Dissolved gas content forecasting in power transformers based on Least Square Support Vector Machine (LSSVM)

Roberto J. Fiallos

Abstract—Taking into account the chaotic characteristic of gas production within power transformers, a Least Square Support Vector Machine (LSSVM) model is implemented to forecast dissolved gas content based on historical chromatography samples. Additionally, an extending approach is developed with a correlation between oil temperature and Dissolved Gas Analysis (DGA), where a multi-input LSSVM is trained with the utilization of DGA and temperature datasets. The obtained DGA prediction from the extending model illustrates more accurate results, and the previous algorithm uncertainties are reduced.

A favourable correlation between hydrogen, methane, ethane, ethylene, and acetylene and oil temperature is achieved by the application of the proposed multi-input model.

***Index Terms*—Dissolved gas analysis (DGA), Gas chromatography, machine learning, Least Square Support Vector Machine (LSSVM).**

I. INTRODUCTION

Power transformers constitute one of the most important equipment in an electrical power system. These assets are generally efficient, reliable, and capital intensive, with an expected service life of 40 years or more.

Thermal or electrical stress contributes to insulating system deterioration within power transformers. Mineral oil and/or paper degradation is associated with abnormal functionality and possible incipient faults in the equipment, consequently, different types of hydrocarbons and carbon oxides are produced.

The composition of the gas dissolved in mineral insulating oils can be analyzed by the application of a diagnostic tool called Dissolved Gas Analysis –DGA, which detects and evaluates internal failures and their development trends.

A correct interpretation of DGA results is required to forecast and prevent failures with significant accuracy. References [1] and [2] explain concepts regarding power transformers insulating system composition, the degradation process of mineral oil and cellulose, the effects of operating conditions on gas production, and procedures utilized to detect and analyze possible failures.

The amount of available DGA data has a significant impact on the accuracy of the final results. Data analytic methods for power transformers involve amounts of data without existing formula or equation to correlate variables. As a result, machine learning algorithms have been used to diagnose and forecast dissolved gas concentration levels in power transformers, which are based on learning information directly from past DGA data and adapting their performance for future predictions.

Consequently, this project aims to predict dissolved gas content trends applying real chromatography data. A specific objective refers to obtaining high accuracy in the forecast values, where the randomness behaviour of the DGA data must be reduced by the application of processing techniques.

A Least Square Support Vector Machine (LSSVM) is implemented and validated. Finally, considering the influence of the operating conditions in the dissolved gas content into the power transformer, a correlation between oil temperature and DGA is also proposed to improve the predictions.

Motivated by the above-mentioned difficulties, a Least Square Support Vector Machine model (LSSVM) for DGA data predictions is constructed in this project, where historical real DGA data obtained from the industrial sector is used for training and testing the proposed algorithm. As part of the present work, a pre-processing stage is used to reduce the randomness DGA behaviour, which in addition to the LSSVM capabilities contribute to obtaining more accurate predictions.

As mentioned before, gas content changes are hugely affected by power transformer operating conditions, thereby a correlation between dissolved gas content and oil temperature is included as an extending approach of this project. The construction of a multi-input LSSVM model is developed with the application of DGA and oil temperature data in the training period. The main goal of the second proposed algorithm is to increase the accuracy of the forecasting DGA values.

II. DISSOLVED GAS ANALYSIS METHODS

All transformers generate gases of some amount at normal operating conditions. Occasionally, this generation can lead to severe faults within the transformers. A dissolved gas analysis, which is the most common type of transformer monitoring can provide important data to increase the availability of power transformers. This analysis is based on chromatography methods, where oil samples are analyzed in laboratories. A number of gases (hydrogen, methane, ethane, ethylene, acetylene), and the relationship between each other help to identify the type of faults at an early stage [1].

A. Key gas method

The method is dependent on the gas released at various temperatures of oil and cellular (paper) decomposition due to faults. The fault is determined by calculating the relative proportions of the gases. These significant gases are known as ‘key gases’. The four general fault types are described by [1], [3].

B. *Ratio Method*

The ratio method is a technique which involves the calculation of key gas ratios and comparing these ratios to a suggested limit. Some of the most commonly used techniques are Doernenburg ratios and Rogers's ratios. The Doernenburg method is one of the effective diagnostic tools available but is less used due to its complexity. In this method, the concentration of one of the principle gas needs to be two times the other gases to be possible to calculate the ratios. The Rogers ration method is an advanced form of Doernenburg method and has almost same principle. But the requirement of needing significant concentration of principle gases is not there. The faults are chosen accordingly with the gases and the ratios [4].

C. *Duval's Triangle*

This is one of the most preferred and also a highly-recognized method in IEC guidelines used for the gas analysis. It is recommended for its supreme accuracy in determining the faults. The advantage of this method is that it requires only 3 gases to analyze all types of potential faults within the transformer. The 3 gases are methane (CH4), acetylene (C2H2), and ethylene (C2H4). The construction of the triangle is in such a way that one calculates the total accumulated amount of three key gases and divides each gas by the total of the three gases and the percentage associated with each gas is found. The arrived values are plotted on a triangle as in the figure to arrive at a diagnosis [2]. Figure 1 illustrates the relative percentages of the 3 gases, which are plotted on each side of the triangle from 0% to 100% [5]. According to the relationship between the 3 gases, the diagnosis can be obtained from the fault zones in the triangle (Table 1).

III. LEAST SQUARE SUPPORT VECTOR MACHINE ALGORITHM (LSSVM)

Least square support vector machine (LSSVM) requires a reduced quantity of data to predict the future time series. ''Based on the available time series, network internal parameters are tuned using an appropriate tuning algorithm'' [6]. LSSVM is a reformulation of the traditional SVM, and it is more suitable to solve the regression problems [7]. Basically, LSSVM approach refers to solving a set of linear equations, due

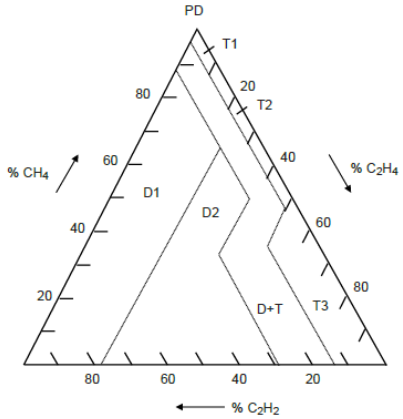


Figure 1 Duval's Triangle [2]

Table 1 Duval's triangle fault zones [2]

Code	Fault zone
T1	Low-temperature thermal fault (T<300°C)
T2	mid temperature thermal fault (300°C to 700°C)
T3	High-temperature thermal fault (T>700°C)
D1	discharges of low energy
D2	discharges of high energy
D+T	mix of thermal and electrical faults
PD	partial discharges

to equality instead of inequality constraints in the problem formulation [8].

Given a training dataset $\{x_k, y_k\}$, where $x_k \in R^m$ is the input data, and $y_k \in R$ is the corresponding output data. In literature [7], a linear equation of higher-dimensional feature space is defined as:

$$f(x) = w^T.\varphi(x) + b \quad (1)$$

where φ(.) is a nonlinear mapping of data from input space into a higher-dimensional feature space. The optimization problem can be described by the following equations:

$$min\, J(w,e) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{k=1}^{N} e_k^2 \quad (2)$$

Subject to $y_k = w^T\varphi(x_k) + b + e_k$, $k = 1,2,\dots,N$, where $w \in R^m$ error variable $e_k \in R$, and b is bias. J is the loss function, and γ is an adjustable constant [8]. The Lagrangian function is defined according to the optimal function (2):

$$L(w,\alpha_k,b,e_k) = J + \sum_{k=1}^{N}\alpha_k[y_k - w^T\varphi(x_k) - b - e_k] \quad (3)$$

Regarding to equation (3), α_k represents the Lagrange multipliers which also support vector $\alpha_k \in R$ [8]. According to the linear KKT system [6], the first-order derivatives of L are:

$$\frac{\partial L}{\partial w} = 0 \quad \rightarrow \quad w = \sum_{k=1}^{N}\alpha_k\,\varphi(x_k) \quad (4)$$

$$\frac{\partial L}{\partial \alpha_k} = 0 \quad \rightarrow \quad w^T\varphi(x_k) + b + e_k - y_k = 0 \quad (5)$$

$$\frac{\partial L}{\partial b} = 0 \quad \rightarrow \quad \sum_{k=1}^{N}\alpha_k = 0 \quad (6)$$

$$\frac{\partial L}{\partial e_k} = 0 \quad \rightarrow \quad \alpha_k = \gamma e_k \quad (7)$$

After eliminating w and e_k, matrix equation (8) is gotten [7], which is a set of nonlinear equations to be solved in α and b. These implicitly omissions correspond to creating an ε-insensitive zone in the underlying cost function, which is clear from the condition for optimality equations (4), (5), (6), and (7) [9].

$$\begin{bmatrix} 0 & \eta_l^T \\ s & \Omega + \gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha_k \end{bmatrix} = \begin{bmatrix} 0 \\ y_k \end{bmatrix} \quad (8)$$

where $\Omega = K(x, x_k)$, I is the identity matrix, $\eta_l^T = [1 \dots 1]$, $s = [1 \dots 1]^T$.
Therefore, the resulting LSSVM model for function estimation becomes [9].

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \quad (9)$$

The parameters α_k and b in equation (9) represent the solution to the linear system. Similar to the standard SVM, $K(x, x_k)$ is the kernel function, and in the case of function estimation, RBF kernels can be applied. RBF kernel function has an advantage in comparison with SVM, because it has only two additional tuning hyper-parameters (Y,σ).

IV. DISSOLVED GAS CONTENT PREDICTION BASED ON LSSVM – METHODOLOGY AND VALIDATION

Handling the available data and finding the right algorithm refer the most important challenge in machine learning techniques. Firstly, pre-processing techniques must be applied to attenuate the randomness behaviour of the dissolved gases content samples before using this data as an input of the LSSVM model.

Figure 2 describes the workflow implemented with LSSVM model. The first step in the training and testing periods refers to the pre-process of dissolved gases content data.

According to [7], the pre-processing techniques are required to attenuate the stochastic characteristics of the time sequence data and regularized its performance, in this manner carry out a reasonable prediction to a certain extend. Two different techniques are applied as data preparation before the machine learning algorithm: removing outliers from the series (smoothed) and data normalization. Both techniques have been chosen considering the performance of the LSSVM in the testing stage. Practical DGA sample data are a sequence of random observations taken over different periods of time, because of this some gas content measurements differ significantly in magnitude. The performance of the first technique is shown in Figure 3, which is applied to the ethane dataset. It can be noticed how the original data is rescaled in order to eliminate anomalies and avoid possible inconsistencies in the training period of the machine learning. A data normalization is also applied as a pre-processing method. The dataset is normalized in the range [0, 1] according to equation (10), before applying the DGA samples as an input of the LSSVM.

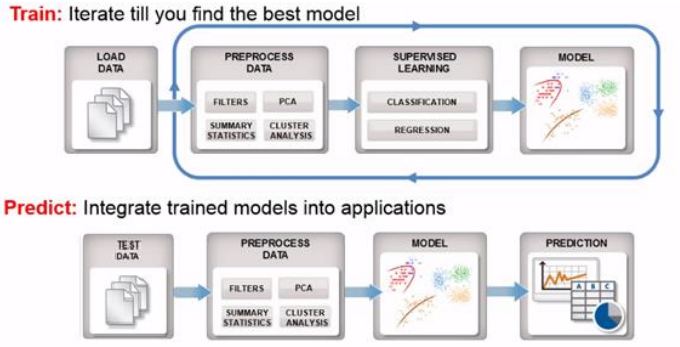


Figure 2 Machine learning workflow [10]

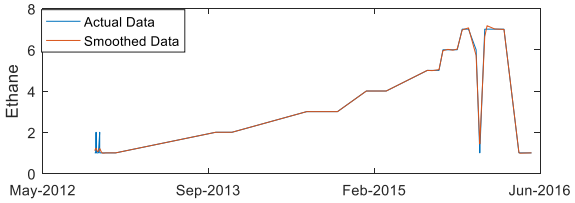


Figure 3 Ethane smooth data

$$y(t) = \frac{x(t)}{max(x(1),x(2),\dots x(n))} \quad (10)$$

where $= 0,1, \dots, n$, x(t) represent the DGA time-series dataset, while y(t) is the normalized parameter [6].

The LSSVM forecasting model is implemented based on the MATLAB LS-SVMlab toolbox. In this work, LSSVM is applied as time-series prediction (function estimation) based on the pre-process data, as describes

4. The available data corresponds to 52 samples and it is split into the training and testing datasets. The training dataset corresponds to 75% of the total data (39 samples), and it is applied to build the LSSVM model, while the remaining 25% (13 samples) is used to verify the model performance.

A. *Training the model*

The machine learning algorithm is built and trained using the optimal (Y, σ) hyper-parameters combination, and the total training set. In the proposed model, a robust training function is applied as training function, which is more suitable in the case of data containing non-Gaussian noise or outliers [11]. This specific function improves the final model performance, as a result of the support values influence corresponding to noise and outliers is decreased, and their corresponding large errors can be avoided.

The LSSVM algorithm requires an input training dataset and their corresponding output training dataset in order to build the model. The raw DGA data is used as input, and the results of the pre-process methods (smoothed or normalized) data is the corresponding output dataset in the training period.

After the iterative process, the model performance has the sufficient accuracy in order to starts with the testing stage, where the average error is collected and calculated, and the new parameter combination is replaced. The iterative process is repeated until approach the stopping criteria [6]. Considering the best cross-validation performance and the minimized error, the optimal (Y, σ) hyper-parameters are chosen [9].

B. *Testing model*

The trained model must be integrated into the prediction application, substituting the training dataset by the testing dataset into the LSSVM model, and in this way, the estimation values can be obtained [6]. In order to verify the LSSVM forecasting model performance, a testing dataset is applied to see how it will respond with unknown data. Using the remaining 25% of the available DGA data, the proposed algorithm is validated against the actual values from the corresponding analysis, which error is used to verify the LSSVM model forecasting ability.

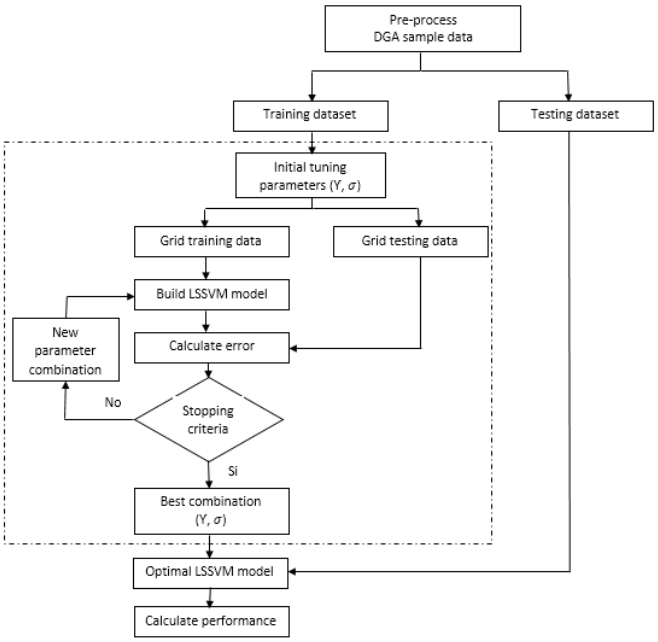


Figure 4 LSSVM flowchart of the proposed model [6].

C. *Validation of DGA forecasting data based on LSSVM*

The dataset contains chromatography samples of three power transformers collected between October 2012 and May 2016, where the gas concentration values of hydrogen (H2), oxygen (O2), nitrogen (N2), carbon monoxide (CO), methane (CH4), carbon dioxide (CO2), ethylene (C2H4), ethane (C2H6), and acetylene (C2H2) have been included.

The DGA forecasting values based on LSSVM model for hydrogen data are shown in Figure 5, where the superposition curves of actual and predicted DGA dataset is demonstrated. Clearly, it can be noticed that a high performance has been achieved with the LSSVM forecasting values for the different gases. Regarding Figure 6, this describes the LSSVM results in the environment of the training data [11], and the corresponding obtained optimal hyper-parameters (Y,σ).

An excellent correlation between the raw DGA sample and the corresponding pre-process data is defined by the applied machine learning. Most of the gases illustrate a well-defined function correlation between the raw data and the pre-process

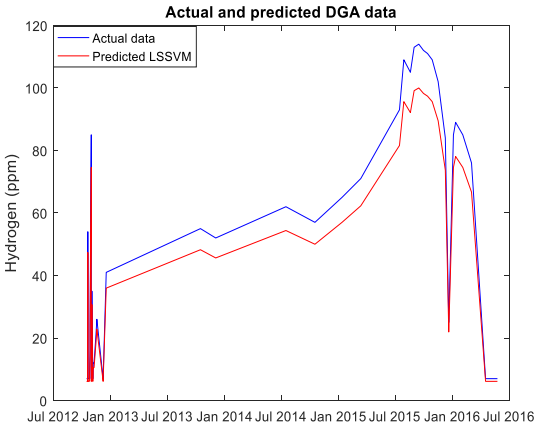


Figure 5 Actual and predicted DGA data using LSSVM model – hydrogen

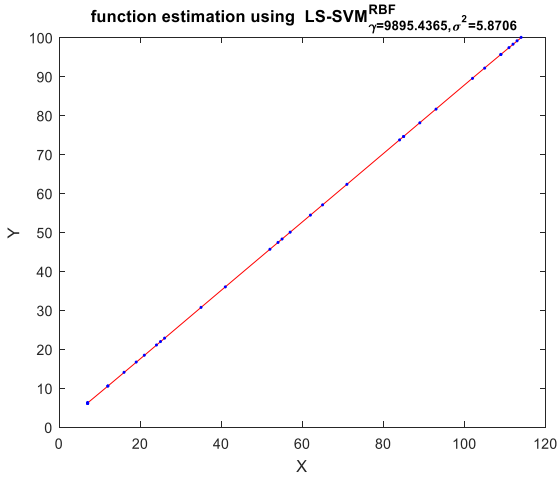


Figure 6 LSSVM performances in the training period

output in the training stage, where the regulation optimal parameter (Y) is obtained through the solution of the linear LSSVM, and the optimal kernel parameter (σ) is determined by choosing the midrange of values through an iterative process until its error is minimized [7].

The LSSVM forecasted results are validated in comparison to the actual corresponding data. The predicted values of H2, O2, CO, CO2, C2H4, C2H6, and C2H2 demonstrate a low mean absolute percentage error (MAPE), which varies in the range 0.1154 - 19.9 %.

Consequently, the developed LSSVM algorithm demonstrates an effective performance in the training and testing periods, where a relatively small of datasets have been applied. In some cases the pre-process stage and the robust functions, which are applied in the training stage of the proposed model, apparently cannot avoid the randomness characteristic completely. For instance, nitrogen (N_2) and methane (CH_4) forecasting values show higher rates of MAPE (35.76% and 36.48% respectively) in comparison with the rest of gases.

Hence, it can be considered that these two cases do not provide enough effectiveness in the prediction of future trends of gas production, and some misinterpretations can be generated.

In overall, a high performance is achieved by the LSSVM model. Its effectiveness is demonstrated by the similar trends described in Figure 5, and the corresponding error rates in each case. Owing to the possible issues that can be produced by an over/underestimation of gas dissolved content, an alternative approach will be developed in the next section, where some operating conditions of the power transformer will be included in order to improve the gas prediction.

V. CORRELATION BETWEEN GAS CONCENTRATION LEVELS AND OPERATING CONDITIONS

As mentioned before and according to [2], any gas formation results from a stress of some kind (thermal or electric) inside the equipment, additionally, the authors in [12] state that the insulation system quality depends on the mechanical (temperature, vibrations) and electrical (voltage levels, loading) influences. Hence, evaluate the status of the power transformer considering further parameters such as environmental

influences and operating conditions can contribute to a much better interpretation and understanding of the dissolved gas production changes, and the subsequently malfunction detection that eventually can lead to failure.

Available data can be used to analyze the condition of power transformers and planning maintenance task based on real asset's condition instead of every certain period of time, which benefits might not have a significant impact on the transformer performance.

A. *Temperature influences on DGA*

Reference [2] states that the different gases require specific temperatures in order to accumulate as a stable recombination product. It means that gases are formed depending on fault type and temperature. For instance, gases such as acetylene require temperatures of at least 800°C to 1200°C to show an accumulative trend [2], ethylene with hot spots between 150°C and 1000°C [13], and carbon oxides (CO and CO_2) can be formed at temperatures higher than 105°C.

Indeed, temperature are strongly linked with gas production and consequently with abnormal oil and paper degradation into the power transformer. In literature [4], results obtained from transformers with different features and operating conditions demonstrate that the solid insulator life-cycle at high loading and/or high operational temperatures decreases as result of abnormal circumstances. For these reasons, temperature measurements corresponding to the same intervals when the DGA samples were obtained have been included to build a multi-dimensional algorithm and improving the accuracy of gas concentration level predictions.

B. *Multi-input LSSVM model*

The applied LS-SVMlab toolbox has a multi-dimensional capability in order to include additional input and/or output variables. The work presented in [12] refers to the arising of nonlinear behaviour in time-series predictions conducted by aggregating data from multiple sources.

As mentioned in [9], the LSSVM multilayer network is first trained on subsets of data *D1*,…, *Dm*, and followed by a nonlinear combination, which is determined by solving a parametric optimization problem. In fact, this implementation also uses a kernel function (RBF) to obtaining the hyper-parameters through an iterative process (10-fold cross-validation) in the training period.

The multi-input LSSVM algorithm is first trained on subsets of data *D1*, *D2*, …, *Dm*, and the combination of the models is determined by solving a parametric optimization problem, which provides an interacting cooperation for the ensemble and in this way realize collective intelligence [9].

In this work, multiple input and output values are used in the training of the novel LSSVM algorithm, where the input vectors refer to the actual DGA and temperature data, while the corresponding normalized values are applied as output vectors.

As documented in [14], the machine learning method automatically correlates particular patterns of oil temperature with historical DGA data in the training period. The novel LSSVM model is built based on the input datasets and the hyper-parameters (Y, σ) obtained from the training stage.

The multi-input LSSVM algorithm performance is tested by the application of unknown DGA data. In this case, the input testing dataset contains DGA samples as a unique variable to establish the expected gas concentration level changes into the power transformer. Similar to [11], the proposed LSSVM model treats the DGA sample date as an event interval, while the temperature values contain several measurements for the corresponding DGA interval. Owing to this difference between the amount of DGA data and temperature measurements in every interval used in the present work, cumulative statistics should be applied to characterize the temperature contribution to the dissolved gas concentration level changes.

C. *Multi-input LSSVM model validation*

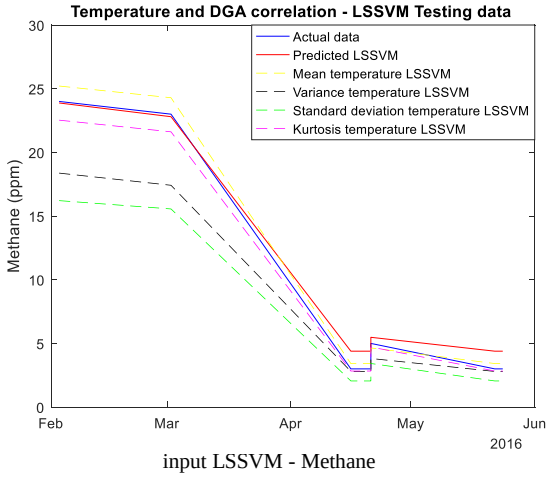
The actual DGA data and the characterize vector obtained from oil temperature measurements by the application of cumulative statistics are applied as input values for the training period of the multi-input LSSVM model. The same pre-process methodology used in the first LSSVM algorithm is applied to attenuate the randomness behaviour of DGA data and the representative feature vectors of temperature for each descriptive statistics method (mean, variance, standard deviation, and kurtosis). The normalized values of both datasets are applied as the corresponding output of the novel model training.

The multi-input LSSVM algorithm is built based on the obtained hyper-parameters (Y, σ), the DGA samples and the characterize temperature values throughout the training period for each used descriptive statistics method.

The performance of the novel model is verified through the substitution of the training datasets by unknown testing data. In this stage, the algorithm is tested by the application of unused DGA data as unique input. The multi-input LSSVM model responses are validated in comparison to the actual DGA and the values predicted by the earlier LSSVM model for every gas included in this work.

As can be seen in Figure 7, many experiments with the inclusion of temperature patterns in the training period of the novel LSSVM model have been conducted to identify the best performance. Some of the new forecasts indicate improvements in accuracy, others have not shown important changes, while in some cases the values are less accurate in comparison to the earlier predictions obtained by the first LSSVM model.

Figure 7 Temperature and DGA correlation - Testing values based on multi-input LSSVM - Methane



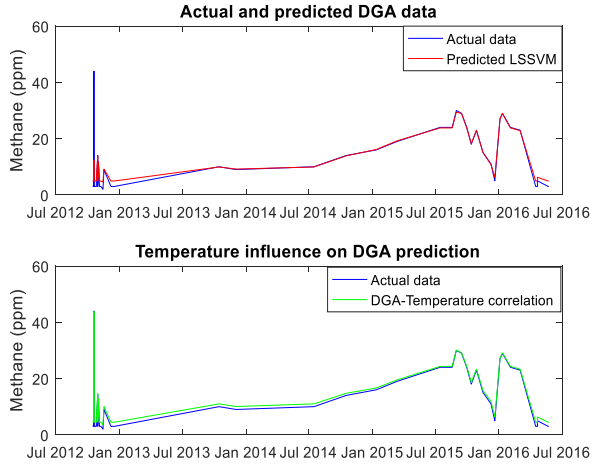


Figure 8 Methane time-series comparison between DGA forecasting model and temperature correlation model

Taking into consideration the mean absolute percentage error (MAPE) calculated values, evidently, the forecasting values of hydrogen (H_2), methane (CH_4), and ethane (C_2H_6) have been improved mainly by the application of kurtosis as feature extraction method of the temperature measurements. Comparing the results obtained from the first and second models, the mean absolute percentage error of hydrogen predictions is improved from 12.16% to 5.87%, methane MAPE decreases from 36.48% to 5.69%, whereas ethane shows a drop from 7.7% to 5.65% in its corresponding MAPE.

Obviously, the correlation between temperature patterns and hydrogen, methane, and ethane has an important influence on the corresponding forecasting values. One of the least accurate predictions obtained by the first proposed LSSVM model represents methane content, whose uncertainty is reduced by 30% with the inclusion of kurtosis as feature extraction of the temperature measurements into the novel model as Figure 8 indicates.

To sum up, the novel LSSVM model developed with the correlation between DGA and oil temperature patterns indicates the influence of this operating conditions of the power transformer in certain gas concentration behaviour, whose relationships must be interpreted bearing in mind the International Standards referred in [1] and [2].

VI. CONCLUSIONS

Considering the least accurate results obtained from the first LSSVM proposed model, a multi-input novel LSSVM model is developed with the inclusion of oil temperature patterns with the main aim of improving the previous predictions values.

Temperature condition has a significant impact in dissolved gas content changes taking into account the improvements in the predictions obtained with the application of this novel model. Therefore, as part of the extending approach, a correlation between DGA and oil temperature is found by the application of multi-input LSSVM model. According to the obtained results, the most notable improvements in the forecasting values are obtained with the application of kurtosis as feature extraction of temperature due to it reflects the changes between the temperature measurements. An excellent correlation between oil temperature and hydrogen, methane, ethane, ethylene and acetylene is reached in the three utilized power transformers. Some of the obtained relationships can be linked to the interpretation of the gas analysis. In contrast, the nitrogen (N_2) forecasting values show a considerable inaccuracy, whose MAPE value is around 35.76%. The application of oil temperature in the training model utilized in the multi-input LSSVM model developed as extending approach has not affected either (56.93%) and can be considered as a weakness of the proposed models. Considering the interpretations of DGA given by [2], oxygen and nitrogen are found in oil as a result of contact with atmospheric air, which can be stated as the reason for the lack of correlation with oil temperature.

In conclusion, the obtained forecasting DGA data contain important accuracy for the three power transformers used in this project, and it can bring sufficient certainty to applying further analysis.

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