN model give confidence intervals, at a level of 90%, corresponding roughly to 2.5 times the band error. In this work the authors used two ANN [2]. The first one (ANN_1) predicted 24 hour load curves while the second one (ANN_d) was used to produce an error dispersion measure of the diagrams estimated by ANN_1.

This result is worse if it is compared with the results we have obtained with our FIS approach. In our case, a 87% confidence interval corresponds to 1.5 times the band error and a 96% confidence interval corresponds to 2 times the band error - therefore, it may be estimated that the 90% confidence interval corresponds roughly to 1.7 times the band error. This means that our load curve prediction model based on a FIS is more accurate.

Fig. 16 characterizes the relation between bandwidth factors and percentage of real curve points included in the confidence band (inclusion factor). The black line is related with results obtained in this work while the dashed line represents results from [2].

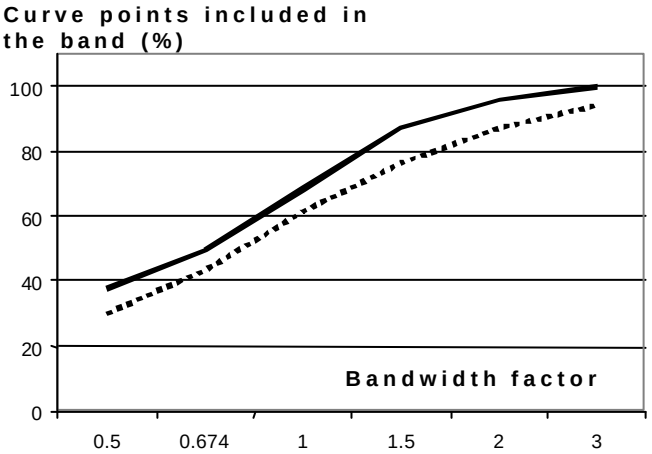

Fig. 16. Inclusion factor versus bandwidth for the ANN model [2] (dashed line) and for the FIS model (black line).

d) *Accuracy estimation* - the estimation of confidence interval was performed by a simple but effective strategy, by using standard deviations for each hour during a day. This kind of approach has the advantage of providing the planners with confidence intervals for each type of consumer connected to a low voltage substation as well as the interval for the total load curve of the substation. The previous ANN approach would generate only confidence intervals for the aggregate of the LVS consumers.

IX. CONCLUSIONS

This paper reports some phases of the development of a Load Curve estimator for Low Voltage substations, based on the coupling of a number of Fuzzy Inference Systems of the Takagi-Sugeno type. This development has been possible thanks to the availability of real data collected by EDP, the Portuguese utility for power distribution.

Using such data, sets of FIS have been developed. These "pure model" FIS are then coupled together and their results added to generate predictions for sets of consumers of mixed types.

The results are remarkably close to curves resulting from real data, which is in a way pleasantly surprising, considering that there are n measurements involved in the predictions and these are based only on contract and billing information from the commercial files of the utility, plus the knowledge of the connection of each consumer to its Low Voltage substation.

The results of our FIS approach have been compared with the results obtained with a previous model based on ANN, demonstrating the superiority of the new model in the accuracy of the predictions, measured in terms of percentage of load curves included in a band around the estimated curve.

These results may be extremely useful for distribution planning, such as practiced by EDP. A prediction in the growth of certain type of consumers, derived from economical forecasts, land development or simply load re-allocation among substations, may now be translated into a forecast on the shape of the load curve and, of course, its peak.

Also, in Distribution Management Systems, the availability of such predictions will be extremely helpful in the operation of MV networks in all cases where no on-line measurements are available regarding nodal consumption (at LV substations), which is a rather normal case.

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XI. BIOGRAPHIES

Tatjana Konjic graduated and obtained her M.Sc. and Ph.D. degrees in Electrical Engineering from the University of Tuzla, Bosnia & Herzegovina, in 1989, 1995 and 2003 respectively. She got support from the TEMPUS programme of the EU and worked for some time at INESC Porto, in Portugal. She is presently lecturer at the University of Tuzla. Her interests are in Power Systems and the application of Computational Intelligence Techniques.

Vladimiro Miranda received his graduation, Ph.D. and Agregado degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977, 1982 and 1991, all in Electrical Engineering. In 1981 he joined FEUP and currently holds the position of Professor Catedrático. He is also currently Director of INESC Porto. He has authored many papers and been responsible for many projects in areas related with the application of Computational Intelligence to Power Systems.

Izudin Kapetanovic received his graduation, and master degrees from Faculty of Electrical Engineering, University of Sarajevo, and Ph.D. degree from Faculty of Electrical Engineering, University of Tuzla, Bosnia and Herzegovina, in 1974, 1985, and 1987, respectively. In 1975 he joined Faculty of Electrical Engineering in Tuzla and currently he holds the position of Professor. He is also presently Rector of the University of Tuzla.