Learning Uncertainty of Wind Speed Forecasting Using a Fuzzy Multiplexer of Gaussian Processes

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Abstract

The smart power systems of the future will be able to accommodate wind power at a maximum efficiency by utilizing available information. For instance, information pertained to wind speed is essential in forecasting the overall amount of power generated by wind farms. Information is used to offset the inherent stochasticity of wind power and improve wind speed forecasting precision. In this work, an intelligent methodology for quantifying the uncertainty of wind speed pertained to forecasting is introduced. The introduced methodology adopts a set of Gaussian processes to assemble a model of the uncertainty of the forecasted speed. Results are taken on a set of real-world wind speed data.

1 Introduction

It is generally expected that the integration of renewable energy sources (RES) in the power grid is one of the cornerstones toward attaining sustainable energy systems [1]. Renewable energy is not only a sustainable source of energy, but most importantly, it may contribute in greener and less polluted cities of the future. With respect to energy sources, solar and wind are the most prominent and promising power sources [2].

Wind power is produced by the operation of wind mills. The driving force behind the wind power production is the wind intensity as it is expressed in terms of speed. Scheduling wind power production is a very challenging task and difficult to fully conduct. For instance, during consumption peak hours, when there is a great need for excess power, wind farms might not produce any power because of the lack of wind. In contrast, wind power may be available during times in which the load demand is very low, e.g., after midnight. In addition, the lack of efficient solution for large scale electricity power, contributes in wasting part of the produced wind power.

Smart power systems come to fill the gap in efficient utilization of wind power. They are the result of the integration of power systems with information technologies [3]. The overall idea is that the use of information with power systems may compensate for the lack of physical storage. One of the crucial tools in implementing smart power systems is anticipation [4]. Anticipation promotes planning and subsequent scheduling of production and consumption activities; in other words, it allows the intelligent management of the power system.

With respect to wind power production, anticipation may be adopted for wind speed forecasting. Speed forecasting allows wind farm operators to schedule the operation of the wind mills and estimate the amount of produced energy at specific day times. In addition, it assists i) the system operator to schedule the operation of the plant units, and ii) the market operator to determine the cost of power ($/Kwh). Overall, wind speed forecasting is a effective tool for the efficient and economically operation of the power system [2].

Advancements in information technologies have made feasible the coupling of power systems and data driven approaches. This coupling has greatly benefited anticipation techniques that monitor sensor measurement and are able to estimate the state of the system in real time. In such information rich environment, wind speed forecasting has been also positively affected by the utilization of data driven methods. In particular, machine learning techniques are adopted to learn the wind speed patterns and provide predictions over future speed values.

Uncertainty quantification in wind speed forecasting is crucial in smart management of the power grid [5]. In particular, it allows the system operator to plan the electricity market operation and determine the electricity prices [6]. Hence, several approaches have been developed that quantify the uncertainty in wind speed forecasting: its importance has been identified in building the next generation power system, and as a result several models have been proposed [7-12].

In this work, a new methodology for learning the uncertainty of wind power forecasting from historical data is being presented. The methodology aims in providing an interval of values over the real value of the wind speed for a very short-term prediction horizon. The main idea behind the proposed methodology is the development of a synergistic framework of Gaussian Processes [13] with a fuzzy logic system; the latter will be the multiplexer of the various uncertainties computed by the multiple kernel machines into a single value [14].

The rest of the paper is organized as follows. In the next section a brief introduction to learning Gaussian processes is given, while in section 3 the methodology for uncertainty quantification is introduced. Section 4 presents a set of results and lastly section 5 concludes the paper.

2 Background

In machine learning parlance, a learning kernel k(x,x) is any valid analytical function that can be recast in the form given below:

$$\kappa\left(x_1, x_2\right) = \varphi(x_1)^T \cdot \varphi(x_2) \tag{1}$$

where φ(x) is a valid mathematical function, and x_1, x_2 are input vectors. The formulation expressed in Eq. (1) is known as the kernel trick [15]. The form of the kernel is determined by the system modeler, and is usually selected in such a way to express the belief of the modeler over the properties of the data.

Gaussian processes are stochastic models whose joint distribution is also Gaussian. Similar to univariate Gaussian distribution that is defined by two parameters, i.e., mean and variance, a Gaussian process is defined by its mean and covariance functions respectively: mean:=$m(x)$ and covariance:= $C(x',x)$:

$$GP \sim N(m(x), C(x',x)) \ . \tag{2}$$

In the machine learning realm, Gaussian processes can be expressed as a function of a kernel. The kernel is inserted into the Gaussian process via the covariance function. More specifically, the covariance function is set equal to a kernel:

$$C(x_1, x_2) = \kappa\left(x_1, x_2\right) \tag{3}$$

while the mean value is set equal to zero:

$$m(x) = 0 \tag{4}$$

that is a convenient choice for formulating the kernel based Gaussian processes [15].

Therefore, kernel-modeled Gaussian processes are identified as Bayesian learning machines and as such they provide a predictive distribution over unknown values that follows a Gaussian distribution with mean and covariance given below respectively [16]:

$$m(x_{N+1}) = \mathbf{k}^T \mathbf{C}_N^{-1} \mathbf{t}_N \tag{5}$$

$$\sigma^2\left(x_{N+1}\right) = k - \mathbf{k}^T \mathbf{C}_N^{-1} \mathbf{t}_N \tag{6}$$

where $\mathbf{t}$ is the vector of target values, $\mathbf{C}_N$ denotes the NxN matrix of covariances among the N training datapoints, $\mathbf{k}$ denotes the vector of covariance values between the new $N+1$ and each of the N points, and lastly k is a scalar value. It should be noted that the formulas in (5) and (6) are evaluated with the aid of a kernel function that is selected by the system modeler.

Therefore, we observe that the predictive distribution defined by both Eq. (5) and (6) strongly depends on the selection of the kernel form. This is also the strength of the Gaussian processes: the predicted output can be controlled by the modeler via the proper selection of a kernel.

3 Uncertainty Learning Methodology

The cornerstone of the proposed method is the adoption of a set of Gaussian processes and their fusion using a simple fuzzy inference system. The goal of the proposed methodology is to utilize a set of different kernel-modeled Gaussian processes to individually learn the uncertainty in wind power data, and subsequently to fuse the individual values using a fuzzy multiplexer into a single one, as it is depicted in Fig. 1. The block diagram of the proposed methodology is given in Fig. 2, with the individual steps to be explicitly presented.

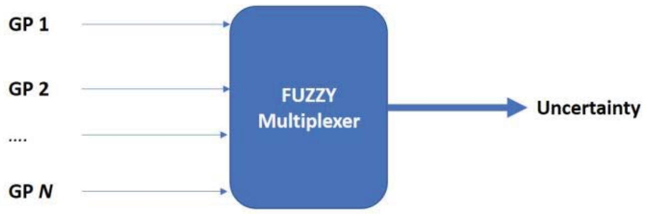

Fig. 1 Gaussian Processes and Fuzzy Multiplexer for learning Uncertainty

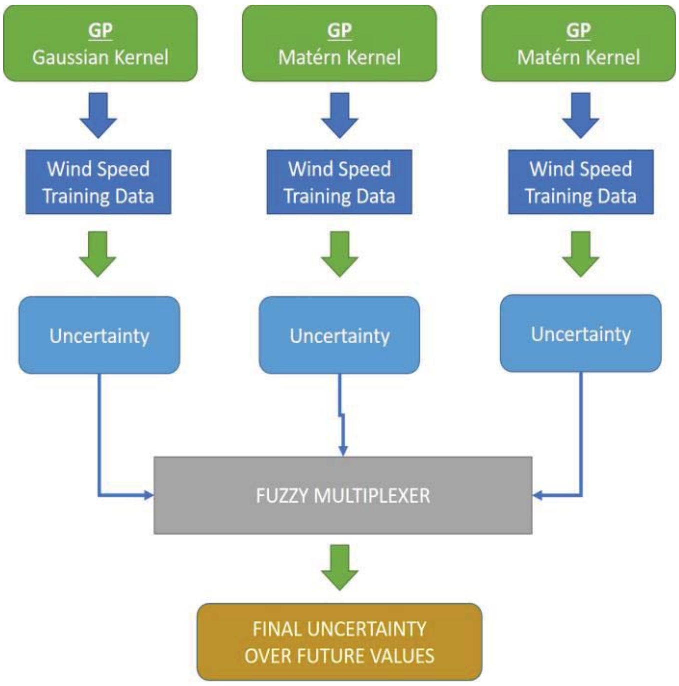

Fig. 2 Block diagram of proposed methodology for learning uncertainty in wind speed forecasting

We observe in Fig.2 that there is an initial set of three Gaussian processes, and more specifically: i) a Gaussian process equipped with a Gaussian kernel, ii) a Gaussian process equipped with the Matérn Kernel, and iii) a Gaussian process with the Neural net kernel [15]. The analytical forms of the three kernels are given below:

Gaussian Kernel:

$$k(\mathbf{x}_1,\mathbf{x}_2) = \exp\left(-\frac{\|\mathbf{x}_1-\mathbf{x}_2\|^2}{2\sigma^2}\right) \quad (7)$$

where σ^2 is a kernel parameter evaluated at the training phase by using the training data.

Matérn Kernel:

$$k(\mathbf{x}_1,\mathbf{x}_2) = \left(\frac{2^{1-\theta_1}}{\Gamma(\theta_1)}\right)\left[\frac{\sqrt{2\theta_1}\,|\,\mathbf{x}_1-\mathbf{x}_2\,|}{\theta_2}\right]^{\theta_1} K_{\theta_1}\left(\frac{\sqrt{2\theta_1}\,|\,\mathbf{x}_1-\mathbf{x}_2\,|}{\theta_2}\right) \quad (8)$$

that has two positive-valued parameters denoted as θ_1, θ_2, and a modified Bessel function denoted as $K_{\theta 1}()$.

Neural Net Kernel:

$$k(\mathbf{x}_1,\mathbf{x}_2) = \theta_0 \sin^{-1}\left(\frac{2\tilde{\mathbf{x}}_1^T\Sigma\tilde{\mathbf{x}}_2}{\sqrt{\left(1+2\tilde{\mathbf{x}}_1^T\Sigma\tilde{\mathbf{x}}_1\right)\left(1+2\tilde{\mathbf{x}}_2^T\Sigma\tilde{\mathbf{x}}_2\right)}}\right) \quad (9)$$

where $\tilde{\mathbf{x}} = (1, x_1, ..., x_D)^T$ is an augmented input vector, θ_0 is a scale parameter and $\mathbf{\Sigma}$ the covariance matrix of the input vector [16].

In this work, the most recent observations of wind speed are utilized to train (i.e., the most recent measurements comprise of the training dataset) the Gaussian process models and learn the inherent uncertainties. In the next step the independent uncertainties are put together in the form of a linear combination:

$$y = \sum_{i=1}^{N} b_i x_i^2 \quad (7)$$

where x^2 are the individual uncertainties, i.e., from Gaussian process, N is the population of GP models, and b are the weight coefficients.

The weight coefficients are evaluated by a set of Fuzzy rules that together with the model in Eq (7) consist of a fuzzy multiplexer. The multiplexer aims at quantifying the learning rate of the Gaussian processes over the training datasets (i.e., most recent measurements). For this reason, we fuzzify two variables: the input training error (MAPE) that spans the range [0%-100%], and the output coefficient [0, 1]. The fuzzy sets are depicted in Fig. 3 and 4.

The fuzzy rules defined for the evaluating the coefficients are given below:

- IF Error is LOW, THEN Coefficient is HIGH
- IF Error is MEDIUM, THEN Coefficient is MEDIUM
- IF Error is LOW, THEN Coefficient is HIGH.

Hence, if training error is high then then fuzzy rules will evaluate the coefficient close to zero while if the training error is low the coefficient will be closer to one. In that way the individual uncertainties are fused using the linear schema in Eq. (3) based on the most recent performance of them. In that way, we are able to identify the Gaussian processes that exhibits the best performance in the most recent past and aspire that they will have similar performance in the very near future.

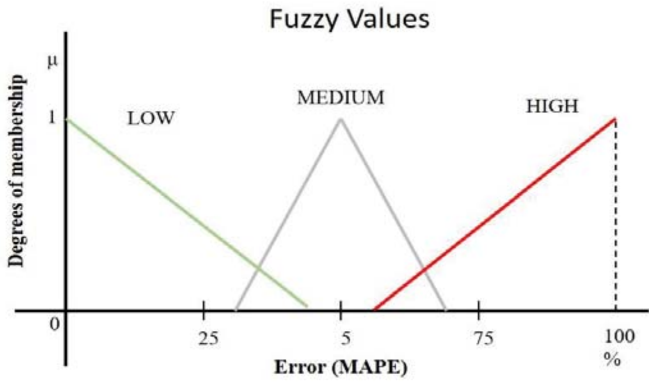

Fig. 3 Fuzzy values of the input variable training error

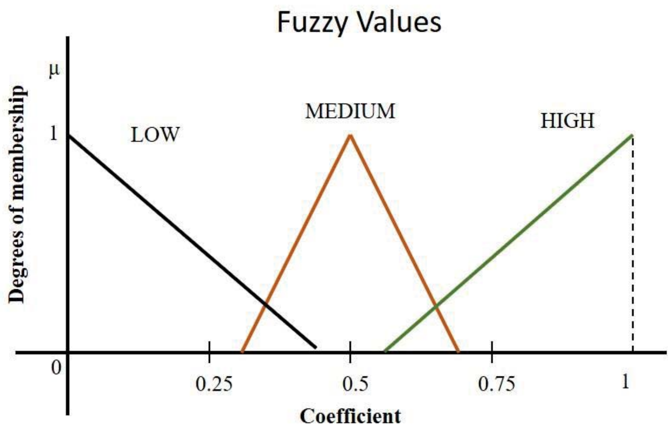

Fig. 4 Fuzzy values of the output variable coefficient

The proposed method provides intervals of values pertained to wind speed forecasting. The computed coefficients are inserted into (7) and then the intervals are taken in the form of [m-y, m+y] with m being the mean forecasted value by the Gaussian processes.

Therefore, the presented methodology utilizes the uncertainties of each GP model in such a way to improve the overall forecasting uncertainty by providing narrower forecasting intervals.

4 Results

Testing will be performed on a set of real-world data taken from the NREL National Lab located in Colorado, USA [17]. In particular, the hourly wind speed data from the period of July 7, 2017 to August 13, 2017.

The following process were obtained for obtaining the results: the training data was comprised of the all the hourly wind speed observed values of one day before the target day. Hence, the training dataset comprised of the 24 most recent wind speed values. Then, the training of the three GP models was conducted and the training error was measured. Next, the training errors computed for each of the models were fed to the fuzzy multiplexer, which computed the respected coefficients. Then the trained linear model, Eq. (7), is used to define the uncertainty over the next 24 wind speed values. In other words, an interval of values is the "area" in which the forecasted values will most probably land. The obtained results are presented with respect to the mean standard deviation for the aforementioned period, and presented in Table 1. The standard deviation expresses half of the prediction interval and subsequently determines the width of the forecasting interval (full width is +/- σ).

We observe in Table 1 that the three Gaussian process models individually provide higher standard deviation over the forecasted values than that of the fuzzy GP model. Therefore, we observe that the mean forecast standard deviation was reduced by using the proposed methodology. This observation implies that fuzzy multiplexing the uncertainties of the individual models based on their training error provided a lower uncertainty. The use of the three fuzzy rules added an extra information processing layer which reduced the degree of uncertainty [18].

Figs 5-8 visualize the predicted forecasted uncertainty taken with the fuzzy multiplexer for four of the tested days. In particular, we present the days July 15, July 20, August 1, and August 10.

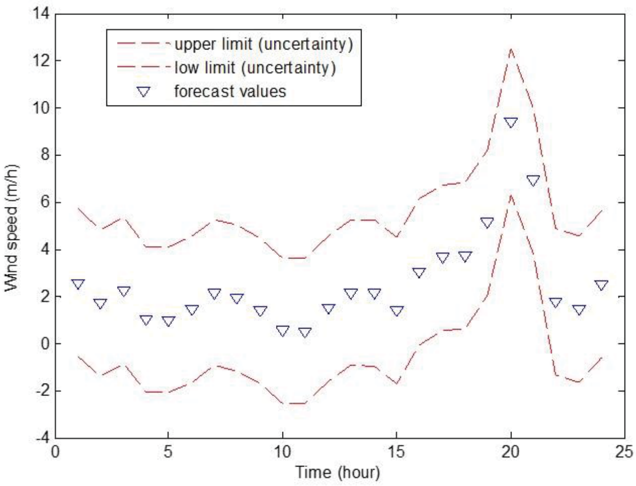

Fig. 5 Forecasted interval, i.e., mean forecast and variance, for the day of July 15

We observe in Figs. 5-8 that the predicted interval, which has been computed by the fuzzy multiplexer, is surrounding the forecasted values and is narrow. This narrow interval may be provided together with the forecasted values as the final wind speed prediction (predicted values is provided together with uncertainty). Therefore, the presented methodology will become a useful tool for the operation of the smart power system by decreasing forecast uncertainty, as it is exhibited by results in Table 1. Furthermore, we observe in Table 1 that the reduction with the presented model reduces the mean uncertainty by 30% compared to GP-Matérn model, which is the best among the three individual GP models.

Table 1 Mean Average predicted Standard Deviation for the tested Time Period

Time Period	Mean Forecast Standard Deviation			
	GP Gaussian	**GP Matérn**	**GP Neural Net**	**Fuzzy GP**
Jul 13-Aug 13	3.2553	2.6937	3.3837	2.013

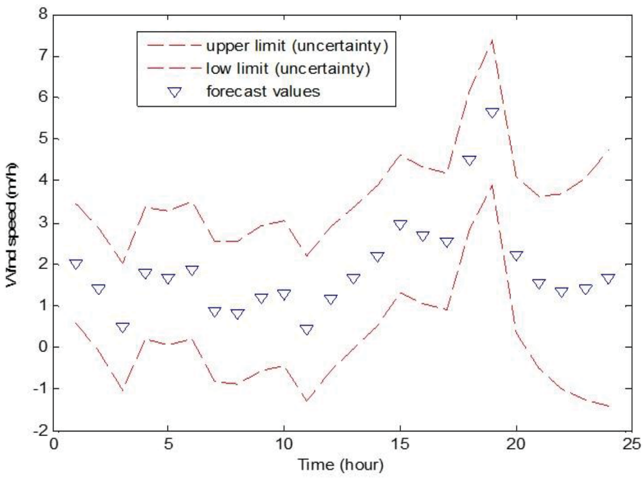

Fig. 6 Forecasted interval, i.e., mean forecast and variance, for the day of July 20

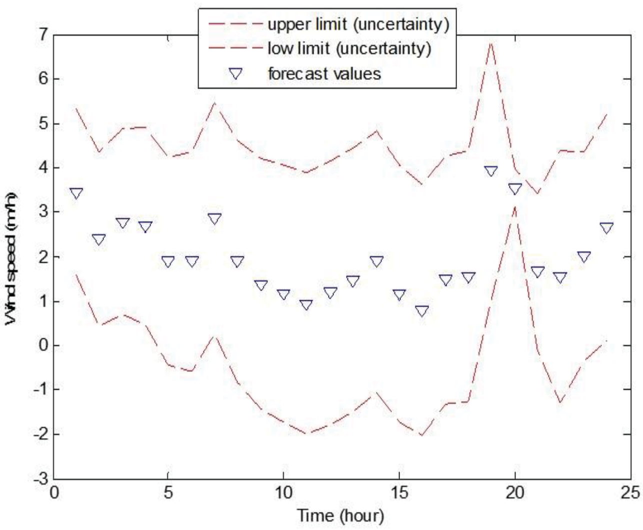

Fig. 7 Forecasted interval, i.e., mean forecast and variance, for the day of August 1

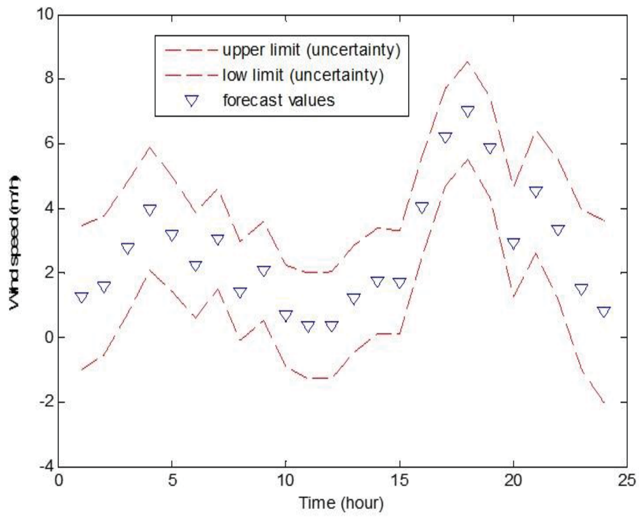

Fig. 8 Forecasted interval, i.e., mean forecast and variance, for the day of August 10

5 Conclusion

In this work, we presented a new intelligent methodology for learning the uncertainty of wind speed from recent measurements and subsequently improve the forecast uncertainty. To attain this, we introduced the synergistic use of kernel-modelled Gaussian processes with a fuzzy multiplexer. The goal of the fuzzy multiplexer is to fuse the individual uncertainties computed by individual GP models. Fusion takes place by a set of simple fuzzy rules that compute the coefficient values of a linear model, that provides the forecasted uncertainty.

Results obtained on a set of real-world measurements taken exhibit that the presented methodology reduces the forecasted uncertainty as compared to each individual GP models. In particular, we observe a 30% reduction of uncertainty compared to the best among the three GP models.

In the future, we plan to create a finer fuzzy multiplexer by increasing its resolution with respect to number of fuzzy sets and fuzzy rules. In addition, we plan to utilize a higher number of GP models that are equipped with other kernels that are not been used in the current study.

6 References

[1] Barth, R., Weber, C., Swider, D. J.: 'Distribution of costs induced by the integration of RES-E power'. Energy Policy, 2008, 36, (8), pp. 3107-3115
[2] Alamaniotis, M., Karagiannis, G.: 'Genetic Driven Multi-Relevance Vector Regression Forecasting of Hourly Wind Speed in Smart Power Systems', Proc. IEEE PES Innovative Smart Grid Technologies – North America, Washington D.C., USA, February 2018, pp. 1-5
[3] Tsoukalas, L. H., Gao, R.: (2008, April). 'From smart grids to an energy internet: Assumptions, architectures and requirements' Proc. Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, April 2008, pp. 94-98
[4] Tsoukalas, L. H., Gao, R.: 'Inventing energy internet: The role of anticipation in human-centered energy distribution and utilization', Proc. SICE Annual Conference, 2008, pp. 399-403
[5] Alamaniotis, M., Karagiannis, G.: 'Integration of Gaussian Processes and Particle Swarm Optimization for Very-Short Term Wind Speed Forecasting in Smart Power', International Journal of Monitoring and Surveillance Technologies Research, 2017, 5, (3), pp.1-14
[6] Wang, X., Sideratos, G., Hatziargyriou, N., Tsoukalas, L.H.: 'Wind speed forecasting for power system operational planning', Proc. of International Conference on Probabilistic Methods Applied to Power Systems, September 2004, pp. 470-474
[7] Wang, S., Xu, Q., Zhang, G., Yu, L.: 'Modeling of wind speed uncertainty and interval power flow analysis for wind farms', Automation of Electric Power Systems, 2009, 21, pp.82-86
[8] Lange, M.: 'On the uncertainty of wind power predictions—Analysis of the forecast accuracy and statistical distribution of errors', Journal of Solar Energy Engineering, 2005, 127, (2), pp.177-184
[9] Constantinescu, E.M., Zavala, V.M., Rocklin, M., Lee, S., Anitescu, M.: 'A computational framework for uncertainty quantification and stochastic optimization in unit commitment with wind power generation', IEEE Transactions on Power Systems, 2011, 26, (1), pp.431-441
[10] Lange, M., Heinemann, D.: 2003, June. 'Relating the uncertainty of short-term wind speed predictions to meteorological situations with methods from synoptic climatology', Proc. of the European Wind Energy Conference & Exhibition, June 2003, pp 1-6
[11] Jung, J., Broadwater, R.P.: 'Current status and future advances for wind speed and power forecasting', Renewable and Sustainable Energy Reviews, 2014, 31, pp.762-777
[12] Antoniou, I., Pedersen, S.M., Enevoldsen, P.B.: 'Wind shear and uncertainties in power curve measurement and wind resources', Wind Engineering, 2009, 33, (5), pp.449-468
[13] Mori, H., Kurata, E.: 'Application of gaussian process to wind speed forecasting for wind power generation', Proc. IEEE International Conference on Sustainable Energy Technologies, 2008, pp. 956-959
[14] Alamaniotis, M., Agarwal, V., Jevremovic, T.: Anticipatory monitoring and control of complex energy systems using a fuzzy based fusion of support vector regressors', Proc. of the 5th International Conference on Information, Intelligence, Systems and Applications, July 2014, pp. 33-37

[15] Rasmussen C.E.: ‘Gaussian processes for machine learning’ (MIT Press, 2006)
[16] Alamaniotis, M., Tsoukalas, L.H.: ‘Fusion of Gaussian Process Kernel Regressors for Fault Prediction in Intelligent Energy Systems’, International Journal on Artificial Intelligence Tools, 2016, 25, (4), p.1650023
[17] Andreas, A., Wilcox, S.: ‘Observed atmospheric and solar information system (oasis); tucson, arizona (data)’ NREL Report No. DA-5500-56494, 2010
[18] Alamaniotis, M., Agarwal, V.: “Fuzzy Integration of Support Vector Regressor Models for Anticipatory Control of Comple Energy Systems’, Int. Journal of Monitoring and Surveillance Technologies Research, April 2014, 2, (2), pp. 26-40