INL/CON-13-30245
PREPRINT

Anticipatory Monitoring and Control of Complex Energy Systems using a Fuzzy based Fusion of Support Vector Regressors

Future of Instrumentation International Conference

Miltiadis Alamaniotis, Vivek Agarwal, Tatjana Jevremovic

October 2013

Anticipatory Monitoring and Control of Complex Energy Systems using a Fuzzy based Fusion of Support Vector Regressors

Miltiadis Alamaniotis
Nuclear Engineering Program
The University of Utah
Salt Lake City, UT, USA
miltos.alamaniotis@utah.edu

Vivek Agarwal
Department of Human Factors, Controls, and Statistics
Idaho National Laboratory
Idaho Falls, ID, USA
vivek.agarwal@inl.gov

Tatjana Jevremovic
Nuclear Engineering Program
The University of Utah
Salt Lake City, UT, USA
Tatjana.jevremovic@utah.edu

***Abstract*—This paper places itself in the realm of anticipatory systems and envisions monitoring and control methods being capable of making predictions over system critical parameters. Anticipatory systems allow intelligent control of complex systems by predicting their future state. In the current work, an intelligent model aimed at implementing anticipatory monitoring and control in energy industry is presented and tested. More particularly, a set of support vector regressors (SVRs) are trained using both historical and observed data. The trained SVRs are used to predict the future value of the system based on current operational system parameter. The predicted values are then inputted to a fuzzy logic based module where the values are fused to obtain a single value, i.e., final system output prediction. The methodology is tested on real turbine degradation datasets. The outcome of the approach presented in this paper highlights the superiority over single support vector regressors. In addition, it is shown that appropriate selection of fuzzy sets and fuzzy rules plays an important role in improving system performance.**

Keywords— complex energy systems; anticipatory control; support vector regressors; fuzzy inference; monitoring

I. INTRODUCTION

Complex systems are characterized as those systems that cannot be modeled by just a single and simple equation, but they rather require a more complicated description. Therefore, control of complex systems is challenging and requires thorough and careful actions to be taken by the system operator. Even an initially insignificant error may propagate throughout the system and finally cause huge damage, if not detected and handled properly.

An example of an engineered complex system is nuclear power plants, which are comprised of many interconnected systems and subsystems [1]. Hence a nuclear plant operator is ought to monitor a large number of operational parameters and observe their evolution before making any decision and/or take any action. Action planning and in-time decision contributes to reliable power plant operation, enhances plant's safety [2], and minimizes costly repairs and maintenance.

Control of complex energy systems is an active research area and a plethora of methodologies have been proposed or are under development. For instance, predictive control has been applied in a complex system in [3], while the method of transition logic based control is introduced in [4]. Other methods include feedback control with structural decomposition [5], piece-wise linear controllers [6], and neural network based proportional-integral-derivative (PID) controller [7]. Furthermore, intelligent tools have also been widely adopted for controlling complex systems, such as fuzzy logic [8-10], neurofuzzy systems [11-13], ensemble-based controllers [14], and multi-agent systems [15].

Anticipatory monitoring and control are based on the assumption that anticipation of future system states or future operational variable values can be part of the overall control strategy. So, the operator can make diagnosis or control decisions over system behavior by using information of the current and anticipated future state/variable values. Anticipatory systems are systems that contain a predictive model of themselves or their environment; the predictive model allows the forecasting of the operational parameter evolution i.e., how and when it transits from the current to the future state [16, 17].

In the current manuscript, a methodology for monitoring and controlling complex energy systems within the framework of anticipatory systems is presented. A set of support vector regressors (SVR) [18, 19] is trained to predict the value of the operation variable ahead-of-time. Each prediction is inputted to a fuzzy logic inference mechanism [20], which fuses them and subsequently provides a single predicted value. During fusion the SVR with the closest prediction receives higher contribution in the next prediction [1-2]. Control decisions are based on the current (current state) and the predicted values (anticipated state). The proposed methodology is benchmarked against the prediction of a sample mean of SVR.

In the next sections, the proposed methodology is described, including a short introduction to support vector regression, and results on monitoring of turbine degradation the control decision that should be made with respect to turbine maintenance are given. The last section concludes the paper and gives future directions.

II. METHODOLOGY

A. Introduction

The proposed approach involves learning and new knowledge synergistically through existing experimental datasets, data based intelligent models, and first-principles formulation. The model output is a set of future predicted measurements that are obtained using current observed measurements as well as historical datasets. With such a tool the operator will be able to monitor the system and make control decisions ahead-of-time since he or she knows the current and future state of the system [1].

The proposed anticipatory approach for monitoring and control of complex energy systems is depicted in Fig. 1.

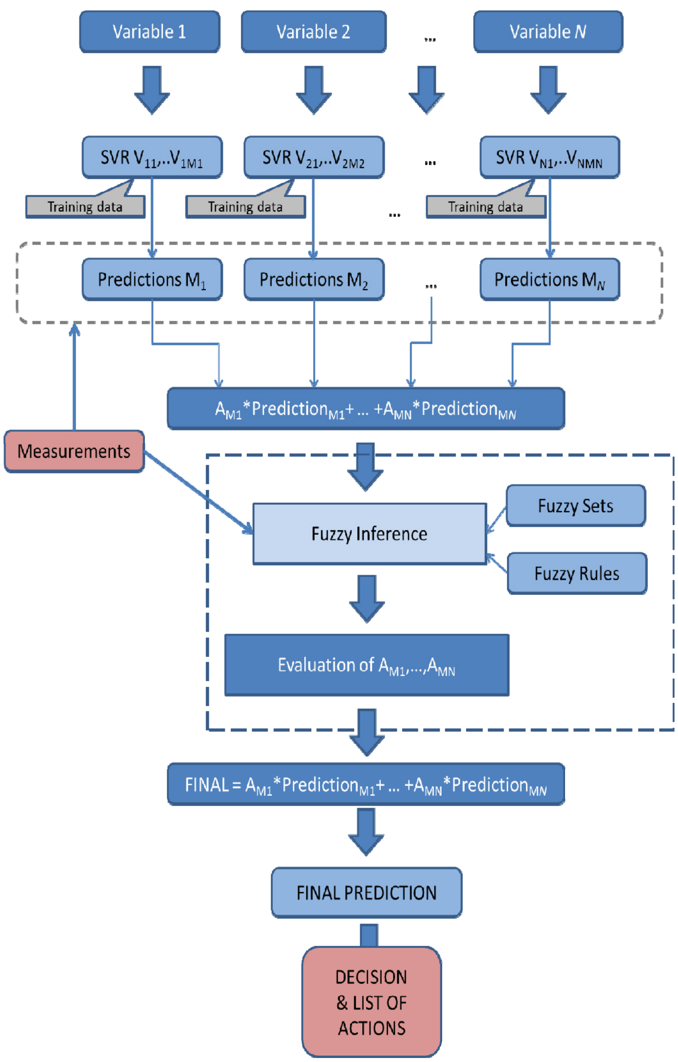

Fig. 1. Anticipatory based methodology for complex energy system monitoring.

B. Support Vector Regression

Initially, a group of system variables should be identified, i.e., variables 1 to N in Fig. 1, that are important and represent system functionality. Once the variables are identified, historical datasets for those variables are retrieved from databases. It should be noted that one or more histories may be associated with one variable. For instance, for a particular component's degradation, which is the result of many unknown factors, there may exist a plethora of historical datasets, each one being a recorded degradation for the same component.

Assuming that we have a set of N variables, then the recorded histories for each variable are denoted as $M_1,\ldots,M_N$ respectively (e.g. variable 1 has M_1 histories). Next, a set of support vector regression models is created; one model for each available historical dataset. More specifically, the number of SVR models is equal to the number of available histories, i.e., $M_1+\ldots+M_N$. The SVR models are equipped with a Gaussian kernel whose analytical formula is given below

$$k(x_1,x_2)=\exp\left(-\left\|x_1-x_2\right\|^2/2\sigma^2\right) \qquad (1)$$

where σ^2 is a hyperparameter evaluated (trained in machine learning parlance) by the training datasets [21].

In the next step, each SVR model is trained using the respective historical dataset (i.e., training data in Fig. 1). Once the training phase is over, the regression models are used for prediction making of ahead-of-time values. The length of the ahead-of-time prediction horizon depends on the modeler and may contain several steps (from 1 up to k steps).

In addition to the available histories, the proposed anticipatory system implements a real time feedback mechanism by utilizing recently arrived measurements to update its predictions. More specifically, when a new measurement is obtained, it is incorporated to the historical training datasets. In other words each training test is augmented with the recently measured value. Therefore, each SVR model is retrained using the respective augmented dataset and new predictions are obtained regarding the ahead-of-time predictions. Hence, new anticipated values are obtained and decision strategy may be altered accordingly. Overall, it should be noted, that each regressor provides an individual prediction with respect to a system variable.

C. Fusion of Support Vector Regressors

Once the individual predictions are collected, they are inputted to the next module where they are fused as per equation below

$$FP=A_{11}P_{11}+\ldots+A_{M_{\#}N}P_{M_{\#}N} \qquad (2)$$

where FP denotes the final prediction, A_{nm} is the linear coefficient and P_{nm} is the predicted value of SVR for variable n=1,..,N and dataset m=$M_1,\ldots M_N$ respectively (as shown in Fig. 1). The value obtained with (2) consists of the final prediction of the system. However, prior to final prediction, evaluation of linear coefficients ought to take place.

D. Fuzzy Inference

Linear coefficients in (2) are evaluated through a fuzzy inference system as shown in Fig. 2. More particularly, a fuzzy inference system equipped with a set of fuzzy sets and associated fuzzy rules is adopted for evaluating linear coefficients.

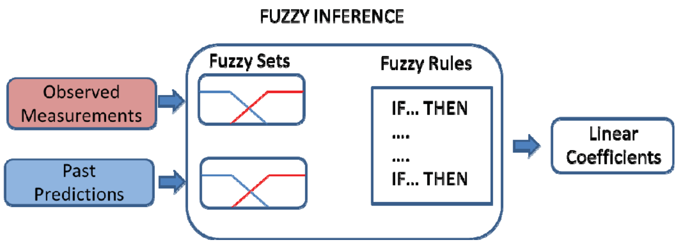

Fig. 2. Block diagram of fuzzy inference mechanism for linear coefficient evaluation.

The inference engine uses the most recent predicted value for which the respective measurement has been observed. For instance assume at timepoint $t-1$ predictions are made for timepoint t, and at timepoint t a measurement is observed, the inference engine will make a prediction for timepoint t+1 by 'comparing' measured value at timepoint t with predictions made for t (i.e., predictions at t-1). The input to fuzzy inference module is a set of values denoting the absolute error between an SVR's recent prediction and the respective measurement:

$$Error = |O_t - P_t| \tag{3}$$

with O_t being the observed value at step *t*, and P_t the respective prediction. The error in (3) is computed for every SVR. Next, all errors are fed into the fuzzy rule system whose output is a set of values that consist of the linear coefficients in (2). It should be noted that coefficients are in the range [0, 1]. In other words the inference mechanism assesses the most recent predictions and provides appropriate weight contribution to each SVR model. Fig. 3 presents the fuzzy sets used for the fuzzification of input error values while Fig. 4 presents the output sets used in the tested case in the next section. The output sets expresses the quality of predictions based on the error. The inference mechanism implements the following fuzzy rules for the input variable *Error* and the output variable *Quality*:

- If *Error* is VERY SMALL, then *Quality* is VERY GOOD.
- If *Error* is SMALL, then *Quality* is GOOD.
- If *Error* is MEDIUM, then *Quality* is MEDIUM.
- If *Error* is LARGE, then *Quality* is BAD.
- If *Error* is VERY LARGE, then *Quality* is VERY BAD.

E. Final Prediction and Decision Making

Once all linear coefficients are evaluated, then the final prediction is computed by (2). In other words, the final predicted value is the weighted sum of the support vector regressors' individual predictions.

At last, the final predicted value is used to design a series of actions that can be taken based on that value. For instance:

- If output belongs to [a, b], then take action 1.
- …
- If output belongs to [y, z], then take action *S*.

Therefore, based on the anticipated value, respective control decisions can be taken.

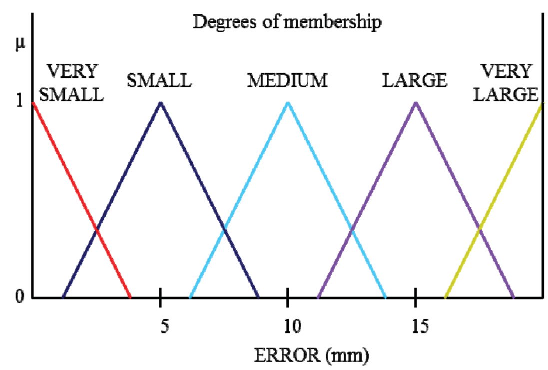

Fig. 3. Fuzzy sets for fuzzifyng absolute error (Eq. (3)) (used in section III).

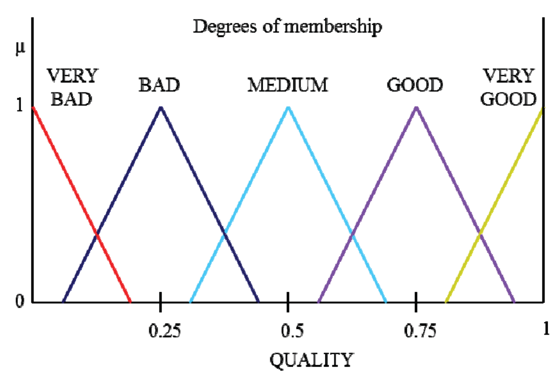

Fig. 4. Fuzzy sets for expressing quality of prediction (used in section III), where 0 denotes the worst and 1 denotes the best quality.

III. Results on Monitoring Turbine Degradation

The presented anticipatory system is applied on a simple case of monitoring turbine degradation [22]. Datasets contains five different real measured histories of turbine blade degradation and can be found on *Reliasoft Corp.* website [23]. The datasets include measurements obtained with regard to crack length of a turbine blade. The turbine fails at the time the blade crack is 30mm long. Turbine is an essential component in energy industry and its 24/7 monitoring is essential for safe and reliable energy production. In addition, its ahead-of-time maintenance or replacement is economical. Thus, by predicting the crack length evolution ahead-of-time (i.e., anticipate next measurements), the operator can make control decisions ahead-of-time and minimize operational or maintenance cost.

Furthermore, the fuzzy sets and the fuzzy rules were implemented. In general, the fuzzy part of the methodology depends on modeler's expertise and/or experience on the operation of the complex system. The latter is one of the big advantages of the methodology since it can incorporate human experience in the model. SVR parameters ([18, 19]) were taken equal to C=10 and ν=0.5 after a trial and error method; for more information on SVR models, refer to [18, 19].

In the current work the results are obtained as follows: the four out of five histories are used to train four support vector regressors respectively (i.e., N=1 and M_1=4 in Fig. 1). The single SVR models are used for making individual predictions that are fed to the fuzzy inference system (Figs. 3 and 4), and therefore, a final prediction is provided regarding the next crack length measurement (i.e., one step ahead-of-time prediction). Then, we consider that a measurement is obtained and compared to the final prediction. It should be mentioned that prediction results are given with respect to absolute error (see (3)).

Results are given in Table I for five timepoints, i.e., five single ahead-of-time predictions. To make it clearer, Table I is populated as follows: four historical datasets are used to train four SVRs, while the fifth is used for testing the methodology. In the first step, a prediction is made regarding the first measurement (prediction for timestep 1); then we assume that the first measurement is obtained (measurement at timestep 1), compare measured values to predicted values and compute error. This procedure is followed for all five timesteps and at each time the respective error is recorded with respect to all tested methods (i.e., Table I). It should be highlighted that Table I provides the absolute error in prediction of one and only one measurement; this is the reason that there is no particular trend in error as prediction process goes on.

It should be noted that Table I presents, for benchmark purposes, the results taken with a simple mean SVR estimation. More specifically, the mean value of single SVR predictions is computed and used as a next measurement predictor. In addition Table II presents indicative control decisions that the operator makes after a prediction is made.

Overall, we observe in Table I that the proposed anticipatory system provided low error in all cases. However, it was not the best predictor since at each step an individual support vector regressor provided a lower error. We observe that the lowest error is provided by a different regressor at each step, and not consistently from the same model at all steps. Therefore, we conclude that the methodology exhibits a degree of robustness and is preferable compared to an individual SVR. The latter statement is supported by the fact that we do not know a priori which SVR will give the lower error at each step. Adoption of the proposed system allows us not to worry about the best model at each step. The above conclusion is supported by the Fig. 5 as well. The anticipatory approach has an average error of 2.99 while error computed for SVR2 is little bit lower, i.e., 2.88. However, SVR2 reduced its average error because of steps 2 and 4 (small error), while it provided high error in the rest steps. So, it is preferable to use the anticipatory system which consistently gives low error, than a single regressor whose error fluctuates (e.g. very small in one step → very big in the next step). Furthermore, we observe in Table I and Fig. 5 that the use of the fuzzy inference mechanism improved the average error compared to the simple mean SVR estimation.

TABLE I. ABSOLUTE ERROR RESULTS FOR TESTING DATASET 5

Model	**Absolute Error in each Timestep**				
	Step 1	**Step 2**	**Step 3**	**Step 4**	**Step 5**
SVR 1	8.4144	3.7375	2.6128	4.7067	4.6991
SVR 2	6.6667	0.7143	2.7635	0.7696	3.1124
SVR 3	4.1336	5.6234	4.8352	2.3418	2.1364
SVR 4	5.1667	1.2076	1.4873	3.8796	7.7523
SVR Average	6.0954	2.2169	0.7993	1.7535	4.4251
SVR Anticipatory	6.1823	2.1473	0.4800	1.8772	4.2994

TABLE II. POSSIBLE CONTROL DECISIONS FOR TESTING DATASET 5

Model	**Timesteps**				
	Step 1	**Step 2**	**Step 3**	**Step 4**	**Step 5**
Anticipatory Output (mm)	16.1823	17.1473	20.48	24.1228	28.7006
Failure Threshold	30 mm				
Control Decision	Turbine should continue operating	Turbine should continue operating	Turbine should continue operating	Turbine needs repair	Turbine should be replaced - Stop system operation

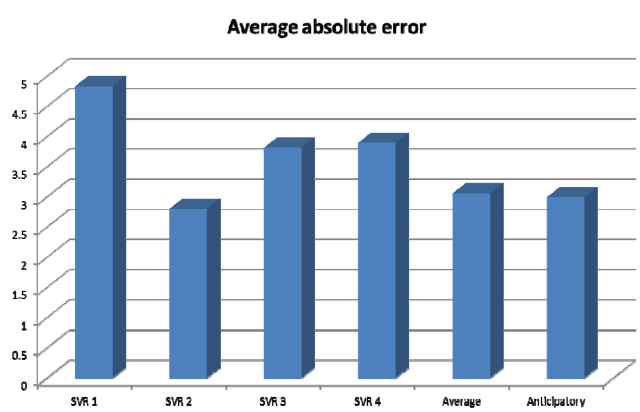

Fig. 5. Average absolute error (steps 1-5) for each method

IV. CONCLUSION

A new methodology for monitoring and control of complex systems was presented and tested on a set of real world measurements. The methodology used synergistically a set of support vector regressors and fuzzy logic to implement an anticipatory based monitoring and control of complex systems. Results demonstrated its potentiality over the use of single support vector regressors or mean of SVR predictions.

Future work will focus on applying the proposed system on a higher variety of datasets taken from energy industry, while more kernel function will also be adopted for prediction making.

DISCLAIMER

This information was prepared as an account of work sponsored by an agency of the U.S. Government. Neither the U.S. Government nor any agency thereof, nor any of their employees, makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness, of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. References herein to any specific commercial product, process, or service by trade name, trade mark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the U.S. Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the U.S. Government or any agency thereof.

REFERENCES

[1] L. H. Tsoukalas, and J. Reyes-Jimenez. "A hybrid expert system-neural networks methodology for anticipatory control in a process environment," Proceedings of the 3rd international conference on Industrial and engineering applications of artificial intelligence and expert systems-Volume 2. ACM, pp. 1045-1053, 1990.

[2] M. Alamaniotis, A. Ikonomopoulos, and L. H. Tsoukalas, “Probabilistic kernel Approach to online monitoring of nuclear power plants,” Nuclear Technology, vol. 177 (1), pp. 132-144, 2012.

[3] V. Chandan, S. Mishra, and A. G. Alleyne, “Predictive control of complex hydronic systems,” Proceedings of the 2010 American Control Conference, pp. 5112-5117, 2010.

[4] D. M. Auslander, M. Lemkin, and H. An-Chyau, “Control of complex mechanical systems”, Proceedings of the 12th Triennial World Congress of the International Federation of Automatic Control, pp. 741-744, 1994.

[5] D. C. Collins, “Structural decomposition and control of complex systems,” IEEE systems, man and cybernetics group annual symposium, pp. 153-159, 1971.

[6] J. Lu, “Switching control: from single rules to complex chaotic systems,” Journal of Systems Science and Complexity, vol. 16(3) pp. 404-413, 2003.

[7] S. H. Lin, “PID neural network control for complex systems,” Proceedings of International Conference of Computational Intelligence for Modelling, Control and Automation, pp. 166-171, 1999.

[8] S. Giove, “Fuzzy methods for complex systems: forecasting, filtering and control,” Proceedings of Soft Computing, pp. 162-169, 1997.

[9] M. Jamshidi, “Fuzzy control of complex systems,” Soft Computing, vol. 1(1), pp.42-56, 1997.

[10] Q. Sun, R. Li, and P. Zhang, “Stable and optimal adaptive fuzzy control of complex systems using fuzzy dynamic models,” Fuzzy Sets and Systems, vol. 133(1), pp.1-17, 2003.

[11] L. H. Tsoukalas, “Neurofuzzy anticipatory systems: a new approach to intelligent control,” International Journal of Artificial Intelligence Systems Tools, vol. 6(3), pp. 365-395, 1997.

[12] L. H. Tsoukalas, “Neurofuzzy approaches to anticipation: a new paradigm for intelligent systems,” IEEE Transactions on Systems, Man and Cybernetics, vol. 28(4), pp. 573-582, 1998.

[13] J. N. Lin, and S. M. Song, “A novel fuzzy neural network for the control of complex systems,” IEEE international Conference on Neural Network, vol. 3, pp. 1668-1673, 1994.

[14] S. Li, “A new perspective on control of uncertain complex systems,” Proceedings of Joint 48th IEEE Conference on Decision and Control and 28th Chinese Control Conference, pp. 708-713, 2009.

[15] N. R. Jennings, and S. Bussman, “Agent-based control systems: Why are they suited to engineering complex systems?,” IEEE Controls Magazine, vol. 23(3), pp. 61-73, 2003.

[16] K. Nabeshima, K. Inoue, K. Kudo and K. Suzuki, Nuclear Power Power Plant Monitoring with Recurrent Neural Network, Int. J. Knowl. –Based Intell. Eng. Syst., vol. 4, pp. 208-212, 2000.

[17] Meng Qinghu, Meng Qingfeng, Feng Wuwei, , Forecasting Conditions of Reactor Coolant Pump Based on Support Vector Machine, WRI Congress on Computer Science and Information Engineering, pp. 293-297, 2009.

[18] C. M. Bishop, Pattern Recognition and Machine Learning, New York, Springer, Chapter 7, 2006.

[19] N. Christianini and J. Shawe-Taylor, An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, Cambridge University Press, UK, 2000.

[20] L.H. Tsoukalas, and R.E. Uhrig, Fuzzy and Neural Approaches in Engineering, Wiley, New York, 1997.

[21] M. Genton, “Classes of kernels for machine learning: A statistics perspective,” J. Mach. Learning Res., vol. 2, pp. 299-312, 2001.

[22] G. Liu, N. Hu, Y. Zhao and J. Wu, Parameter Simulation in Performance Monitoring System of Steam Turbine Unit for a Fossil-Fuel Power Plant, in Proc. of the 2002 International Conference on Machine Learning and Cyberbetics, pp. 1249-1252, 2002.

[23] Reliasoft Corp.: www.reliasoft.com