Prediction of compressor efficiency by means of Bayesian Hierarchical Models

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Prediction of Compressor Efficiency by means of Bayesian Hierarchical Models

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Abstract. The prediction of time evolution of gas turbine performance is an emerging requirement of modern prognostics and health management systems, aimed at improving system reliability and availability, while reducing life cycle costs. In this work, a data-driven Bayesian Hierarchical Model (BHM) is employed to perform a probabilistic prediction of gas turbine future behavior. The BHM approach is applied to field data, taken from the literature and representative of gas turbine degradation over time for a time frame of 7-9 years. The predicted variable is compressor efficiency collected from three power plants characterized by high degradation rate. The capabilities of the BHM prognostic method are assessed by considering two different forecasting approaches, i.e. single-step and multi-step forecast. For the considered field data, the prediction accuracy is very high for both approaches. In fact, the average values of the prediction errors are lower than 0.3% for single-step prediction and lower than 0.6% for multi- step prediction.

INTRODUCTION

Gas turbine industry currently faces new challenges to improve operational flexibility, system reliability and availability, with the final aim of cost effectiveness and sustainability. Thus, modern prognostics and health management (PHM) becomes a fundamental target for GT buyers and the capability to efficiently predict future deteriorated characteristics of a GT unit can allow the development and implementation of a robust and efficient maintenance strategy by using information gathered via condition monitoring and planning maintenance actions before failures occur [1 - 5]. In this manner, economic losses caused by system breakdowns and unnecessary repair actions can be lowered.

The complexity of GT units, the interaction between its components and the challenge of modeling transient behavior and its effects on performance and useful life [6] restrict the development and application of model-based prognostic approaches and, consequently, suggest the use of observed data to predict system future state. Therefore, data-driven models are more widespread in the literature than physics model-based approaches for the purpose of GT prognostics.

It should be noted that the accuracy of a data-driven prognostic system is clearly influenced by the quality of processed data. To this aim, Ceschini *et al*. [7] developed a comprehensive tool for Detection, Classification and Integrated Diagnostics of Gas Turbine Sensors (named DCIDS) that aims at improving data quality by removing anomalies. The methodology was applied to gas turbine field data [8] and subsequently extended to identify the most frequent GT sensor faults [9].

Since the uncertainty associated with maintenance actions and recovery effectiveness can be high [10, 11], GT measured variables can be treated as random variables. Therefore, data-driven methods developed by means of a statistical approach are more suitable to perform system prognostics. To discriminate among different available methodologies, Zaidan *et al*. [12] suggest several motivations to develop a forecasting algorithm based on a Bayesian approach. The same authors also established a prognostic methodology based on a Bayesian Hierarchical Model (BHM) to optimally exploit a large amount of data from multiple units to enhance prediction reliability.

The BHM prognostic technique was applied by Losi *et al.* in [13] to simulated and field data representative of gas turbine power output degradation over time. The BHM-based prognostic method was investigated in [13] by studying

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the effect of different amounts of training trends on model prediction accuracy through a parametric analysis on the number of past trends and engine fleet sizes. Moreover, unlike [12], the prognostic technique applied in [13] was tested by performing both single- and multi- step predictions. The analyses conducted in [13] for the prediction of GT power output confirmed that BHM reliability was very good, also in case of data trends characterized by high heterogeneity of degradation rates and even in case of variable degradation rate.

Losi *et al.* also developed in [14] an innovative BHM-based diagnostic methodology. In this case, the BHM approach was adapted to simulate a virtual sensor representative of reliable sensor behavior, in agreement with the measured data of healthy sensors used for training the methodology. The BHM diagnostic methodology was applied to a field time series with implanted spikes and bias faults of different magnitude. The analyses were carried out by varying both fault magnitude and number of faulty sensors within the pool. The BHM diagnostic methodology exhibited good detection capabilities in several scenarios characterized by different numbers of faulty sensors within the pool.

In this work, the BHM approach is applied to predict GT turbine deterioration over time, represented by GT compressor efficiency values, of which field data are taken from the literature. As made in [13], two different forecasting approaches, i.e. single-step and multi-step forecast, are adopted to test BHM prediction accuracy.

BAYESIAN HIERARCHICAL MODELS APPLIED TO PROGNOSTICS

The Bayesian Hierarchical Model (BHM) approach was described in detail by Losi *et al.* in [13]. Therefore, it is briefly recalled in this paper and the most relevant features which characterize its application to predict GT compressor efficiency data are discussed.

A Bayesian Hierarchical Model (BHM) is a statistical model which combines a Bayesian approach with regression analysis within a hierarchical framework. Regression analysis allows the study of the underlying relationships between the predictor variable(s) (e.g. time) and the monitored variable(s) (e.g. compressor efficiency). The Bayesian approach treats regression coefficients as random variables, while the hierarchical framework allows model parameters to vary at more than one level.

The main components of Bayesian inference are (i) the *prior distributions*, which describe the probability distributions of model parameters supposed before observing the data and (ii) the *likelihood function*, which represents the information that data provide about model parameters. The BHM involves *individual* prior distributions, associated with each particular unit, and *common* prior distributions, associated with the whole set of data, e.g. collected from multiple GT units.

The goal of the Bayesian inference is to update prior probability distributions of the parameters to posterior distribution by incorporating the information provided by the data, according to Eq. (1):

$$\text{posterior} \propto \text{likelihood} \times \text{prior} \tag{1}$$

The final aim of the Bayesian analysis is performing predictive inference, i.e. predicting the probability distribution of future unobserved data points.

The idea of Bayesian multi-level modeling is to handle data available in a hierarchical structure, so that group effects can be accounted for. For instance, gas turbine engines can be grouped according to different criteria such as belonging to the same customer, same site or same industrial application. Therefore, degradation data generated by GT engines are hierarchically structured and the BHM methodology is suitable to prognosis purposes.

At the lowest level, the BHM handles degradation properties of individual units, while parameters of a higher level are related to the whole fleet of units and allow the variability of the degradation process of each unit to be taken into account. In this way, information about the health state can be shared among units and the model can grasp similarities of behaviour within the group of engines. A considerable amount of data can be used to perform inference, to improve the estimation of future observations.

Methodology

The predictive methodology comprises four main steps, as shown in Fig. 1. Step 1 consists of the estimation of model prior parameters by exploiting recorded observations taken in the past (i.e. past data). Step 2 combines historical data trends (past data) and real-time observations (real-time data) from multiple units to provide the training dataset to estimate the likelihood function for each unit. Step 3 exploits the information held by the training dataset as a base of knowledge to perform inference on model parameters. Finally, at step 4, the outputs of step 3 are used to predict future unobserved values over a desired time horizon and provide an estimation of future engine degradation behavior.

The BHM employed in this paper, and also in [13], consists of two levels. The first level relies on degradation trends from individual units; its model parameters, i.e. vector of regression coefficients $\boldsymbol{w}_j$ and noise variance σ_j^2, are modelled by a Gaussian distribution and an Inverse Gamma distribution, respectively. The second level of the hierarchy expresses similarities on regression coefficients of individual unit degradation data by means of the definition of a common Gaussian distribution for the random variables $\boldsymbol{w}_j$. The mean $\overline{\boldsymbol{w}}$ and covariance matrix V of this distribution are random variables estimated by using the data. The pooled mean $\overline{\boldsymbol{w}}$ is modelled by a Gaussian distribution, while the inverse of the covariance matrix V^{-1} follows a Wishart distribution. Prior distributions of the pooled mean and covariance matrix as well as the unit noise variances are defined to complete the hierarchical model; their specifications are reported in [12, 13]. A first order regression analysis is adopted in this paper, as made in [12-14].

As anticipated above, information from both past and actual data are taken into account through the individual likelihood functions to update prior probabilities. The joint posterior probability density of all model parameters is computed by means of the Bayes' theorem, based on data as well as prior distributions, according to Eq. (1).

The complexity of the multi-level model employed in this paper does not allow to obtain a closed-form solution for the joint posterior distribution. This means that a sampling-based method is required to perform inference on model parameters. In particular, the specifications of prior distributions allow the computation of posterior conditional probabilities for all the parameters of interest. Thus, the Gibbs sampler is a very suitable tool for fitting the statistical model considered in this paper. From posterior conditional densities, Gibbs sampling produces a sequence of draws for the model parameters which, after a suitable "pre-convergence" period, have converged in distribution to the joint posterior probability, according to Eq. (2):

$$\{\boldsymbol{w}_j^{(g)}, (\sigma_j^2)^{(g)}, \overline{\boldsymbol{w}}^{(g)}, (V^{-1})^{(g)}\}, \quad g = 1, 2, ..., G \tag{2}$$

where G is the total number of generated draws.

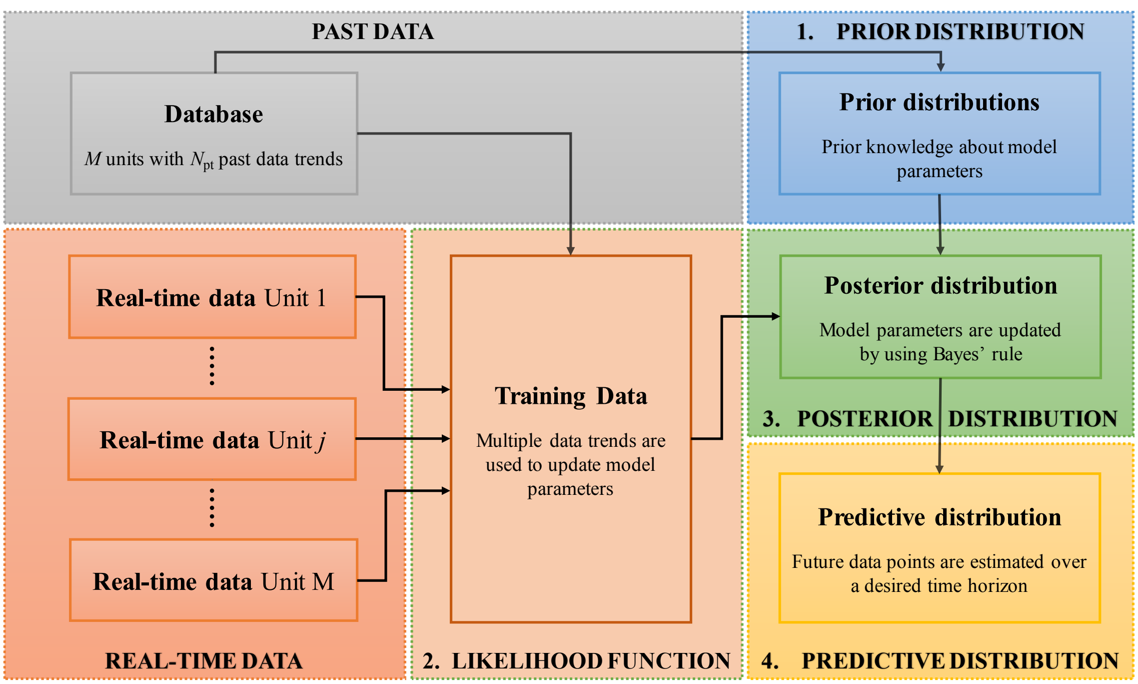


FIGURE 1. Block diagram of BHM applied to prognostics [13]

BHM Prediction

By using the outputs of the Gibbs sampler, the predictive distribution of future data points is calculated and extrapolated over a desired time horizon by performing Monte Carlo integration which uses draws taken from the Gibbs sampler sequence after the "post-convergence" period B. Therefore, the number of values predicted by the BHM at each time point is equal to (G–B). In this paper, in agreement with [13], the following values are selected: G=1000; B=100.

A draw from the predictive distribution can be obtained from the following normal distribution:

$$(\boldsymbol{y}^*_{\mathrm{BHM}})^{(\mathrm{g})} \sim \mathcal{N}(X^* \boldsymbol{w}_{\mathrm{j}}^{(\mathrm{g})}, (\sigma_{\mathrm{j}}^2)^{(\mathrm{g})} I) \tag{3}$$

where X^*contains the time vector of future data points $\boldsymbol{t}^*$.

According to the definition provided in Eq. (4), the mean of the simulated values $(\boldsymbol{y}^*_{\mathrm{BHM}})^{(\mathrm{g})}$, which are ($G$–$B$) in total (900 in the simulations carried out in this paper), can be used to produce a prediction of gas turbine trajectory over time, while the standard deviation defined in Eq. (5) provides a measure of prediction scatter:

$$\boldsymbol{y}_{\mathrm{BHM}} = \frac{1}{G-B} \sum_{g=B+1}^{G} (\boldsymbol{y}^*_{\mathrm{BHM}})^{(\mathrm{g})} \tag{4}$$

$$\boldsymbol{\sigma}_{\mathrm{BHM}} = \sqrt{\frac{1}{(G-B)-1} \sum_{\mathrm{g}=B+1}^{G} \left[(\boldsymbol{y}^*_{\mathrm{BHM}})^{(\mathrm{g})} - \boldsymbol{y}_{\mathrm{BHM}}\right]^2} \tag{5}$$

CASE STUDY

The analyses carried out in this paper consider field data collected on three Alstom heavy-duty gas turbine power plants (Alstom gas turbines GT13, GT24, GT26) characterized by high degradation rate. The field datasets include compressor efficiency values collected over a time frame of 7-9 years and are used for testing the prognostic method on a real-world case study. The field data considered in this paper are the same datasets considered by Venturini and Therkorn in [15] and are reported in Fig. 2.

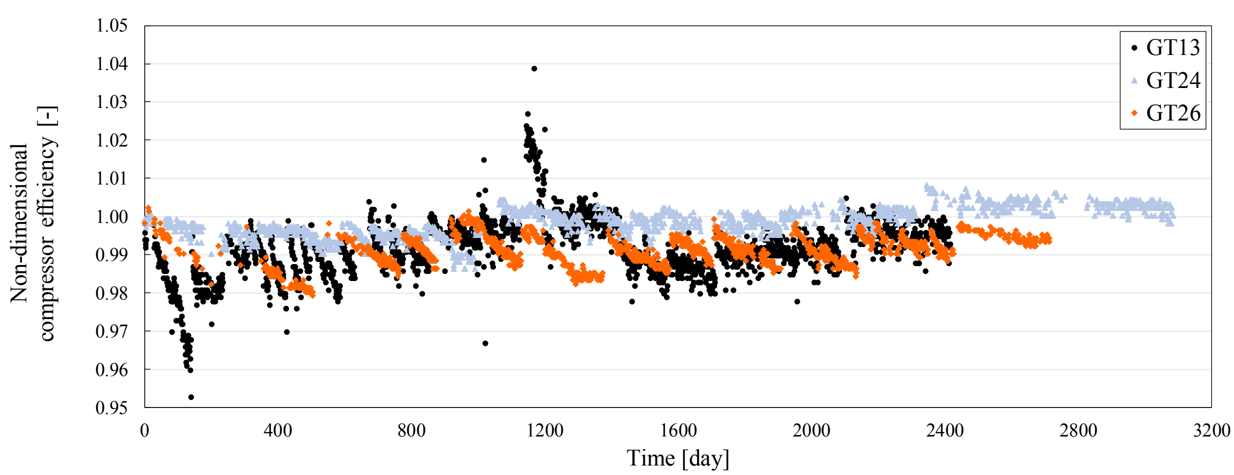


FIGURE 2. Compressor efficiency field data [15]

As discussed in [15], the raw data were preprocessed by means of Alstom monitoring tools and reduced to only one value per day, calculated as the average value during a 5-minute time interval. They were also corrected to ISO conditions and base load operation to identify the degradation trend. Therefore, the scatter of the field data due to measurement uncertainty can be considered negligible compared to the rate of change due to GT health state degradation. As made in [15], the non-dimensional compressor efficiency values reported in Fig. 2 were obtained by dividing each measured value by the corresponding value at the beginning of the trend.

The field data consist of 76 data trends in total, not equally distributed across the three engines because the time frames of observation are different, and each trend has a different duration T_k (expressed in days) and downtime between two subsequent trends. The degradation datasets of GT13 consist of 34 trends, while both GT24 and GT26 have a degradation history composed of 21 trends.

Data Feed

This Section describes the procedure adopted to supply input data to BHM. First, past degradation trends from multiple units are used to compute both individual and common prior distributions. Then, all training trends, i.e. past information contained in the degradation database and the real-time trend from each unit in the model, are fed into the BHM. The unit under prognosis, i.e. the j-th unit, is assumed to begin with no data while all others, i.e. the training units (which are $M-1$ in total) have full information in the model, i. e. the latest degradation trend of each training unit is completely known. Such information is added to the model to predict the real-time trend for the j-th unit under prognosis. As new data for the unit under prognosis are available, the prediction of the unit trend is updated.

The total number of training trends used by the BHM is given by Eq. (6):

$$N_{\mathrm{tr}} = (M-1)(N_{\mathrm{pt}}+1) \tag{6}$$

The synthetic index N_{tr} summarizes the whole amount of information used for training the methodology, by accounting for both the number of engines and past trends. This in turn allows the extension of the results presented in this paper and thus the derivation of rules of thumb for field application.

Each degradation trend of each gas turbine is forecasted and all the remaining trends or a subset of trends are supplied to the prognostic methodology to train the predictive model. In particular, N_{tr} values of 10, 15 and 20 are investigated in this paper for sensitivity purposes.

The simulation tests are carried out by considering the forecasting trend as a new unit with no past degradation information. In this case, an average across the fleet of the individual priors was calculated to initialize the prognostic algorithm, as suggested by Zaidan *et al*. in [12]. With regard to the training dataset, it is assumed that $M = 2$, according to the analyses performed by the authors in [13]. This means that the prognostic tool is applied for predicting the future behavior of a single engine.

Prediction Reliability Assessment

The parameter considered to assess BHM prediction reliability is the relative root mean square error RMSE, which is calculated as the root mean square of the differences between the predicted values of the observations and the measured values, as described in Eq. (7):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e^2(t_i)} \tag{7}$$

where N is the number of predictions and e is calculated for each time point in the range [0; T]. The capabilities of the BHM prognostic method are assessed by considering two different forecasting approaches, i.e. single-step and multi-step forecast, which allow the evaluation of subsequent value (SV) prediction error e_{SV} and last trend value (LV) prediction error e_{LV}, respectively. The two errors are defined as follows:

$$e_{\mathrm{SV}}(t_i) = \frac{y_{\mathrm{meas}}(t_i) - y_{\mathrm{BHM}}(t_i)}{y_{\mathrm{meas}}(t_i)} \tag{8}$$

$$e_{\mathrm{LV}}(t_i) = \frac{y_{\mathrm{meas}}(T) - y_{\mathrm{BHM}}(T)}{y_{\mathrm{meas}}(T)} \tag{9}$$

It is worth noting that the predictions of $y_{\mathrm{BHM}}(t_i)$ and $y_{\mathrm{BHM}}(T)$, estimated by using Eq. (4), are made by exploiting the information held by a knowledge base of N_{tr} trends and real-time data of the engine under prognosis acquired until time $t_{i\text{-}1}$. Therefore, the error on the last value of the trend $e_{\mathrm{LV}}(t_i)$ depends on both the time point t_i under consideration and the number of time points from $t_{i\text{-}1}$ to T, which, is different from one trend to another.

Moreover, BHM prediction reliability is also assessed in terms of success rate (SR), once again for both single- and multi-step prediction. A success is obtained if the conditions expressed in Eqs. (10) and (11) are verified for single- and multi-step prediction, respectively:

$$y_{\mathrm{BHM}}(t_i) - k * \sigma_{\mathrm{BHM}}(t_i) \leq y_{\mathrm{meas}}(t_i) \leq y_{\mathrm{BHM}}(t_i) + k * \sigma_{\mathrm{BHM}}(t_i) \tag{10}$$

$$y_{\mathrm{BHM}}(T) - k * \sigma_{\mathrm{BHM}}(T) \leq y_{\mathrm{meas}}(T) \leq y_{\mathrm{BHM}}(T) + k * \sigma_{\mathrm{BHM}}(T) \tag{11}$$

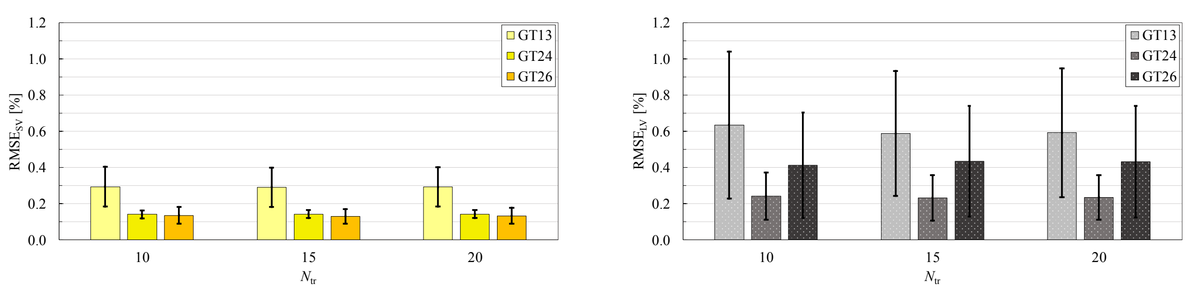
Then, SR is estimated by calculating the rate between the number of successes and the total number of predictions N. The parameter k defines the tolerance bandwidth on BHM point forecast, i.e. $y_{\mathrm{BHM}}(t_i)$.

RESULTS AND DISCUSSION

The prediction errors are shown in Fig. 3, which reports the average $\mathrm{RMSE}_{\mathrm{SV}}$ (a) and $\mathrm{RMSE}_{\mathrm{LV}}$ (b) values for GT13, GT24 and GT26. The average values of $\mathrm{RMSE}_{\mathrm{SV}}$ vary between 0.1 % and 0.3 %, while the values of $\mathrm{RMSE}_{\mathrm{LV}}$ vary between 0.3 % and approximately 0.6 % for all the investigated N_{tr} values. Therefore, the results highlight the very good capabilities of the prognostic methodology based on BHM. Moreover, as already documented and discussed in [13], it can be noted that the prediction errors are sensitive to the considered engine. In particular, for all the values of $N_{\mathrm{tr},}$ the prediction error achieves the highest values on GT13 and GT26 data. Moreover, for each value of RMSE, Fig. 3 also reports the standard deviation of error values obtained on forecasted trends, to highlight the prediction error variability. Even if a training dataset composed of 20 trends is used, the prediction errors on GT13 and GT26 are characterized by higher variability compared to GT24. Instead, the average values of $\mathrm{RMSE}_{\mathrm{SV}}$ and $\mathrm{RMSE}_{\mathrm{LV}}$ for GT24 are equal to 0.15 % and 0.25 % if at least 10 degradation trends are used to train the methodology, respectively, and the prediction errors obtained on the forecasted trends are close to the average value.

In fact, the behavior over time of GT13 and GT26 engines is considerably different from GT24 as can be observed in Fig. 2. These two GT units are characterized by degradation trends with very different degradation rates; thus, highly heterogeneous trends are both predicted and used to train the BHM. This makes the prediction of BHM more challenging. In spite of this, the $\mathrm{RMSE}_{\mathrm{SV}}$ is, in most cases, lower than 0.4 %, while $\mathrm{RMSE}_{\mathrm{LV}}$ is usually lower than 1.0 %. It has to be noted that a similar behavior was observed for the prediction of power output degradation trends [13].

Maximum values of $\mathrm{RMSE}_{\mathrm{SV}}$ and $\mathrm{RMSE}_{\mathrm{LV}}$ (not reported in this paper for the sake of brevity) are also very low from an engineering point of view. In fact, the maximum $\mathrm{RMSE}_{\mathrm{SV}}$ is equal to 0.75 % and 0.25 % for GT13 and, GT24 and GT26, respectively; while the maximum $\mathrm{RMSE}_{\mathrm{LV}}$ exceeds 1.0 % only for GT13 and GT26.



(a) (b)

FIGURE 3. BHM prediction error for subsequent value prediction (a) and trend last value prediction (b)

The optimal forecasting capabilities of BHM methodology are confirmed by analyzing the SR. As made for the RMSE, also the SR was calculated for all the degradation trends of each unit. For the sake of brevity, only the results for N_{tr}=10 are reported in this paper. In fact, in agreement with the analyses carried out in [13], BHM prediction accuracy on compressor efficiency degradation trends are slightly influenced by the number of training trends N_{tr}, if N_{tr} is higher than 10.

A sensitivity analysis on the values of k, in the range from 1 to 3, was carried out. In fact, the simulated values $\boldsymbol{y}^*_{BHM}$ are drawn from a normal distribution (see Eq. (3)) and therefore almost all values should be within three standard deviations.

Figure 4 shows the average values of SR_{SV} and SR_{LV} for the three considered values of k. The average SR_{SV} is equal to 70% for k=1 for all the GT units and increases up to 93 % if k=2 and 98 % if k=3. It should also be observed that no noticeable difference is highlighted among the three GT units, unlike the analysis of $RMSE_{SV}$ results.

Instead, as expected, the success rate on trend last value prediction SR_{LV} is lower than the success rate on subsequent value prediction SR_{SV}. The decrease is mostly highlighted at k=1, while both the SR_{SV} and the SR_{LV} are higher than 90 % if k is assumed equal to 3. Moreover, a significant variability across GT units, which decreases by increasing the value of k, is observed.

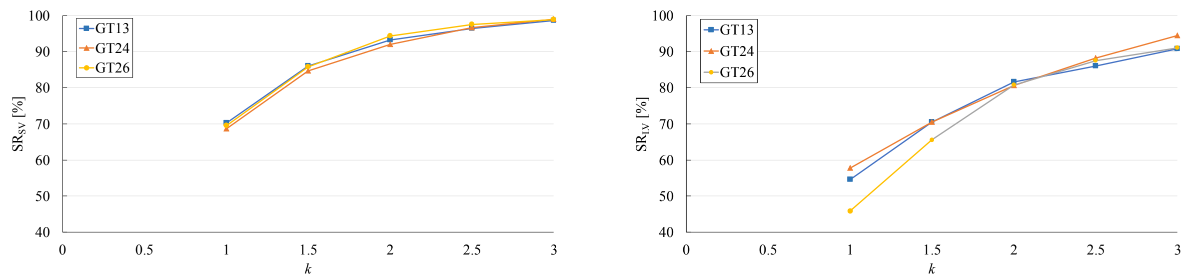


FIGURE 4. Success rate for subsequent value prediction (a) and trend last value prediction (b)

CONCLUSIONS

In this work, a BHM was applied to predict compressor efficiency deterioration over time by mean of field data taken from the literature. Degradation data trends covered a time frame of 7-9 years and were highly heterogeneous. Two different forecasting approaches, i.e. single-step and multi-step forecast, were adopted to test BHM prediction accuracy.

The results proved the optimal capabilities of the BHM-based prognostic methodology. In fact, the average prediction error for single-step prediction was usually lower than 0.3 %, while the average prediction error for multi-step prediction never exceeded 0.6 %, regardless of the considered gas turbine and number of training trends. The BHM prediction capabilities were also quantified by means of success rate. By considering a bandwidth equal to two standard deviations, the success rate of the single-step prediction was equal to approximately 90 %, while the success rate of multi-step prediction was in the order of 80 %. These results proved the high accuracy of BHM predicted outputs.

NOMENCLATURE

B	Gibbs sampler "pre-convergence" period	t	time index
e	error	T	degradation phase duration
g	Gibbs sampler iteration	V	variability on regression coefficients
G	Gibbs sampler total iteration number	$\boldsymbol{w}$	vector of regression coefficients
k	Parameter in Eqs. (10) and (11)	$\overline{\boldsymbol{w}}$	vector of common mean
M	fleet size	X	design matrix
N	number	y	health index
$\mathcal{N}$	Normal distribution	ε	data random error
p	probability density function	σ	standard deviation

Subscripts and Superscripts

BHM	predicted by means of the BHM	pt	past trends
j	engine label	SV	subsequent value
LV	last value	tr	training
meas	measured		

Abbreviations

BHM	Batesian Hierarchical Model	PDF	Probability Density Function
GT	Gas Turbine	PHM	Prognostic and Health Management
MCMC	Markov Chain Monte Carlo	RMSE	Root Mean Square Error
OLS	Ordinary Least Square	SR	Success Rate

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