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An Adaptive Fuzzy Approach to Predictive Overload Protection Systems for Power Transformers

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The improving of the utilization factors of mineral-oil-filled power transformers is of critical importance in the competitive market of electricity. Utilities need to change dynamically the loadability rating of transformers without penalizing their serviceability. As a key issue of loadability all aspects of the thermal performance, and in particular those related to the determination of tolerable windings hot-spot temperature (HST), overload practice and its impact on remanent life expectation should be investigated. So, this paper deals with a methodology for the identification of a Takagi-Sugeno-Kang (TSK) fuzzy model able to reproduce the thermal behaviour of large mineral-oil-filled power transformers for implementing a protective overload system. The TSK fuzzy model, working on the load current waveform and on the top oil temperature (TOT), gives an accurate global prediction of the HST pattern. In order to validate the usefulness of the approach suggested herein, some data cases, derived from various laboratory applications, are presented to measure the accuracy and robustness of the proposed fuzzy model.

Key words: power distribution transformers, thermal overload protection systems, fuzzy control, smart relay

I INTRODUCTION

Deregulation, privatization and competitive markets for electricity have effected sustained changes in the organizational structures of the electricity supply industry as well as in the operation of power systems. The liberalized market and the infeasibility of the network's reinforcement in highly populated regions, due to environmental concerns, have greatly taxed the existing transmission and distribution infrastructure. This has induced utilities to change radically their attitude towards the loadability of many electric components and, particularly, of power transformers, which are amongst the capital-intensive assets of any electric company.

Following a »doing more with less« strategy, utilities try to balance overloading of power transformers against extending their life and maintaining system reliability. These conflicting needs can only be satisfied by implementing a real time estimation of the dynamic loadability rating of a transformer, determining the maximum load possible without causing thermal and mechanical damages to the equipment itself. The adoption of a dynamic loadability rating strategy will put at disposal an additional overload performance capability in emergency conditions, which implies lower lost revenues or costly upgrades for utilities. However, the ability of a utility of making intelligent decisions about transformer loading is dependent on knowledge both of the location and of the temperature of the transformer's hot-spot. The technical life of a transformer is, in fact, related to the deterioration of its insulation due to thermal ageing and, in this sense, the windings hot spot temperatures (HSTs) at the top or in the centre of the high or low voltage winding are the main factor limiting the loading capability of power transformers [1–3].

In the past years, several technologies have been proposed for direct measuring and monitoring HST of transformer windings. From some evaluations it was concluded that the fiber optic sensing technology meets the requirements of the transformer application [4]. Because the location of hot spots is a guess and considering the costs associated to the measurement of the HST of transformer windings, power systems researchers have oriented their attention to the development of indirect and »non invasive« estimation methodologies. Such calculation methods, starting from a reduced set of information, are able to identify the transformer thermal state by the modeling of the winding thermal dynamics. At present, the loadability of a transformer is calculated by applying transient heating equations using the transformer's specific thermal characteristics. The inputs for loading capability calculation are the load curves, the TOT rise over ambient, and ambient operating temperature conditions, assuming a fixed conservative profile for them. As detailed reported in [5], the equations for the hot spot winding temperature estimation are estimated by a model named top-oil rise model which represents an improvement of those ones proposed in the IEEE Transformer Loading Guide [6], and is based on some simplifying assumptions such as: the oil temperature profile inside the winding increases linearly from bottom to top; the difference between the winding temperature and the oil temperature is constant along the winding; the HST rise is higher than the temperature rise of the conductor at the top of the winding, introducing a correction conservative factor; the ambient temperature drives the oil temperature up and down with the same time constant as the winding temperature does; the solar flux incidence is neglected. Since this method is based on simplified thermal equivalent models and requires some specific transformer data, which can vary considerably from one transformer to another, it becomes susceptible to parameter variations. These parameter variations affect the accuracy of the calculations and, considering that the loss of life is an exponential function of HST, the adoption of thermal models can produce a substantial error in determining the real-time transformer overloadability rating. Thus, today in order to protect power transformers conservative safety factors are overly applied and the transformers are underutilized to keep suspected hot spot portions of the conductor from overheating and failing prematurely. Consequently, the calculated maximum power transfer may be 20–30 % less or worse than the real transformer capability. These motivations have led to studies to investigate the possibility of adopting softcomputing-based methodologies in order to estimate transformer thermal dynamics. In this field, the authors of this work have proposed several methodologies, which using a set of routinely measured variables, such as the TOT and load current, identify the unknown evolution of the HST profile by using neural network, local learning, and affine arithmetic based thermal models [7, 8, 9, 10]. From previous experiences, it was derived that for the accurate and reliable prediction of the thermal behaviour of a transformer it is essential to achieve high accuracy in the results, both during load cycling and in presence of overload conditions, and, at the same time, to have the ability to manage the parameters uncertainties interdependencies and the diversity of uncertainty sources.

On these bases, in the present paper a rule-based system with fuzzy inference is proposed in order to obtain an accurate model for the prediction of the thermal behaviour of a transformer. Similarly to neurocomputing, fuzzy inference allows to approximate nonlinear functions with finite fuzzy rules. The main advantage of a rule-based system over the neural network is to capture cause and effect in the inference process. A self-organizing fuzzy model generation strategy is adopted for selecting the optimal structure of the fuzzy model. On the basis of given input-output numerical data, the methodology generates a Takagi-Sugeno-Kang (TSK) fuzzy model, characterized by high accuracy and a small number of rules. In order to obtain the model, fuzzy clustering methods for partitioning the input-output space, combined with genetic algorithms (GA), and recursive least-squares (LS) optimization methods for model parameter adaptation, are used.

The TSK fuzzy model, working on the load current waveform and on the TOT rise over ambient temperature profile, permits to implement a predictive overload protection system through the prediction of the windings HST pattern.

Moreover, to achieve transparency in the control great attention is paid in finding abstract methods and technologies capable to handle in a high-level fashion low-level constraints of an environment characterized by various and different devices. Therefore, it is developed a general framework that permits the designer to focus on the control policy, considering as essential requirements the following points:

- the framework should offer all the functionalities required by the control devices;
- the framework provides high-level features to define advance fuzzy control for the various control devices;
- the framework should allow to self-tuning fuzzy logic control by means of a learning mechanism.

These three objectives are reached by defining a multi-layer architecture composed of different levels each of them giving a view of the physical world to control, varying the high/low level perception and management of the control and of the device. Control device independence and transparency is available thanks to a pure fuzzy-oriented mark-up language (built-on XML) able to manage fuzzy concepts, fuzzy rules and fuzzy inference engine directly.

II IDENTIFICATION OF TSK MODEL FOR THE TRANSFORMER'S THERMAL BEHAVIOUR

As well known TSK identification technique is a powerful tool for modelling complex nonlinear systems. A TSK model describes the global behaviour of a system by using a multimodel approach: the input space is decomposed into fuzzy regions and the system is approximated in every region by simple local models, typically linear or affine models. Therefore, the global behaviour of the system is described by a combination of interconnected subsystems with simpler models, which are local linearizations of the nonlinear dynamic system [11, 12].

The main objective of the proposed identification procedure is to identify the structure and parameters of the TSK best model that minimises, on a typical daily load pattern, the global error between the measured and the estimated windings HST profiles. The proposed data-driven algorithm for the generation of a TSK fuzzy model makes use of genetic algorithms, fuzzy clustering and recursive least-squares procedure.

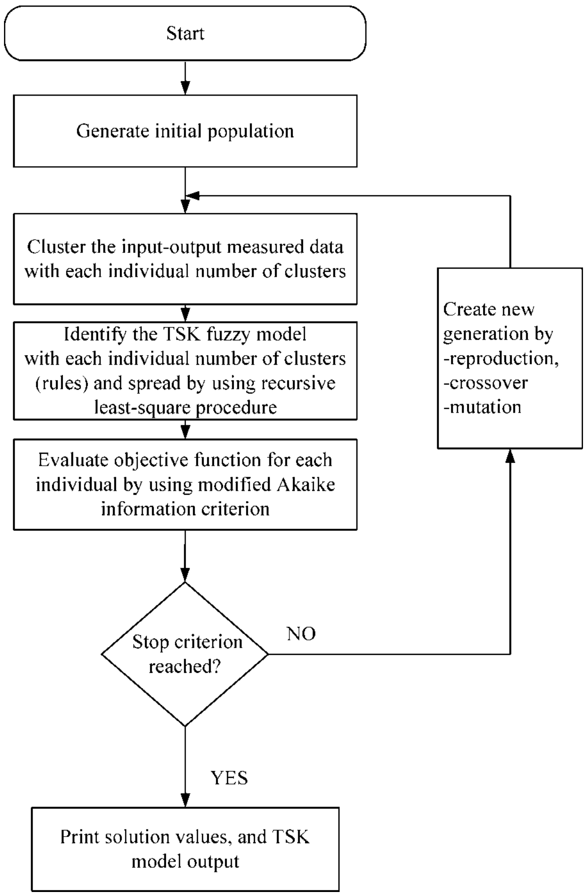

Fig. 1 Flow chart of the TSK identification algorithm

In Figure 1, the flow chart of the algorithm is reported. It's mainly based on a Genetic Algorithm (GA) having a chromosome of two elements: (N_r, r), where N_r is the number of clusters and r the membership functions spreads. For each possible chromosome, the corresponding TSK model is identified in two steps:

1. a fuzzy clustering technique is applied, with a number of clusters equal to N_r;
2. assuming the centers furnished by the previous step, the number of rules equal to N_r and the spreads of the memberships functions equal to r, the model's parameters are identified by a recursive least-squares procedure.

Once the TSK model is identified, its fitness function is evaluated, and the GA stops when the prefixed stop criterion is reached. Before to furnish some details on the fitness function of the GA and on the other features of the GA in terms of the selection mechanism and genetic operators, in the following subsections the data acquisition, the partitioning of the input-output space and the model's parameters identification techniques are detailed discussed.

A. Data Acquisition

In order to obtain data for both identification and testing of the TSK fuzzy model, laboratory tests were developed.

The purpose of the test program is to simulate the stress, due to a severe overload, acquiring, through a measurement station, the rms load current, the transformer top oil temperature, the weather conditions and the corresponding windings hot spot temperature, which will be used to evaluate the TSK model performance.

Referring to the weather conditions, since the transformer is located inside the laboratory, only the ambient temperature is considered, because the contribution of solar heating, wind speed and other meteorological parameters to the windings HST rise is negligible.

The measurement station is formed of three thermocouples to measure the windings HST of the medium voltage and low voltage windings and the TOT [7, 8]. To measure the load current a hall effect current transducer is used. The ambient temperature is monitored through a digital thermometer located far enough away from the power transformer so that the impact of heat dissipated from the transformer on the ambient temperature can be neglected. All sensors are interfaced with a data acquisition unit, which is used also for controlling the transformer tap-changer, and a data logging system records the temperature registered by each sensor at 5-min intervals.

With the above-mentioned measurement station, the test program is executed simulating various realistic daily transformer loading current. The gathered data are then organised into three different sets: one training set and two validation sets.

B. Input-Output Space Partitioning Technique

The identification of the TSK model implies the existence of a knowledge base consisting of a set of input/output measured data samples. The knowledge base is obtained from the measurement station, as schematically reported in Figure 2 where:

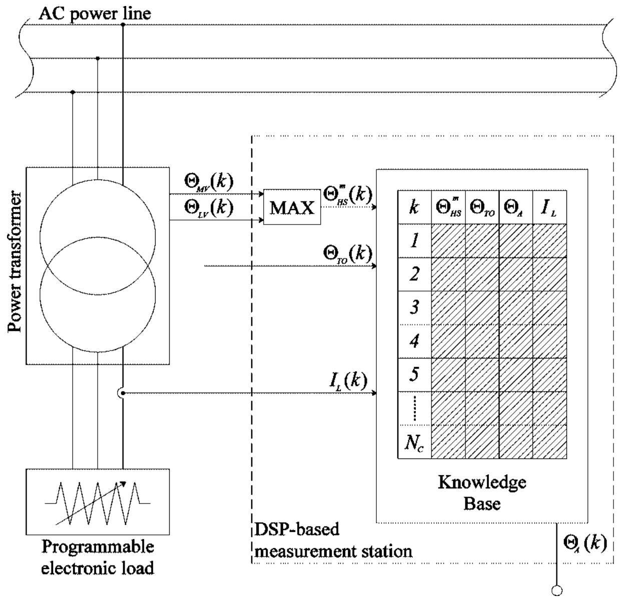

Fig. 2 Schematic representation of laboratory measurement station for knowledge base acquisition

Θ_A is the ambient temperature, [°C]
Θ_{TO} is the top oil temperature, [°C]
Θ^m_{HS} is the measured hot spot winding temperature, [°C]
Θ_{LV} is the low voltage hot spot winding temperature, [°C]
Θ_{MV} is the medium voltage hot spot winding temperature, [°C]
I_L is the load current normalised to rated current [p.u.]

The TSK fuzzy thermal model of the transformer is realized considering as inputs the load current profile together with the TOT profile and as output the corresponding winding HST.

The TSK fuzzy model at each sample instant (k) acquires and processes the load-current and the TOT at sample instant (k) and at some selected precedent sample instants which constitute the history of the inputs. By processing these input variables, the model is able to calculate or predict the corresponding winding HST.

In order to perform partitioning of the input-output space, various approaches can be used. Amongst them pattern-recognition methods of fuzzy clustering, such as fuzzy c-means (FCM) [13–16], are suitable tools for the partitioning process. Using such a method, data samples are organized in clusters, each of which is associated to a centre by using the FCM algorithm, in this manner the TSK model is based on a set of fuzzy IF-THEN rules, extracted by using the FCM clustering technique.

With this approach, clustering becomes the basis of the fuzzy model identification algorithm, inducing the rule-base structure of the fuzzy model.

C. Model structure and parameters identification

For multi-input single-output system, the typical TSK model consists of a set of IF-THEN rules having the following form [15, 16]:

$$R_h : \text{IF } x_1 \text{ is } A_h^1 \text{ and} \ldots \text{and } x_p \text{ is } A_h^p \text{ THEN } y \text{ is } f_h(x), \quad h = 1,\ldots,R \tag{1}$$

$$\text{where} \quad f_h(x) = a_{0h} + a_{1h}x_1 + a_{2h}x_2 + \cdots + a_{ph}x_p \tag{2}$$

in which $x_{1,\ldots,R}$ are the input variables, y is the output variable, $A_h^{1,\ldots,p}$ are the fuzzy sets, and $f_h(x)$ is a linear function. The h-th fuzzy rule of the collection is able to describe the local behaviour associated to the fuzzy input region characterized by the antecedent of the fuzzy rule.

For any input, $\tilde{x}$, the inferred value of the TSK model, is calculated as

$$\tilde{y} = \frac{\sum_{h=1}^{n} A_h(\tilde{x}) \cdot f_h(\tilde{x})}{\sum_{h=1}^{n} A_h(\tilde{x})} = \frac{\sum_{h=1}^{n} \tau_h \cdot f_h(\tilde{x})}{\sum_{h=1}^{n} \tau_h} \tag{3}$$

where the degree of firing of each rule, τ_h, for the current input $\tilde{x}$ is determined by the Gaussian law, which ensures the greatest possible generalization

$$\tau_h = e^{-\alpha\left\|\tilde{x}-x_h^*\right\|^2}, \qquad h = 1,2,..R; \tag{4}$$

where x_h^* is the centre of a rule and $\alpha = 4/r^2$, where r is a positive constant, which defines the zone of influence of the rule. As the consequent of each rule is linear, its parameters, which minimize the overall error between the TSK fuzzy model and the system being modelled, can be determined recursively by least-squares procedure.

The TSK model has to be identified by:

1. determining the centres and spreads of the membership functions (the antecedent part of the model);
2. identifing the parameters of the consequent part by least squares technique.

D. Fitting against complexity

As in many other applications of model identification, one of the important issues of power transformers thermal behaviour representation is the trade-off between fitting the training data samples and reducing the model complexity, in terms of rule-base structure. The simplicity of the model can prevent from both the over fitting, fitting the training data samples too well so that the capacity to generalize the future data samples is lost, and the incomprehensibility and unmanageability. However, the excessive simplicity of the model could penalize its ability to fit the training data, determining a greater fitting error. Hence, a balancing between reducing the fitting error and increasing the model complexity must be done. Amongst the various methods proposed in literature for searching the number of fuzzy partitions and fuzzy rules, in this paper the modified Akaike information criterion (AIC) is applied for fuzzy model construction. In the modified AIC a penalty for the over fitting is introduced so that the complexity of the fuzzy model is determined by the number of fuzzy rules in the model and not only by the number of antecedent and consequent parameters of the rules. The modified AIC, which tends to minimize both the output error and the order of the model, can be defined as [17]:

$$\mathrm{AIC} = N_c \log(\mathrm{MSE}) + 2m_p \tag{5}$$

where N_c is the number of data samples, m_p is the number of parameters in the model, and MSE is the Mean Squared Errors of the identified models. Based on the considerations stated in [17], the single parameter m_p in the above statistical information criteria is replaced and a complexity function is used, which is defined as:

$$s(m_a, m_c, m_r) = m_a + m_c + \mathrm{c}m_r \tag{6}$$

where m_a is the number of antecedent parameters, m_c is the number of consequent parameters, m_r is the number of fuzzy rules constituting the model, and c is a constant that allows the user to incorporate heuristics regarding the relative importance for reducing the number of fuzzy rules.

E. Main features of the Genetic Algorithm

As mentioned before, the data-driven approach for generation of a TSK model is based on genetic algorithms. The GA has a chromosome of two elements: (N_r, r) where N_r represents the number of clusters to be used for clustering, which corresponds to the number of TSK rules, while r represents the spreads of the membership functions. The fitness function to be minimized in the implemented GA is based on the modified AIC and can be defined as follows:

$$f(N, r) = \log(\mathrm{MSE}) + \frac{2(m_a + m_c + cm_r)}{N_c} \tag{7}$$

where the MSE is calculated on the basis of the measured and estimated hot spot winding temperature Θ^e_{HS} [°C]

$$\mathrm{MSE} = \frac{\sum_{k=1}^{N_C} (\Theta^e_{HS}(k) - \Theta^m_{HS}(k))^2}{Nc}. \tag{8}$$

As the other features of the GA it concerns, the selection function adopted is the tournament selection, and as genetic operators the heuristic crossover, and the non-uniform mutation are used.

III USING THE TSK MODEL FOR HST CALCULATION AND PREDICTION

With the availability of powerful high-speed digital signal processors (e.g. DSPs), the protective relay is able to process some of the usual protection functions, also. Today, it is reasonably acceptable that functions, as overload management of power transformers, can be decentralized as the protective relays can effectively handle them. Following this approach, relays based on the proposed fuzzy model that provides both protection, monitoring and overload control of a power transformer can be produced. Fundamentally, the relay has the ability to predict when an overload will occur and to provide a 15/30 minute warning back to the control center where load dispatchers can take preventive load adjustment actions. Moreover, the transformer relay is able to detect overload conditions based on calculated HST and to react in an intelligent manner, adjusting dynamically the overload setting. For such a kind of relay, the proposed TSK model could be used both for on line calculation and prediction of HST.

As mentioned before, the implemented TSK model is characterized by ten inputs, in order to take into account the history of the input variables. Five data samples, spaced of a multiple of five minutes, are used for the load current (at instants k, k-1, k-3, k-5 and k-8) and the remaining inputs are reserved for the TOT data samples at the same instants of time. The model has only one output, the

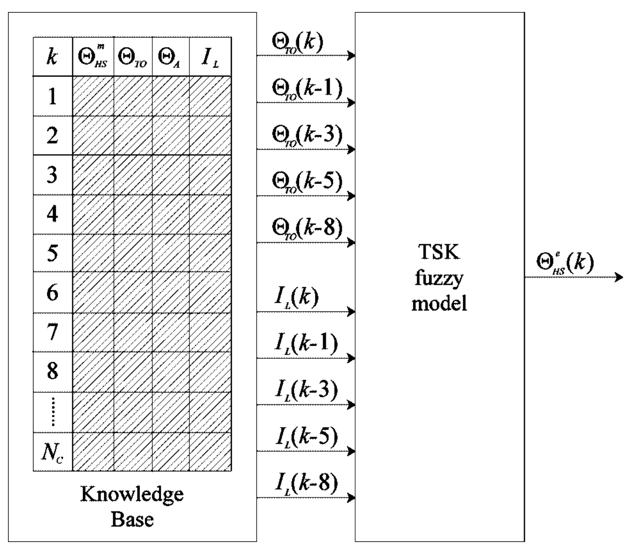

Fig. 3 Schematic input-output representation of the TSK model

windings HST at the time instant k, as reported in Figure 3. For prediction of the windings HST, the output of the model must be estimated at a future instant of time, $k+3$ or $k+6$ if the prediction refers to 15 or 30 minutes respectively, under the assumption that load current and TOT do not change in the future time instants. If the prediction indicates that the windings HST will exceed the trip setting, defined by the user, a warning alarm is activated, and some protection algorithms are executed at relay level for full or partial load transformer trip.

IV A TRANSPARENT ADAPTIVE FUZZY CONTROL FRAMEWORK

Before presenting some data cases, in this section the implementation of a transparent adaptive framework is discussed. The framework, depicted in Figure 4, was developed to produce a fuzzy controller in a »transparent« format, that will be customized on specific hardware constraints through an automatic procedure.

The proposed framework has the ability to trigger a learning process by processing data related to the application domain. An evolutionary module extracts the meaningful rules, by using a designed clustering technique as better described in the next, that constitute the behavior of the fuzzy controller. The obtained legacy fuzzy controller is passed to the FML Converter module that translates it into a markup-based description (fml language). Next step concerns the real implementation of the fuzzy controller on specific hardware. XSLT modules are able to convert fml fuzzy controller in a general purpose computer language using a XSL file containing the translate description. Now, the modeled controller is ready for the hardware chosen for the real control device.

An additional component (local control manager LCM), is provided in order to further specify the action to undertake at the bay level. From the interaction of the LCM with the supervisor service, the learning activation mode is specified.

V EXPERIMENTAL APPLICATION RESULTS

In this section the previously described methodology is employed to identify the best TSK model and to estimate in real time the winding HST of a laboratory prototype mineral-oil-immersed power transformer.

Taking into account the general framework, and considering the abovementioned specific fuzzy control and learning strategies, the following instance of the framework is obtained, as depicted in Figure 5.

In such a scheme, the Supervisor plays an important role in the learning and control phases: at control level it may modify the LCM behavior thanks to wider perception of the overall process;

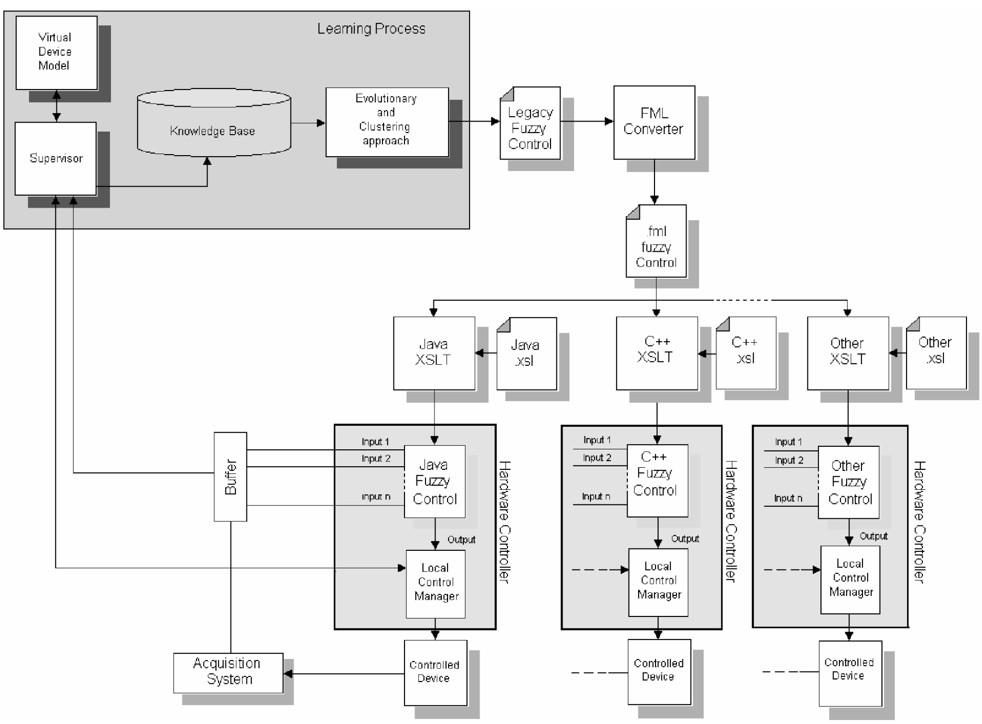

Fig. 4 General framework

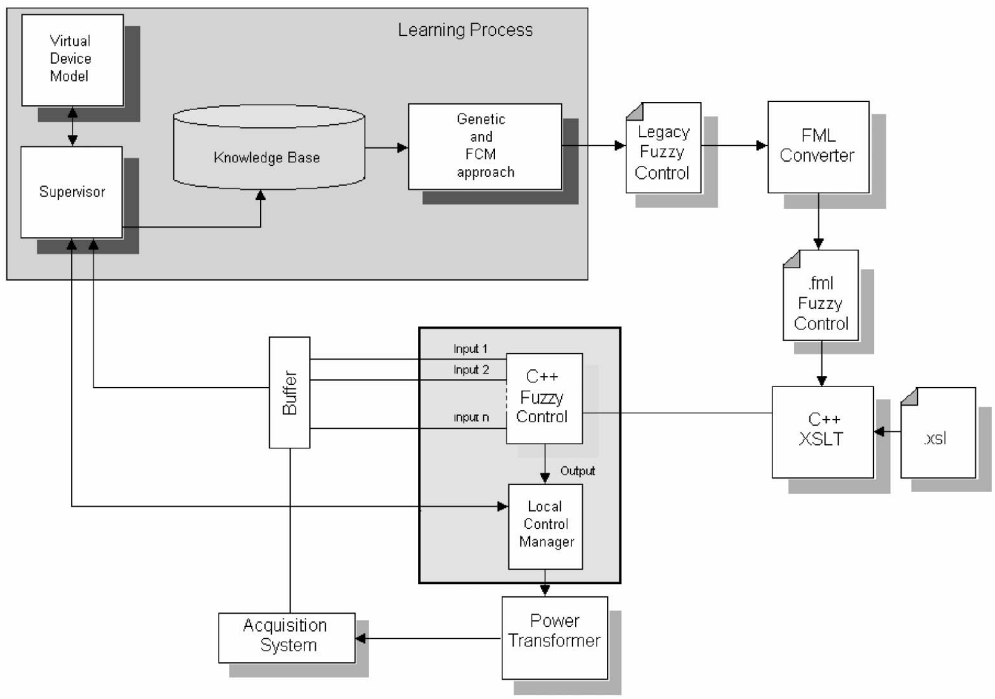

Fig. 5 Instance of the framework customized for the application

at learning level, the Supervisor may command a regeneration of the knowledge base using the information contained inside the Virtual Device Model. This last represents a synthesized model of the physical component. When the knowledge base is upgraded, the training session can be re-executed, with a novel creation of fuzzy control model.

The TSK fuzzy model is identified by using a set of observed data samples (training set) that describe a realistic daily loading current for power transformer, then the generalization and approximation capability of the TSK model are validated with different sets of data (validation sets) describing different and more complex load patterns. The transformer main characteristics are reported in [7]. The purpose of the test program is to simulate the stress due to a severe overload.

The model training set is developed using the experimental data set for the load current profile and the TOT illustrated in Figure 6a.

As it can be noted, the load pattern is relative to a 24-h observation period with $N_C = 288$ data samples. It should be noted that the load pattern does not contain the severest overload condition to guarantee the best generalization capability for the model.

Starting from this training set, the previously described algorithm was employed in order to identify the optimal TSK based transformer model that

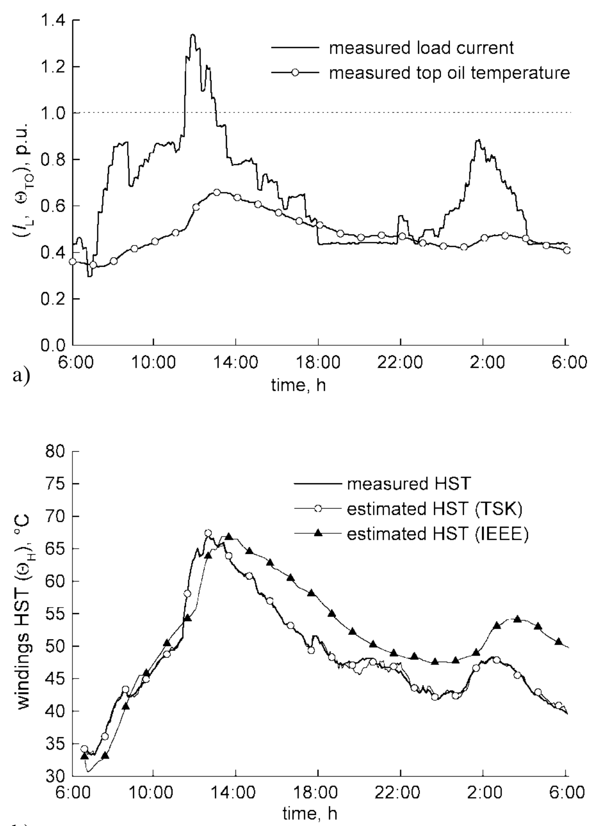

Fig. 6 Training set: a) load current and TOT vs. time, b) windings HST profiles

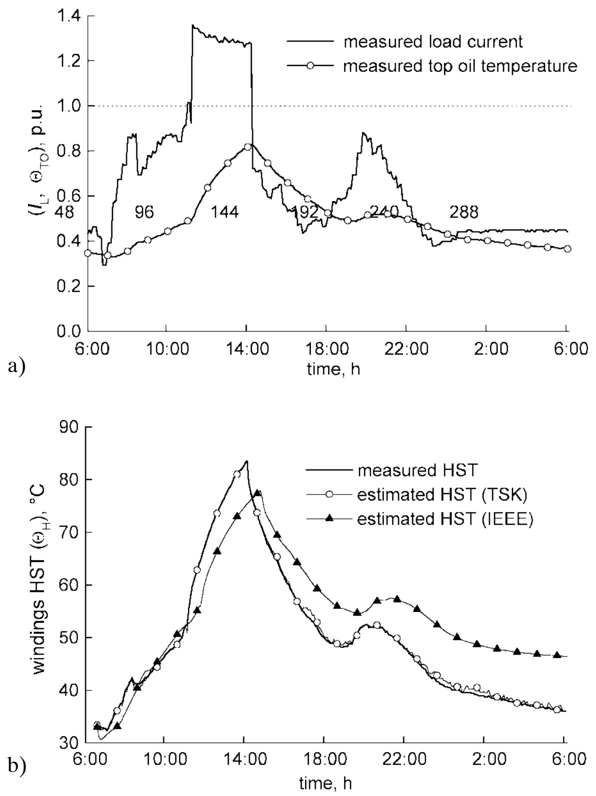

Fig. 7 Validation set with severe overload: a) load current and TOT vs. time, b) windings HST profiles

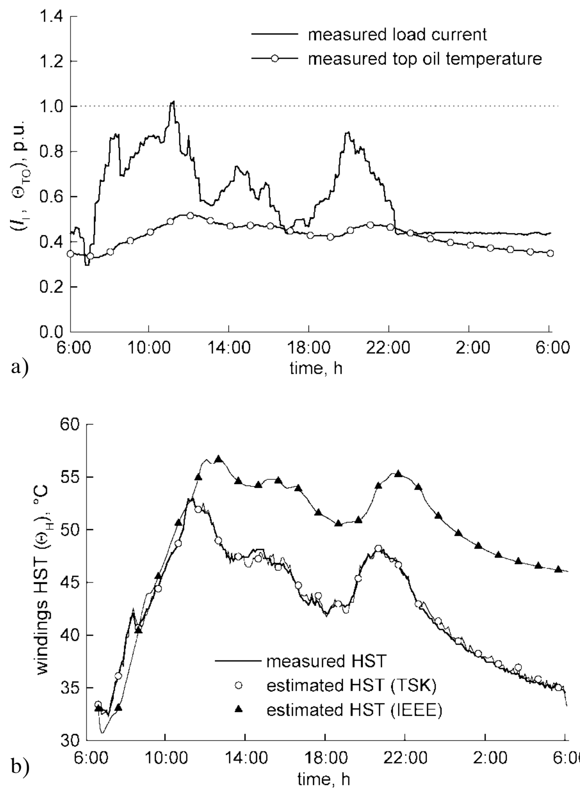

Fig. 8 Validation set without overload: a) load current and TOT vs. time, b) windings HST profiles

minimizes on the training daily loading pattern the fitness function defined before. The learning procedure has identified an optimal TSK model characterized by 2 rules, which guaranties a performance, expressed in terms of the MSE, equal to 0.214. The validity of the identified model is then verified using two further load pattern characterized by a different overload condition.

The output furnished by the identified model using the training data is shown in Figure 6b, where the TSK model estimated, the top oil rise model and measured windings HST curves are shown. Analyzing the hot spot curves in Figures 7 and 8, obtained considering two data sets very different from the training one, a great accuracy is evidenced.

Analyzing the maximum absolute error (MAE) and the error on peak value (EPV), shown in Table I, the ability of the TSK model to correctly identify the winding hot spot time constant in presence of high-magnitude overload applied to the transformer is also evident. From Figure 7b, it's also evident that the accuracy of the IEEE model in the evaluation of the windings HST profile decays rapidly as the overload conditions become severe. As a consequence the current windings HST is greater than the predicted one. Examining the MAE and EPV associated to the two validation sets, it can be seen that by using the TSK model instead of the purely analytical one increased accuracy results are obtained. This is especially true in presence of severe overload.

Table I **Simulation results**

		EPV [°C]	MAE [°C]	MSE
Training set	IEEE model TSK model	0.475 0.174	10.616 2.056	0.214
Validation set (with severe overload)	IEEE model TSK model	5.554 –0.035	10.550 1.803	0.289
Validation set (without overload)	IEEE model TSK model	–3.639 0.120	11.882 1.244	0.145

VI CONCLUSIONS

In this paper a new approach, based on a fuzzy rule based model, for thermal state prediction problems for power transformer has been presented. The proposed approach is well suited for calculation and prediction of windings HST profiles, and is more reliable with respect to top-oil-rise model based on nameplate values.

The used modelling technique, besides revealing a great accuracy in prediction, is also economic in complexity, achieving the best performance in terms of memory occupancy and computational time. The operational structure can guarantee a high flexibility and accuracy when working with power transformers having very different design characteristics.

The proposed multi-layer architecture composed of various levels each of them provides different perception and management of the control and of the device provides the control device independence and transparency thanks to a pure fuzzy-oriented mark-up language (built-on XML) able to manage fuzzy concepts, fuzzy rules and fuzzy inference engine directly.

Using the proposed methodology new relays can be realized to combine protection, monitoring and control function. These new relays can be easily interconnected amongst them and with the control center where load dispatchers perform supervision activities.

With such an approach evolving fuzzy rule-based models can be applied updating the rule-base structure and parameters by a supervised learning.

The favourable responses together with the fast elaboration time lead to consider the TSK based identification technique as an alternative approach to the neural networks for the implementation of an adaptive real-time overload monitoring and protection system for distribution power transformers. In fact, the TSK model can assist the user in the decision making process for the determination of an acceptable level and period of overload, for the prediction of incipient faults and for the dynamic rating and transformer life assessment.

All this allows for an increase in power transformer loadability and, consequently, for an increase of the power system operation margins in presence of overload conditions.

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Adaptivno neizraziti pristup sustavima prediktivne zaštite od preopterećenja transformatora snage. Poboljšanje faktora iskoristivosti transformatora snage punjenih mineralnim uljem od kritične je važnosti na kompetetivnom tržištu električne energije. Zahtijeva se da dinamičke promjene opterećenja transformatora ne utječu na njegovu raspoloživost i pouzdanost. Kako je opteretivost ključna problematika, moraju se istražiti svi aspekti toplinskih svojstava, posebice oni koji se odnose na određivanje dopuštene vršne temperature namota (HST), te učestalost pojave preopterećenja na očekivani životni vijek transformatora. Ovaj se članak bavi metodologijom identifikacije Takagi-Sugeno-Kang (TSK) neizrazitog modela koji može reproducirati temperaturno ponašanje velikih transformatora snage punjenih mineralnim uljem za implementaciju zaštitnog sustava protiv preopterećenja. TSK neizraziti model s praćenjem valnog oblika struje opterećenja i vršne temperature ulja (TOT) daje točnu globalnu predikciju vršne temperature namota. Točnost i robusnost predloženog neizrazitog modela provjereni su na skupovima laboratorijskih podataka kako bi se verificirala korisnost predloženog postupka.

Ključne riječi: transformatori snage, zaštitni sustavi temperaturnog preopterećenja, neizrazito upravljanje, pametni relej

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