A New Adaptive Mamdani-type Fuzzy Modeling Strategy for Industrial Gas Turbines

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***Abstract*—The paper presents a new system identification methodology for industrial systems. Using the original Mamdani fuzzy rule based system (FRBS), an adaptive Mamdani fuzzy modeling (AMFM) is introduced in this paper. It differs from the original Mamdani FRBS in that it applies different membership functions and a defuzzification mechanism that is 'differentiable' with respect to the membership function parameters. The proposed system also includes a back error propagation (BEP) algorithm that is used to refine the fuzzy model. The efficacy of the proposed AMFM approach is demonstrated through the experimental trails from a compressor in an industrial gas turbine system.**

Keywords—Mamdani fuzzy rule based system; adaptive Mamdani fuzzy modeling; back error propagation; industrial gas turbine.

I. INTRODUCTION

The use of industrial gas turbines is widespread, and range in size from truck-mounted units for mobile power plants to high power >100s MW complex systems for power generation. Essential parts of these complex systems are the control and monitoring units, which are required by legislation, and play an important role in ensuring system safety and performance. The adoption of predictive warning algorithms to identify emerging fault conditions has therefore attracted considerable recent attention due to widely recognized benefits of facilitating reduced down-time and assurance of safety [1].

Data driven signal processing based techniques have been applied extensively in condition monitoring for industrial gas turbines [2-4]. However, such techniques can only give warnings after faults have occurred, i.e. when faulted data has been read. In this case, model-based system identification approaches have shown their advantages by providing early warnings from predictions of the complex dynamic systems through use of models.

For large gas turbine systems, which are often custom-designed to meet individual orders, the use of application specific materials and components to satisfy off-shore platform regulations, for instance, often make accurate dynamic models, i.e. white-box models, which capture the detailed physical properties of the operation, normally difficult to obtain. By contrast, the use of black-box models, such as artificial neural networks (ANNs), has therefore been popular, albeit with a loss of knowledge about the physical underpinnings of the system's operation. For instance, [5] has demonstrated ANNs for simulating a gas turbine engine used to a power commercial aircraft in order to control safe operating regions and governing the engine thrust. [6] has also presented the use of ANNs in condition motoring of engine gas generators to improve data quality and for performance trend change detection. Gas turbine health monitoring has been carried on in [7] using ANNs for a high bypass ratio military turbofan engine, where double-component faults have been presented to demonstrate the application of ANNs as a diagnostic tools, and [8] applied a feed forward ANN with a back propagation algorithm to a gas turbine equipped with a waste heat recovery section to simulate and predict various steady-state operating conditions. ANNs have therefore been demonstrably successful for modeling gas turbines — however, the black-box model provides little or no insight of the physical underlying attributes of such complex systems. Furthermore, an effective principle in the modeling field is to only estimate what remains unknown, in order to minimize computational overheads, which are not directly accommodated through black-box modeling [9].

To overcome the shortcomings of white-box and black-box models, here, a new grey-box model is proposed, which combines both human knowledge and black-box estimation to account for complex systems' knowledge acquisition. A fuzzy-rule based system (FRBS) is one of the grey-box models with an additional ability to integrate expert knowledge in the form of 'vague' statements. The Mamdani FRBS is a popular type of fuzzy inference systems [10] that is based on Zadeh's fuzzy algorithms for complex systems [11]. It relies on the calculation of a relational matrix for each rule, and subsequently the overall relational matrix. Finally, the output fuzzy set can be elicited using the composition rule of inference. However, Mamdani FRBS has an inherent drawback that it is not differentiable with respect to membership function parameters, which prevents the use of the back-error-propagation (BEP) algorithm to refine the fuzzy models [12]. Therefore, in this paper, an adaptive Mamdani fuzzy modeling (AMFM) is proposed to remove this limitation. The efficacy of the proposed AMFM approach is demonstrated using results from experimental trials of a compressor on an industrial gas turbine.

II. METHODOLOGY DESCRIPTION

Denote X_m and y_m being the inputs and output of the mth data point. AMFM uses Gaussian membership functions for the premises and bell-shape membership functions for the consequents:

$$\mu_{B_i}(y_m) = \frac{1}{1 + \left(\frac{y - c_i^y}{\sigma_i^y}\right)^2}, \tag{1}$$

where μ is the membership degree that y_m maps to B_i, B_i represents the ith bell-shape membership, c_i^y and σ_i^y are the centre and the spread of the ith membership function of the output y, where $i = 1, \ldots, k$, and k is the number of rules. The Gaussian membership function is a smooth function which can introduce extra smoothness. And the final crisp function is:

$$y^{crisp}(X|\theta) = \frac{\sum_{i=1}^{k} b_i \cdot \mu_i(X) \cdot \int_y \mu_{B_i}(y)dy}{\sum_{i=1}^{k} \mu_i(X) \cdot \int_y \mu_{B_i}(y)dy}, \tag{2}$$

where b_i is the centre of area of the membership function $\mu_{B_i}(y)$ and is the peak c_i^y if $\mu_{B_i}(y)$ is symmetric. y^{crisp} is the final defuzzified output of the FRBS.

$\theta = \left(b_i, \sigma_i^y, c_i^j, \sigma_i^j \middle| i = 1, \ldots, k; j = 1, \ldots, n\right)$ is the parameter vector where each parameter is linked directly to the identified cluster (rule) centres and spreads. Here, b_i is the output of the ith rule; c_i^j and σ_i^j are the centre and spread of the ith membership function of the jth input, and n is the number of the dimensions of the inputs. And $\int_y \mu_{B_i}(y)dy$, which denotes the area under $\mu_{B_i}(y)$ over the output interval $y:[y_L, y_U]$, is calculated using

$$\int_y \mu_{B_i}(y)dy = \sigma_i^y \left[\arctan\left(\frac{y_U - b_i}{\sigma_i^y}\right) - \arctan\left(\frac{y_L - b_i}{\sigma_i^y}\right)\right] \overset{def}{=} g\left(b_i, \sigma_i^y\right). \tag{3}$$

A Mamdani FRBS with the pre-specified number of rules is extracted from the numerical data. However, the initial fuzzy model is not ideal since the membership parameters need to be pruned for further accuracy. A constrained BEP algorithm is thus utilized to obtain a vaccine model, through the construction of which, in terms of its predictive performance, many generations of evolutional search can be saved.

By taking the partial derivatives of (2) with respect to each parameter in θ, the following parameter updating formulas are obtained:

1) Centre of the consequent updating law:

$$b_i(t+1) = b_i(t) - \lambda_1 \cdot \varepsilon_m(t) \cdot \frac{\mu_i(t)(X_m) \cdot \zeta(t)}{\sum_{i=1}^{k} \mu_{i(t)}(X_m) \cdot g\left(b_i(t), \sigma_i^y(t)\right)} + \beta_1 \cdot \Delta b_i(t-1),$$

where

$$\zeta(t) = g\left(b_i(t), \sigma_i^y(t)\right) + b_i(t) \cdot g'(b_i(t)) - g'(b_i(t)) \cdot y^{crisp}\left(X_m|\theta(t)\right)$$

2) Spread of the consequent updating law:

$$\sigma_i^y(t+1) = \sigma_i^y(t) - \lambda_2 \cdot \varepsilon_m(t) \cdot \frac{\mu_i(t)(X_m) \cdot g'\left(\sigma_i^y(t)\right) \cdot \left[b_i(t) - y^{crisp}\left(X_m|\theta(t)\right)\right]}{\sum_{i=1}^{k} \mu_i(t)(X_m) \cdot g\left(b_{i(t)}, \sigma_{i(t)}^y\right)} + \beta_2 \cdot \Delta\sigma_i^y(t-1),$$

3) Centre of the premise updating law:

$$c_i^j(t+1) = c_i^j(t) - \lambda_3 \cdot \varepsilon_m(t) \cdot \frac{g\left(b_i(t), \sigma_i^y(t)\right) \cdot \left[b_i(t) - y^{crisp}\left(X_m|\theta(t)\right)\right]}{\sum_{i=1}^{k} \mu_i(t)(X_m) \cdot g\left(b_{i(t)}, \sigma_{i(t)}^y\right)} \cdot \mu_i(t)(X_m) \cdot \left[\frac{x_m^j - c_i^j(t)}{\left(\sigma_i^j(t)\right)^2}\right] + \beta_3 \cdot \Delta c_i^j(t-1),$$

4) Spread of the premise updating law:

$$\sigma_i^j(t+1) = \sigma_i^j(t) - \lambda_4 \cdot \varepsilon_m(t) \cdot \frac{g\left(b_i(t), \sigma_i^y(t)\right) \cdot \left[b_i(t) - y^{crisp}\left(X_m|\theta(t)\right)\right]}{\sum_{i=1}^{k} \mu_i(t)(X_m) \cdot g\left(b_{i(t)}, \sigma_{i(t)}^y\right)} \cdot \mu_i(t)(X_m) \cdot \left[\frac{\left(x_m^j - c_i^j(t)\right)^2}{\left(\sigma_i^j(t)\right)^3}\right] + \beta_4 \cdot \Delta\sigma_i^j(t-1),$$

where $\varepsilon_m = y^{crisp}(X_m|\theta) - y_m$, $g'(b_i) = g'\left(b_i \middle| \sigma_i^y\right)\Big|_{b_i}$ and $g'\left(\sigma_i^y\right) = g'\left(b_i \middle| \sigma_i^y\right)\Big|_{\sigma_i^y}$. (4)

Here, $\lambda_1 \sim \lambda_4$ and $\beta_1 \sim \beta_4$ are user-specific parameters and are the step sizes and the gains of momentum terms, respectively. A problem with the BEP updating formulas derived above is that they include no constraints with respect to the updating mechanism of the parameters. Therefore, a constraint handling scheme is added which checks the boundary violation for centers during each iteration step, and the violated solutions are assigned to the boundaries [12].

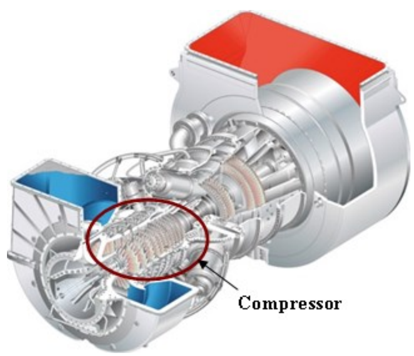
III. CASE STUDY

A. Problem Statement

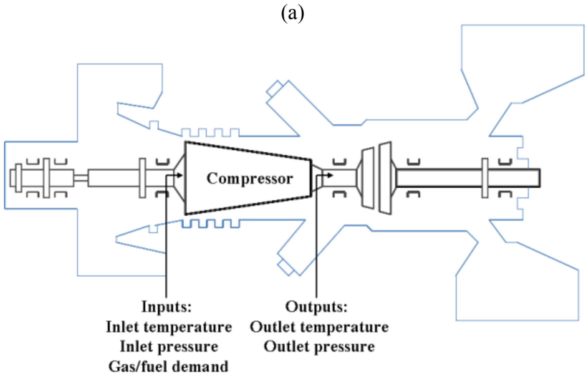
System identification via AMFM is applied to a compressor on an industrial gas turbine system—see Fig. 1. The compressor efficiency during a 3 month period, which contains a washing cycling of the compressor from relatively clean to dirty (efficiency dropping) and undergoing washing (restoring compressor to near optimum design efficiency), is shown in Fig. 2. Data measurements during the time period of a compressor just after washing are used as the training data to build up the model, and 3 sets of test data are collected for each situation with the compressor becoming progressively less clean, as shown in Fig. 2, with 1 day's data in each set for training and testing. In this way, the resulting AMFM model can be used to predict the compressor efficiency trend.

B. AMFM Results

Compressor inlet temperature (°C), compressor inlet pressure (bar) and gas/fuel demand (kW) are considered as the modeling input parameters, and the compressor outlet pressure (bar) is selected as the output vector. The outlet temperature (°C), which can also be considered as an output, can be modeled and predicted through the same procedure.



(a)



(b)

Fig. 1. (a) Schematic of an industrial gas turbine system and position of the compressor; (b) Input and output sensor measurements for a compressor.

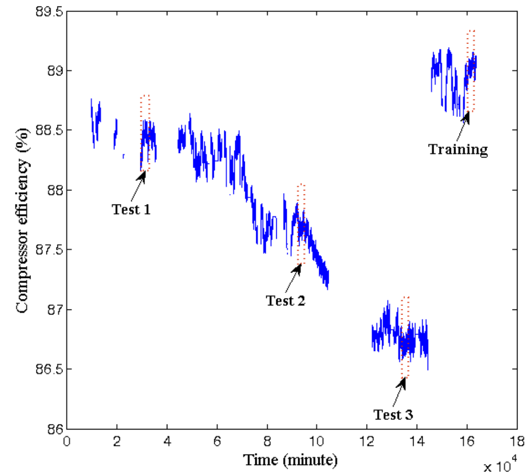


Fig. 2. Training data and test data sets according to compressor efficiency

Here, the initial Mamdani FRBS is extracted by G3Kmeans clustering algorithm, which has been proved to be more robust than k-means clustering [13]. For the training data i.e. the input and output data collected from the time period marked 'Training' in Fig. 2, the predictive performances of the initial Mamdani FRBS, in terms of the root-mean-square error (RMSE) of the predicted outputs and the actual outputs, are shown in Fig. 3, where 10 rules are selected to cover sufficient measurement distributions.

For AMFM, 300 iterations are set, which are the empirical numbers that ensure the convergence of the BEP algorithm. Parameters $\lambda_1 \sim \lambda_4$ and $\beta_1 \sim \beta_4$ are all set to 0.03 in this paper without any loss of generality. Here, the input data are further split randomly into 2 sets, where 25% of the data are used for checking the performance of the model resulting from using the remaining 75% of the training data. Training performance and 'checking' performance are shown in Fig. 4 with respect to iteration number. The predictive performance of the refined Mamdani FRBS through constrained BEP algorithm, AMFM, is shown in Fig. 5. It can be seen that AMFM, after BEP tuning, provides an improved performance compared to original Mamdani FRBS by presenting smaller training and checking RMSEs.

The refined Mamdani FRBS and its membership functions are shown in Fig. 6 showing the 10 rules for the 3 input parameters and the output. The knowledge gained from the distributions and combinations of the membership functions have demonstrated the advantageous properties of the AMFM method by expressing clear semantic meanings of its consequents.

After the AMFM being built, the model is adopted to test the compressor during 3 operating situations, i.e. tests 1~3 in Fig. 2. And the predictive performances (average) of the built model for 3 tests are summarized in Table 1. The results have shown the capability of the proposed modelling method for a compressor efficiency trend changing detection in an industrial gas turbine system.

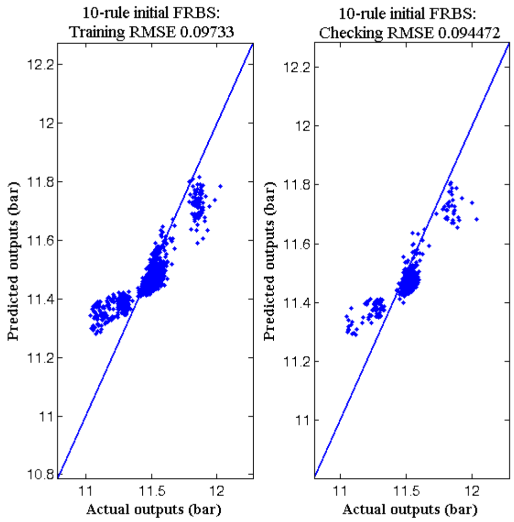


Fig. 3. The predictive performances of the initial Mamdani FRBS

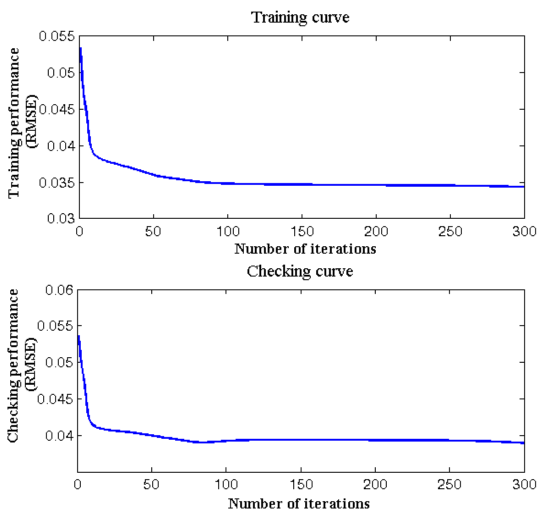


Fig. 4. The training and checking performance curves of the refined Mamdani FRBS

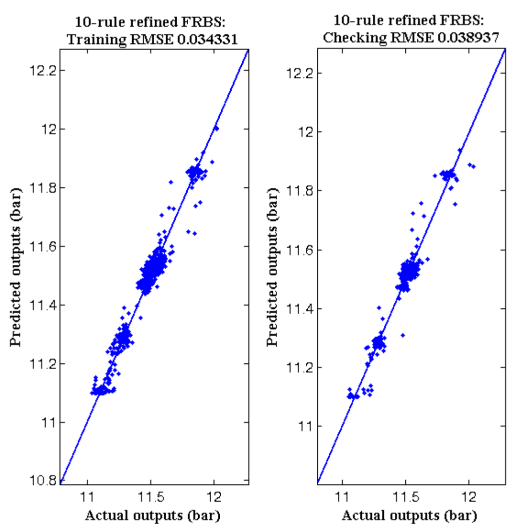
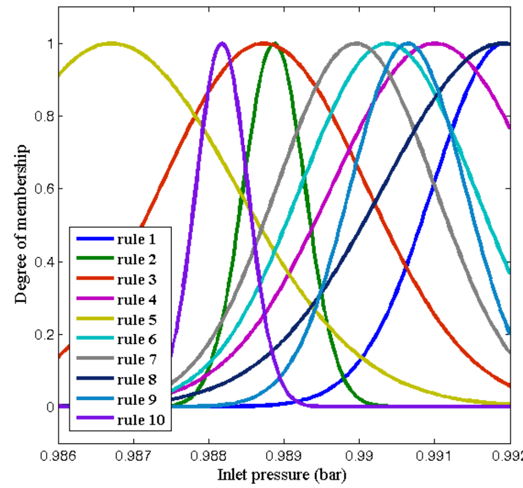
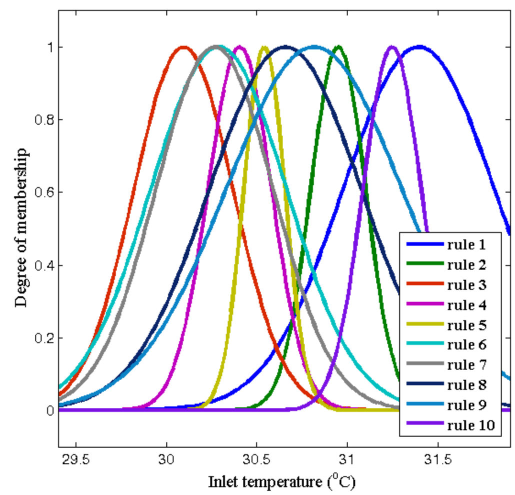


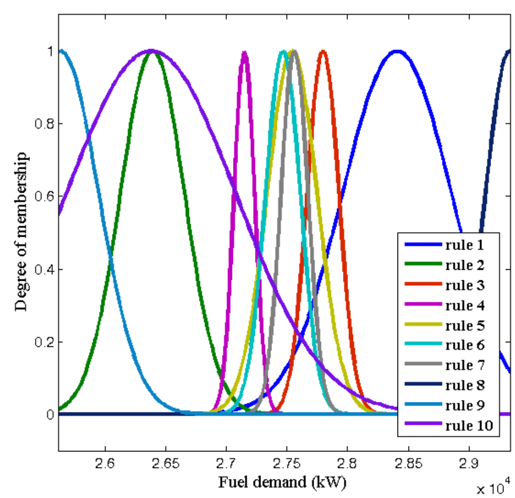
Fig. 5. The predictive performances of the refined Mamdani FRBS



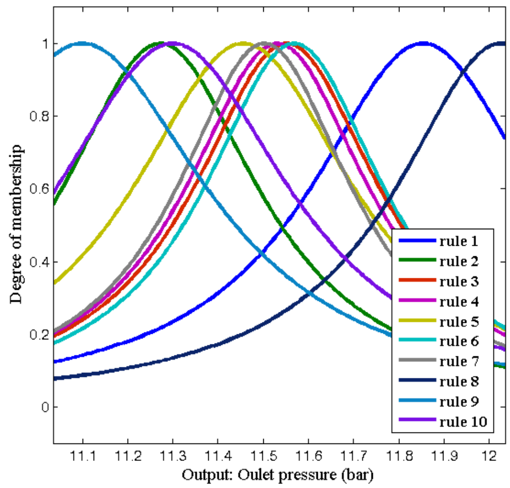
(a)



(b)



(c)



(d)

Fig. 6. Associated membership functions of the refined Mamdani FRBS for (a) Input 1: compressor inlet pressure, (b) Input 2: compressor inlet temperature, (c) Input 3: fuel demand of gas turbine and (d) Output: compressor outlet pressure.

TABLE I
THE PREDICTIVE PERFORMANCES OF AMFM FOR TRAINING DATA AND 3 TESTING DATASETS

	RMSE
Training data	0.0355
Test 1	0.1488
Test 2	0.1676
Test 3	0.2010

IV. CONCLUSION

This paper has proposed a grey-box modeling methodology, which combines both rule based knowledge and black-box estimation. Specially, a refined Mamdani FRBS is proposed and adopted for system identification of a compressor on an industrial gas turbine. AMFM is proposed, where Gaussian membership functions are used for the premises and the bell-shape membership functions for the consequents, so that BEP algorithm can be used to refine the fuzzy models. It is shown that the BEP refined Mamdani FRBS model provides improved modelling performance compared to the original Mamdani FRBS. The efficacy of the proposed method is further demonstrated from the results of RMSEs for detection of compressor efficiency changes.

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