Alarm prediction in industrial machines using autoregressive LS-SVM models

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***Abstract*—In industrial machines different alarms are embedded in machines controllers. They make use of sensors and machine states to indicate to end-users various information (e.g. diagnostics or need of maintenance) or to put machines in a specific mode (e.g. shut-down when thermal protection is activated). More specifically, the alarms are often triggered based on comparing sensors data to a threshold defined in the controllers software. In batch production machines, triggering an alarm (e.g. thermal protection) in the middle of a batch production is crucial for the quality of the produced batch and results into a high production loss. This situation can be avoided if the settings of the production machine (e.g. production speed) is adjusted accordingly based on the temperature monitoring. Therefore, predicting a temperature alarm and adjusting the production speed to avoid triggering the alarm seems logical. In this paper we show the effectiveness of Least Squares Support Vector Machines (LS-SVMs) in predicting the evolution of the temperature in a steel production machine and, as a consequence, possible alarms due to overheating. Firstly, in an offline fashion, we develop a nonlinear autoregressive (NAR) model, where a systematic model selection procedure allows to carefully tune the model parameters. Afterwards, the NAR model is used online to forecast the future temperature trend. Finally, a classifier which uses as input the outcomes of the NAR model allows to foresee future alarms.**

I. Introduction

Alarm systems are present in different applications around us (e.g. fire alarms, cars alarms etc.) and continue to play a key role in a number of industries across the world. They are useful to increase safety in nuclear and chemical plants, to improve reliability and availability of production machines etc. Traditionally, alarm systems were part of the hardware design and were only present if really needed due to their high costs. In modern machinery, thanks to the availability of cheap sensors and fast processors, different alarms can be embedded into machine controllers. The techniques used to process the sensors data with the aim of understanding machine conditions fall within the field of fault detection and diagnostics [1], [2], [3], [4], [5]. One of the most used alarms is based on temperature monitoring. Thermal protections are widely utilized in different applications, from consumer electronics (e.g. laptops, set-top boxes etc.) to complex systems like cars and production machines. In addition to increased safety, these alarms also allow to extend lifetime of the sub-parts of the machines as they control the stresses they are subjected to. Despite all the advantages, the alarm systems could also bring some drawbacks if they are triggered at the wrong times. This happens in production processes where products are produced per batch. In this case, triggering an alarm during a batch production means definitely production losses, which could sometimes be quite high. Therefore, a methodology which monitors parameters leading to alarm triggering and suggests proper control actions on the production speed is needed.

In this paper we consider steel cord production machines, where steel cords are produced sequentially (batch production or run-by-run production). These machines are equipped with thermal protections to increase security of the users and to extend the lifetime of the bearings, which represent the most critical parts of these machines. The triggering of the alarms is based on monitoring the temperature through sensors installed near the bearings and processing the values with respect to a fixed threshold (programmed in the machines controllers).

The main contribution of this paper is related to developing an accurate and robust model for the prediction of temperature towards the threshold value. If the temperature is predicted early enough, an optimization algorithm could be used in the controller of the machine to lower the production speed, in order to finish the current batch without incurring into an alarm and to avoid downtime. Although the technique developed in this work is tuned toward this application, it could be used in other applications dealing with predictive maintenance.

In this paper we make use of Least Squares Support Vector Machines (LS-SVMs, [6]). Support Vector Machines (SVMs, [7]) are a state-of-the-art classification method formulated as a convex constrained optimization problem, where a regularization parameter controls the trade-off between the model complexity and the minimization of the training error. SVMs perform linear classification in a high-dimensional feature space, which corresponds to a non-linear classifier in the original input space. A recent application of SVMs to alarm prediction in a large scale railroad network has been described in [8].

LS-SVMs differ from SVMs for the presence of a quadratic loss function in the primal problem and equality instead of inequality constraints. This typically leads to linear system

solving at the dual level in case of classification and regression problems. Moreover, they have recently shown their usefulness in predictive maintenance as discussed in [9], where an unsupervised learning technique has been used. In this case we apply LS-SVMs to analyse a steel production machine with two purposes:

- predict the temperature of shaft bearings using a nonlinear autoregressive (NAR) model
- forecast future alarms due to excessive heating of the bearings by means of a classifier based on the NAR outcomes.

We show that we are able to construct a model which can predict the incoming alarms with high accuracy. In principle, these forecasts can be used to change the initial settings like the speed of the machine and the spool length, in order to avoid unplanned stops in the production and schedule optimal maintenance operations. Moreover, the proposed methodology is general and can be applied to other kinds of industrial machines

The remainder of this paper is organized as follows: Section II summarizes the LS-SVM modelling framework, Section III describes the dataset used in the experiments, in Section IV the simulation results are presented, and in Section V we draw our concluding remarks.

II. Modelling framework

A. LS-SVMs for regression

Given training data $\{x_i, y_i\}_{i=1}^N$, with $x_i \in \mathbb{R}^{d_x}$ and $y_i \in \mathbb{R}$, the regression problem in the primal space can be expressed as follows [6]:

$$\begin{aligned} &\min_{w,e,b} \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \\ &\text{such that } y_i = w^T \varphi(x_i) + b + e_i, i = 1, \ldots, N. \end{aligned} \tag{1}$$

The expression $\hat{y} = w^T \varphi(x) + b$ indicates the model in the primal space with estimated output $\hat{y}$, and the objective function (1) represents a regularized minimization of the sum of squared error SSE $= \sum_{i=1}^N e_i^2$. With γ we indicate the regularization parameter which controls the trade-off between the regularizer and the SSE on training data. After constructing the Lagrangian and eliminating the primal variables $e = [e_1; \ldots; e_N]$ and w the following dual problem can be derived:

$$\left[\begin{array}{c|c} 0 & 1_{\mathrm{N}}^{\mathrm{T}} \\ \hline 1_{\mathrm{N}} & \Omega + \mathrm{I}/\gamma \end{array}\right] \left[\begin{array}{c} b \\ \hline \alpha \end{array}\right] = \left[\begin{array}{c} 0 \\ \hline y \end{array}\right] \tag{2}$$

where $y = [y_1; \ldots; y_N]$, $1_N = [1; \ldots; 1]$, $\alpha = [\alpha_1; \ldots; \alpha_N]$. Ω denotes the kernel matrix with entries $\Omega_{ij} = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j)$. With $K : \mathbb{R}^{d_x} \times \mathbb{R}^{d_x} \to \mathbb{R}$ we indicate the kernel function and $\varphi : \mathbb{R}^{d_x} \to \mathbb{R}^{d_h}$ denotes the feature map. By using a radial basis function (RBF) kernel, expressed by $K(x_i, x_j) = \exp(-||x_i - x_j||_2^2)/\sigma^2$, one is able to construct a flexible nonlinear model. Finally, after solving the previous linear system, the LS-SVM model for function estimation becomes:

$$\hat{y}(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b. \tag{3}$$

Since problems (1) and (2) describe a general setting, they can be used also to construct a nonlinear auto-regressive (NAR) model. A NAR model describes time-varying phenomena specifying that the output variable depends non-linearly on its own previous values [10]:

$$\hat{y}_{k+1} = f(y_k, \ldots, y_{k-p}) \tag{4}$$

where $\hat{y}_{k+1}$ is the predicted future value based on the previous p values, $f : \mathbb{R}^p \to \mathbb{R}$ is the nonlinear mapping. The parameter p is also called order of the NAR model and has to be properly tuned. In the LS-SVM framework the NAR model can be described by:

$$\hat{y}_{k+1} = w^T \varphi([y_k; \ldots; y_{k-p}]) + b. \tag{5}$$

For multi-step ahead prediction a recursive approach can be used:

$$\begin{aligned} \hat{y}_{k+1} &= f(y_k, \ldots, y_{k-p}) \\ \hat{y}_{k+2} &= f(\hat{y}_{k+1}, \ldots, y_{k-p+1}) \\ &\ldots \\ \hat{y}_{k+m} &= f(\hat{y}_{k+m-1}, \ldots, y_{k-p+m}) \end{aligned}$$

where m is the number of steps ahead. As we will explain in section IV, we use a NAR model in a recursive way to predict the future values of temperature measured in the shafts of a steel production machine. Then, a post-processing step consisting of binarizing the predictions according to a specific threshold is performed. In this way, it is possible to predict possible alarms due to overheating. Furthermore, the prediction of the future values of temperature performed by the NAR model can also be used, in principle, to perform some control actions on the bearing (i.e. lowering the speed to avoid a production stop).

B. Model selection

In order to build-up a good NAR model for time-series prediction, we have to choose very carefully the regularization parameter γ, the RBF kernel bandwidth σ and the order p of the NAR model. The parameters γ and σ are selected using 10-fold cross-validation. The Coupled Simulated Annealing (CSA) is used to minimize the mean absolute error (MAE) in the cross-validation process. CSA allows to reduce the sensitivity of the algorithm to the initialization parameters and meanwhile it guides the optimization process to quasi-optimal runs [11]. The optimal order p of the NAR model is found using a grid search procedure. Furthermore, since we are interested in the binarized outcomes of the NAR model to predict eventual alarms (see next Section), we perform an additional model selection step. The latter consists of re-estimating the bias term b in equation (3) in order to maximize the classification accuracy concerning the possible occurrence of alarms.

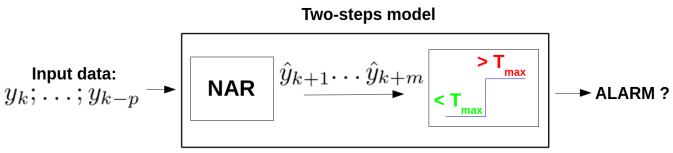


Fig. 1. **Model**: Illustrative picture of the LS-SVM based alarm prediction model. A NAR model of order p produces an m steps ahead recursive prediction. Later on, these predictions are post-processed in order to forecast possible alarms.

III. The industrial use case

The data are collected from a steel production machine used for wire drawing, with the aim of maximizing production capacity based on temperature condition monitoring (see Figure 2). The data are heavy unbalanced: only 61 alarms are present for a total of about 14 000 temperature values. The machine under analysis transforms a given steel wire to a product that meets with the customers requirements. During a production cycle, a wire spool is mounted at the input, it is processed and finally the finished product is removed. When running, energy dissipation causes the machine to heat while a stop, due to a failure or mounting a new spool, causes a cooling. Experimental observations have revealed that certain components in the machines, especially the bearings, tend to degrade faster when high temperatures are measured during operation. Since this early failure of components produces higher costs, the operators prevent high temperatures by shutting down the machine once a threshold $T_{\max}$ is reached. This strategy, however, is not optimal since a different machine setting might avoid the machine to overheat without the need to interrupt the production cycle. Hence a model that estimates the temperature evolution and possible future alarms based on the sensor readings can help to maximize production capacity.

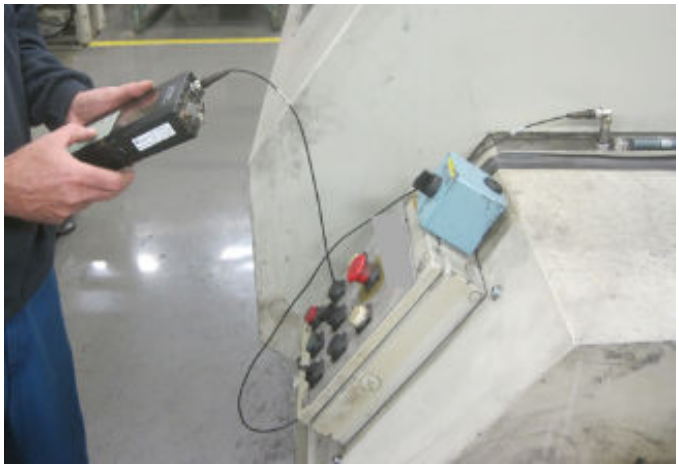


Fig. 2. **Temperature condition monitoring**: this picture illustrates how temperature sensors are used to monitor machine's bearings.

In Figure 3 an example of the time-series of temperature used in the simulations is given.

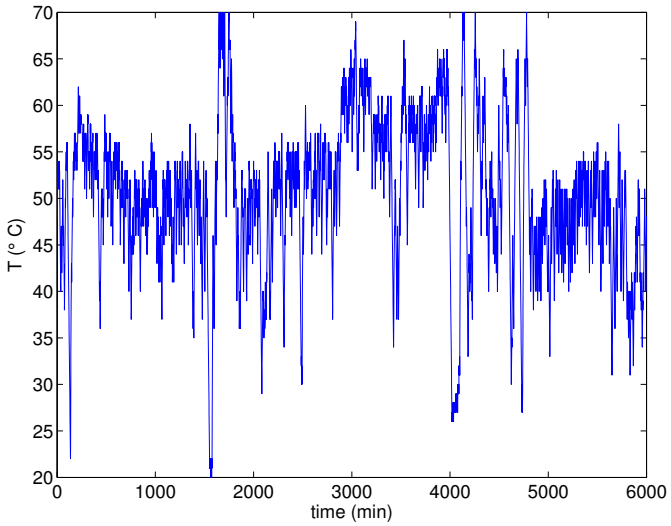


Fig. 3. **Dataset**: Temperature measured on the bearings of the steel production machine during a period of about 21 days. The temperature is logged every 5 minutes for 6000 times.

IV. Experimental results

In this section we show how LS-SVMs can be a powerful tool which can help to perform predictive maintenance, not too early in time in order to exploit component lifetime but also not too late in order to avoid catastrophic failures.

In Figure 1 we depict the model that we use for predicting future alarms due to overheating of the shafts of the steel production machine under investigation. We conceive a two-step model: first we perform nonlinear auto-regression and then we do a post-processing step by binarizing the outcomes of the NAR model. In particular, if in the prediction window $[t+1, \ldots, t+\delta_t]$ the forecasted temperature reaches a value larger than $T_{\max}$ at least once, an alarm is predicted. We adopted this two-step procedure instead of directly training a classifier because the NAR outcomes could be exploited for future control actions (i.e. lowering the speed of the machine based on the predicted temperature trend).

As depicted in Figure 5 we developed a NAR model able to achieve a good performance up to 3 steps ahead prediction (15 minutes). In Table I we observe that the proposed model outperforms simpler techniques like a linear autoregressive model and a zero-order extrapolation method, in terms of mean absolute error (MAE) and squared Pearson correlation coefficient R^2. Moreover, the optimal model has order $p = 20$ and only 20% of the data is used for training and validation. The order of the model has been tuned using a grid search approach (10 randomizations of training and validation sets are considered). The related plot is shown in Figure 4. Furthermore, we select an optimal bias term b in order to have maximum performance on the validation set: basically, we add several Δb to each prediction performed using eq. 5 and we choose the bias term correction yielding maximum classification accuracy of future alarms. The results of our two-step model are shown in Figure 6 (top and center). We can

notice that the proposed method can classify almost all the alarms correctly. However, if on one hand the classification performance is quite good, after adjusting for the bias the error related to the predictions of the NAR model, as expected, increases (see bottom of Figure 6).

Finally, we have run some experiments to learn what are the limits of the proposed alarm prediction system with respect to the time-frame. The results are illustrated in Figure 7, where the true positive rate (TPR) and false positive rate (FPR) achieved by our technique when performing multi-step recursive prediction are reported. We can notice how the performance starts decreasing considerably (low TPR and high FPR) after 5 steps ahead prediction, corresponding to 25 minutes ahead forecast. We also tried to understand if a prediction of the machine state for a complete run would be possible. We observed that for some runs the performance was not satisfactory, while for other runs was good only at the beginning, up to 25 minutes ahead forecast as observed before. In this case a different methodology tailored for run-by-run analysis, like the one developed in [12], can give better results. Also other machine learning algorithms as reinforcement learning might be taken into account in future experiments.

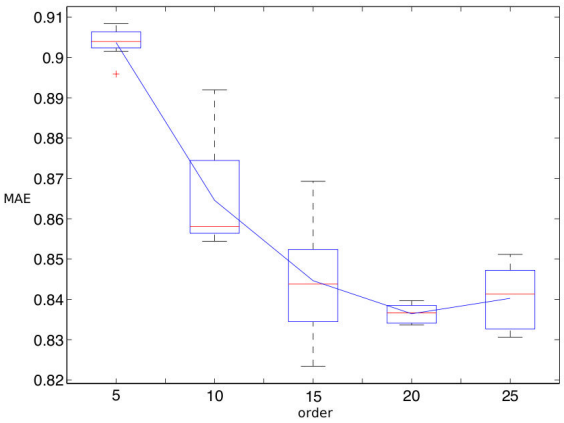


Fig. 4. **Model selection**: Tuning the order of the NAR model. For each possible value of the order analysed in the grid search approach, 10 runs of the model with different training and validation sets are considered. The variability of the results is depicted by means of boxplots, while the line shows the trend of the mean values. The Mean Absolute Error (MAE) refers to the validation set.

	LS-SVM NAR	AR	Standard baseline
MAE	**1.43**	5.74	15.19
R^2	**0.98**	0.91	0.78

TABLE I
NAR RESULTS ON TEST DATA FOR 3 STEPS AHEAD PREDICTION: BEST PERFORMANCE IN BOLD. AR MEANS (LINEAR) AUTOREGRESSIVE MODEL, STANDARD BASELINE REFERS TO A ZERO ORDER FILTER, THAT IS A MODEL THAT AT EACH STEP USES AS PREDICTION THE PREVIOUS VALUE.

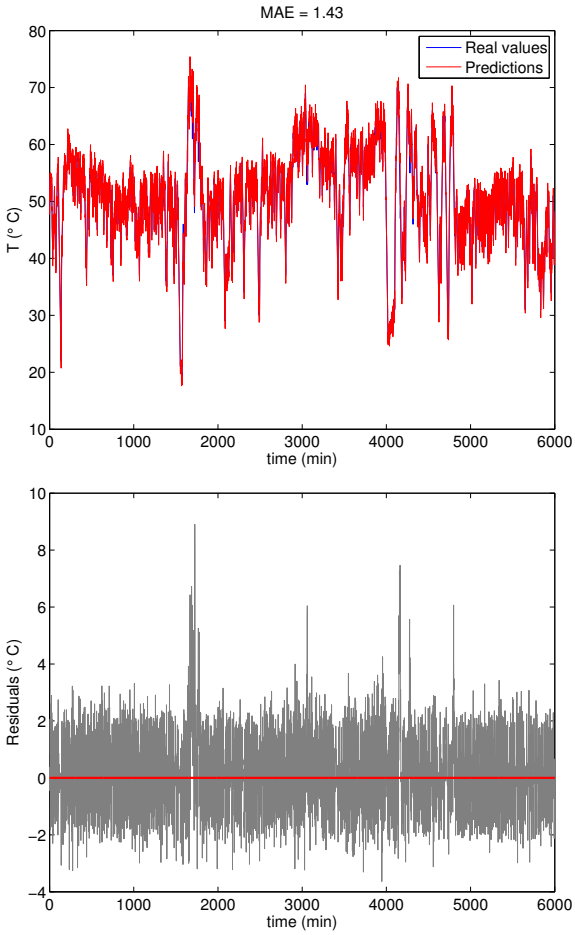


Fig. 5. **Prediction results on the test set**: *(Top)* Temperature measured versus predicted before adjusting for the bias in order to improve the classification performance. *(Bottom)* Difference between measured and predicted values.

V. CONCLUSION

In this paper we have discussed an application of Least Squares Support Vector Machines (LS-SVMs) to the prediction of future alarms due to overheating in steel production machines. The model can predict with a high accuracy the different temperature alarms collected from steel production machines in a time lapse of 15 min. In principle, this allows to conceive an optimization algorithm to embed in machine controllers in order to adequately adjust the machines speed and avoid stops during a batch production. This represents an advantage with respect to current situations, where machines could be shut-down during batch production due to temperature alarms, resulting into high production losses.

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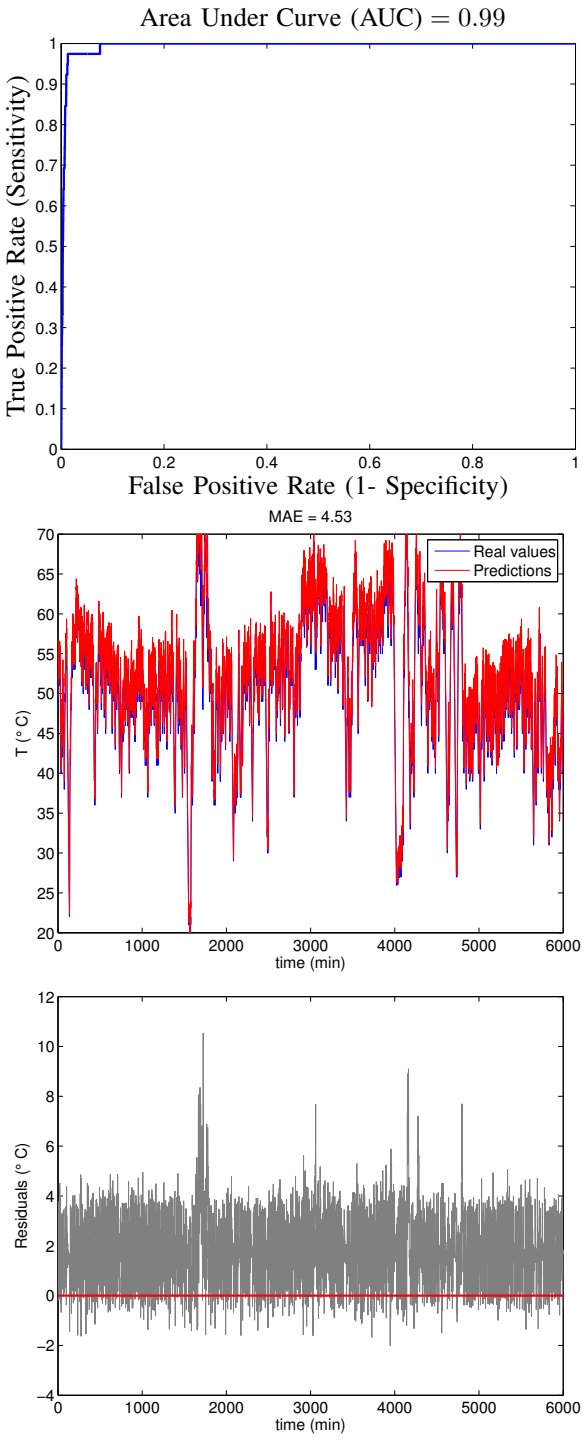


Fig. 6. **Classification results on test data**: *(Top)* ROC curve related to the classification of the alarms. *(Center)* Outcomes of the NAR model after adjusting for the bias: these predictions are binarized to obtain the forecast of the alarms. *(Bottom)* Difference between measured and predicted values of temperature.

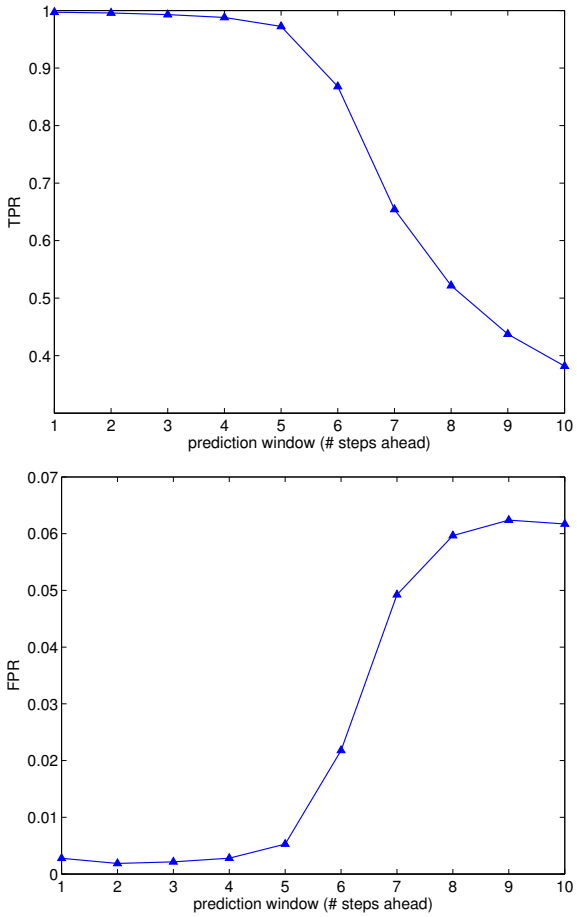


Fig. 7. **Classification accuracy on test data versus time**: *(Top)* True positive rate (TPR) with respect to the lookahead of the alarm prediction performed by the proposed technique. *(Bottom)* False positive rate (FPR) trend. In both plots, a clear drop in the classification accuracy can be observed after 5 steps ahead forecast.

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