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On-line Evolving Cloud-based Model Identification for Production Control

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Abstract:
In this paper we present an on-line evolving fuzzy cloud-based identification method. The evolving part of the algorithm is improved with new mechanisms. In the part of adding clouds (fuzzy rules) a new condition is implemented in addition to existing ones. Moreover, completely new mechanism for removing the "less active" and "less informative" clouds is introduced. All these mechanisms prevent adding new clouds based on outliers or at least help deleting existing ones with little information. The cloud-based method uses vectorized non-parametric antecedent (**IF**) part which relies on the local density of the current data with the existing clouds. The parameters of the consequent (**THEN**) part (functional in this case) were identified using recursive Weight Least Square method.
The comparison between the original and the improved algorithm was provided on simulated data input/output signals acquired from Tennessee Eastman (TE) benchmark process. Firstly, most representative production Performance Indicators (pPIs) were chosen, then for each pPI a model was identified. The provided results (quality measures) of the proposed method were evaluated using on-line and off-line 4-step prediction. These were further compared with the results obtained using eFuMo identification tool.

Keywords: Cloud-based identification, evolving system, production control, Tennessee Eastman process

1. INTRODUCTION

Controlling a modern production systems requires not only the basic technological functions but also model based (data-driven) control of influential performance indicators of interest. The new developments of predictive manufacturing (Lee et al., 2013) tend to improve the functionality and effectiveness by exploiting knowledge contained in the collected data. Other analysis methods are applied to fault detection and diagnosis for industrial process operation (Qin, 2012; Zhang et al., 2015). The applicability of the data-based methods could be improved by considering the system dynamics. Model based fault detection combines the data-driven methods with model-based approaches (Precup et al., 2015). As dynamic models are required, the system identification methods play a crucial role.

Fuzzy modeling is well established technique for approximating and describing complex and non-linear system behavior. One of the most popular tool is Takagi-Sugeno (TS) fuzzy model (Takagi and Sugeno, 1985). Constructing the TS model requires identifying of the membership functions of the antecedent part and the local model's parameters of the consequent part. The identification of such models can be done in an on-line or an off-line manner. In the past few decades a significant number of on-line identification techniques were proposed relying on fuzzy logic (eTS by Angelov and Filev (2004), exTS by Memon et al. (2006), FLEXFIS by Lughofer and Klement (2005), switching eTS by Kalhor et al. (2013), etc.).

Simplest form for the antecedent part was proposed by Angelov and Yager (2011). This new fuzzy rule based (FRB) system, named ANYA, uses non-parametric vectorized antecedent part. It is based on data clouds (sets of previous data samples close to each other) while the membership functions are calculated using relative data density of the current data with the existing clouds. Moreover, the method is able to evolve the structure (adding new fuzzy rules). Originally the evolving mechanism relies on global data density, while in this paper just local density threshold is used. In the recent years ANYA FRB system was used for solving control problems (Angelov et al., 2013; Škrjanc et al., 2014; Costa et al., 2013; Andonovski et al., 2015b) and as a tool for model identification (Rosa et al., 2014; Ali et al., 2012; Blažič et al., 2014, 2015).

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In this paper we propose an improved evolving mechanisms for protecting of adding new clouds (rules) based on outliers. Moreover, a new mechanism for removing "less active" and "less informative" clouds is introduced. The *activity* is a property of the cloud and it is defined as relative number of the data samples associated with particular cloud from its creation. While the other mechanism delete the clouds which obtained less information in comparison with the other clouds.

The proposed cloud-based identification method was tested on input/output data acquired from Tennessee Eastman (TE) (Downs and Vogel, 1993) process model. The TE system is a complex nonlinear, open-loop unstable process and it consists of 41 measured and 12 manipulative variables. Please refer to (Downs and Vogel, 1993) for detail description of the TE process. The production objectives of the systems are usually defined through the production performance indicators (pPIs). For the TE process as the first pPI, an estimation of the production *Cost* was defined by Downs and Vogel (1993). In the (Glavan et al., 2013a,b) the other two pPIs were defined as *Production* and *Quality*. Furthermore, the authors selected the most relevant manipulative input variables (see Table 1).

Table 1. Process manipulative variables selected by Glavan et al. (2013b).

Notation	Controlled variable setpoints
F_p	Production rate index
R_2	Striper level
R_3	Separator level
R_4	Reactor level
R_5	Reactor pressure
R_7	$\%C$ in purge
R_8	Recycle rate
R_9	Reactor temperature
r_2	D/E feed rates

This paper is organized as follows. In Section 2 the cloud-based identification method is presented, while in Section 3 an improved evolving mechanism for adding and removing clouds is presented. Section 4 introduces the experimental results and at the end, in Section 5 the main ideas and results are concluded.

2. CLOUD-BASED IDENTIFICATION OF A DYNAMIC SYSTEM

2.1 Fuzzy rule-based model

Fuzzy systems are sufficient approximation tools for modeling non-linear dynamic processes. In this paper we use the fuzzy rule-based system with non-parametric antecedent part presented by Angelov and Yager (2011). The main difference is the simplified antecedent part which relies on the data relative density. The rule-based form of the i^{th} rule is defined as:

$$\mathcal{R}^i : \text{IF} \quad (\boldsymbol{x}_f \sim X^i) \quad \text{THEN} \quad y_i(k) = f_i(\boldsymbol{x}_f) \tag{1}$$

where the data sample (regression vector) is $\boldsymbol{x}_f(k) = [y(k-1), \ldots, y(k-n_a), u(k-1), \ldots, u(k-n_b)]$ for partitioning of the problem space and the variables y and u denote system input and output, respectively. The operator $\sim$ is linguistically expressed as '*is associated with*', which means that the current data $\boldsymbol{x}_f$ is related with one of the existing clouds X^i according to the membership degree (normalized relative density of the data). The input and the output order are denoted with n_a and n_b, respectively. Note that the input $u(k)$ does not have immediate influence to the output $y(k)$. The partial NARX model of the i^{th} rule is defined as:

$$f_i(k) = \boldsymbol{\theta}_i^T \boldsymbol{\psi}_k \tag{2}$$

where the vector $\boldsymbol{\psi}_k = [\boldsymbol{x}_f,\ 1]^T$ consists of the regression vector $\boldsymbol{x}_f$ (used for partitioning the data space) to which we usually add a regressor 1. The vector of parameters of the i^{th} cloud (rule) is denoted as $\boldsymbol{\theta}_i^T = \left[a_1^i, \ldots, a_{n_a}^i,\ b_1^i, \ldots, b_{n_b}^i,\ r^i\right]$. Once we have declared all the parameter vectors $\boldsymbol{\theta}_i^T$ for each cloud ($i = 1, \ldots c$) we could define the output of the system in a compact matrix form:

$$y(k) = \sum_{j=1}^{c} \beta^j(\boldsymbol{x}_f)\boldsymbol{\theta}_j^T \boldsymbol{\psi}_k = \boldsymbol{\beta}^T(\boldsymbol{x}_f)\boldsymbol{\Theta}^T \boldsymbol{\Psi}(k) \tag{3}$$

where c is the number of clouds (fuzzy rules), $\boldsymbol{\beta}^T(\boldsymbol{x}_f) = \left[\beta^1,\ \beta^2, \ldots, \beta^c\right]$ is the vector of normalized relative densities determined between the current data $\boldsymbol{x}_f$ and all existing clouds, and $\boldsymbol{\beta}^T$ will be discussed in next subsection. The matrix $\boldsymbol{\Theta} = [\boldsymbol{\theta}_1,\ \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_c] \in \mathbb{R}^{(1+n_a+n_b)\times c}$ contains the vectors of parameters for all the existing clouds [1] .

2.2 Identification of the antecedent part

In this subsection we will describe identification method of the non-parametric antecedent part of the fuzzy rule-based system ANYA (Angelov and Yager (2011)). The method starts with zero fuzzy rules (clouds) and the first cloud is initialized with the first data $\boldsymbol{x}_f$ received. For each of the following data the normalized relative densities β^i are calculated and then the current data is associated with one of the existing clouds (according to the maximal density β^i, where $i = 1, \ldots c$) or a new cloud is added (evolving mechanism).

Before calculating the vector $\boldsymbol{\beta}$ we need to calculate the local relative density which is defined by a suitable kernel over the distances between the current data $\boldsymbol{x}_f(k)$ and all the data previously associated with the cloud. The Euclidean distance ($d_{kj}^i = \|\boldsymbol{x}_f(k) - \boldsymbol{x}_f^i(j)\|$) was chosen in this case (also used by Angelov and Yager (2011), Angelov et al. (2013), Škrjanc et al. (2014)), but any other distance could be also used, e.g. Mahalanobis distance was used by Blažič et al. (2014) and Blažič et al. (2015).

The local density γ_k^i of the current data $\boldsymbol{x}_f(k)$ with the i^{th} cloud is defined by Cauchy kernel as follows:

$$\gamma_k^i = \frac{1}{1 + \frac{\sum_{j=1}^{M^i}(d_{kj}^i)^2}{M^i}} \tag{4}$$

where M^i is the number of the data points that belong to the i^{th} cloud. Equation (4) should be rewritten in recursive form for easier implementation as follows:

$$\gamma_k^i = \frac{1}{1 + \|\boldsymbol{x}_f(k) - \boldsymbol{\mu}_k^i\|^2 + \sigma_k^i - \|\boldsymbol{\mu}_k^i\|^2} \quad i = 1, \ldots, c \tag{5}$$

[1] We use the therm of 'existing clouds' because this method evolves and number of clouds changes when some requirements are fulfilled.

where $\boldsymbol{\mu}_k^i$ and σ_k^i denote mean value vector and mean-square length of the data vector from i^{th} cloud, respectively. Both of them, $\boldsymbol{\mu}_k^i$ and σ_k^i, can therefore be recursively calculated as:

$$\boldsymbol{\mu}_k^i = \frac{M^i - 1}{M^i}\boldsymbol{\mu}_{k-1}^i + \frac{1}{M^i}\boldsymbol{x}_f(k) \tag{6}$$

$$\sigma_k^i = \frac{M^i - 1}{M^i}\sigma_{k-1}^i + \frac{1}{M^i}\|\boldsymbol{x}_f(k)\|^2 \tag{7}$$

The mean value and the mean-square length of the data vectors for each new cloud are initialized as $\boldsymbol{\mu}_0^i = \boldsymbol{x}_f(k)$ and $\sigma_0^i = \|\boldsymbol{x}_f(k)\|^2$, respectively. We have to note here that the properties, $\boldsymbol{\mu}_k^i$ and σ_k^i, of the chosen cloud are only updated by using (6) and (7), while the properties of all other clouds are kept constant.

Once we have calculated the local densities γ_k^i where $i = 1, \ldots, c$ we can calculate the degree of membership of the current data $\boldsymbol{x}_f(k)$ with the cloud X^i. This is done according to the normalized relative local density which is defined as follows:

$$\beta^i(\boldsymbol{x}_f(k)) = \frac{(\gamma_k^i)}{\sum_{j=1}^{c}(\gamma_k^j)} \quad i = 1, \ldots, c \tag{8}$$

where c is the current number of existing clouds.

2.3 Identification of the consequent part

In the previous subsection we updated the properties, $\boldsymbol{\mu}_k^i$ and σ_k^i, of the chosen cloud and we calculated the degree of membership $\beta^i(\boldsymbol{x}_f(k))$. Moreover, in the Subsection 2.1 we mentioned that for the consequent part we use a NARX model, which parameters are updated (identified) using the Recursive Weighted Least Squares (rWLS) method:

$$\begin{aligned}
\boldsymbol{\psi}_k &= [\boldsymbol{x}_f(k), \quad 1]^T \\
\boldsymbol{P}_k^i &= \frac{1}{\lambda_r}\left(\boldsymbol{P}_{k-1}^i - \frac{\beta_k^i \boldsymbol{P}_{k-1}^i \boldsymbol{\psi}_k \boldsymbol{\psi}_k^T \boldsymbol{P}_{k-1}^i}{\lambda_r + \beta_k^i \boldsymbol{\psi}_k^T \boldsymbol{P}_{k-1}^i \boldsymbol{\psi}_k}\right) \\
\boldsymbol{\theta}_k^i &= \boldsymbol{\theta}_{k-1}^i + \boldsymbol{P}_{k-1}^i \boldsymbol{\psi}_k \beta_k^i \left(y(k) - \boldsymbol{\psi}_k^T \boldsymbol{\theta}_{k-1}^i\right) \\
& \qquad\qquad i = 1, \ldots, c
\end{aligned} \tag{9}$$

where $\boldsymbol{\psi}_k$ is the extended regression vector, while the second and the third lines in (9) represent the updating mechanisms of the covariance matrix $\boldsymbol{P}_k^i$ and model parameters $\boldsymbol{\theta}_k^i$, respectively. Parameter $\lambda_r \leq 1$ stands for the exponential forgetting factor, where data which appears p samples ago, is weighted by $(\lambda_r)^p$ (Nelles, 2001). The parameter λ_r also prevents that covariance matrix $\boldsymbol{P}_k^i$ becomes too small. It is initialized with a large positive definite matrix, usually a diagonal one ($\boldsymbol{P}_0^i = \alpha I,\ \alpha \gg 1,\ I \in \mathbb{R}^{(1+n_a+n_b)\times(1+n_a+n_b)}$). Once we have identified/updated the parameters of the consequent part in the k^{th} step, we calculate the estimated output as follows:

$$\hat{y}(k) = \sum_{j=1}^{c} \beta^j(\boldsymbol{x}_f(k))\boldsymbol{\theta}_j^T \boldsymbol{\psi}_k = \boldsymbol{\beta}^T(\boldsymbol{x}_f(k))\boldsymbol{\Theta}^T \boldsymbol{\Psi}(k) \tag{10}$$

3. EVOLVING MECHANISMS OF THE CLOUD-BASED METHOD

In this section the evolving procedure of the antecedent part is described. The cloud-based method is capable of evolving the structure in on-line manner using different mechanisms.

3.1 Adding new clouds (fuzzy rules)

As we mentioned earlier this method starts with zero clouds and the first cloud is initialized with the first data sample. Moreover, when some requirements are fulfilled new cloud (fuzzy rule) could be added, and usually, there are certain criteria (detection of nonlinearity in the system, preventing adding clouds based on outliers, etc.). In our case we have four criteria for adding new clouds:

(1) The first criterion is related to the 'closeness' of the current data to all of the existing clouds. In case that all the local densities in the current time stamp are smaller from some threshold, which is mathematically expressed as:
$$C_1^{add} = (\gamma_{max} > \max_i(\gamma_k^i))\,;$$
where $\gamma_{max} \in [0,\ 1]$. The default value of the parameter is 0.75, but in practice any other value from the range could be used. Bigger value of the parameter create more clouds, while smaller value add just few clouds (new fuzzy rules).

(2) The second criterion complements the first one and prevents creating new clouds based on outliers (see Fig. 1). We wait certain number τ_{add} of consecutive samples which satisfy the first criterion C_1^{add} and after that we add a new cloud:
$$C_2^{add} = (k > k_{C_1} + \tau_{add})\,;$$
where k_{C_1} is the number of consecutive samples fulfilling criterion C_1^{add}. The value of the parameter τ_{add} is equal to the dimensionality of the regression vector ($\tau_{add} = n_a + n_b$). If the value of τ_{add} is too big one should think how to deal with the data points k_{C_1} which can be stored in a buffer and used for initializing the next data cloud.

(3) The third criterion is the number of data samples n_{add} that have to pass from the time stamp k_{add} of the last added cloud:
$$C_3^{add} = (k > k_{add} + n_{add})\,;$$
where n_{add} is one of the design parameters of the proposed method and in our previous work was always set to 20 (Škrjanc et al. (2014), Andonovski et al. (2015b), Andonovski et al. (2015a)).

(4) The last criterion is related to the maximum number of the clouds c_{max} allowed to be added:
$$C_4^{add} = (c_{max} > c)\,;$$
where c is number of already existing clouds.

Therefore, if all four criteria (C_1^{add} **and** C_2^{add} **and** C_3^{add} **and** C_4^{add}) are satisfied then a new cloud is added. For this adding mechanism, we have to set tree parameter γ_{max}, n_{add} and c_{max}.

3.2 Removing clouds (fuzzy rules)

Beside all of the criteria that try to prevent adding new clouds based on outliers, we still found out that some of the clouds are "less active" or "less informative". The *activity* is defined as relative number of data samples associated with the cloud, counted from the moment of the cloud's

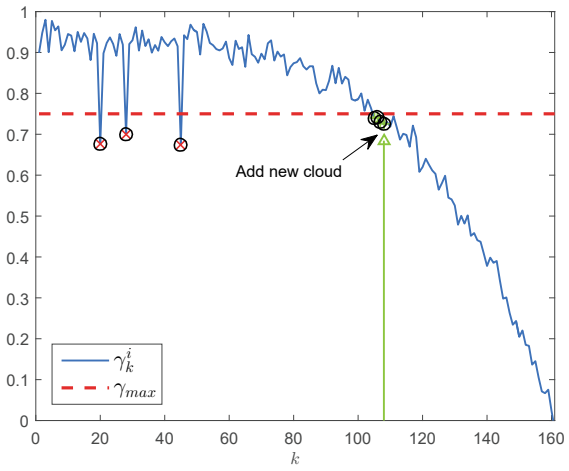

Fig. 1. The red dashed line represent the threshold γ_{max} and the blue line represent the value of maximal density $\max(\gamma_k^i)$ at each step k. The outliers fulfill criterion C_1^{add}, but new cloud is added after τ_{add} consecutive data points.

creation. The condition for removing clouds is expressed as:

$$C_1^{rem} = \left(\frac{M^i}{k-k^i} < \zeta\frac{1}{c}\right) \quad i = 1, \ldots, c;$$

where $\zeta \in [0,\ 1]$ is a constant parameter. If $\zeta = 0$ then removing mechanism is disabled, while if $\zeta = 1$ then with each new added cloud the previous one is removed. Choosing $\zeta = 1$ is not a reasonable solution, and therefore in practice the constant ζ should be within $[0,\ 1)$, usually 0.1 (Dovzan et al., 2015).

When removing clouds we should be very careful and conservative, because we do not want to remove a cloud containing useful information. Using just first criterion C_1^{rem} could possibly lead to such problem. Therefore, beside the criterion C_1^{rem} we propose additional one for removing "less informative" clouds. The *non-informative* is a new property of the cloud and expresses the number of data samples that are most far away from particular cloud. For each data point $\boldsymbol{x}_f(k)$ we calculate all the local densities and find the one with the minimum value $(\min_i(\gamma_k^i))$. That point is associated as "anti-data" to the cloud with minimal density. The number of such points for each cloud is denoted as $\tilde{M}^i$. Finally, second criterion is defined as:

$$C_2^{rem} = \left(1 - \frac{\tilde{M}^i}{k-k^i} < \frac{\zeta}{2}\right) \quad i = 1, \ldots, c;$$

where the ζ is the same parameter as one in C_1^{rem} and has the same value 0.1. The whole mechanism for removing cloud is a logical combination (C_1^{rem} **and** C_2^{rem}).

The whole procedure of the fuzzy cloud-based algorithm is explained through the flowchart presented in Fig. 2. This flowchart represents the procedure for one data sample, and the same steps are repeated for each data sample received. In Fig. 2 we can notice three steps: the identifying of the antecedent part, evolving mechanism (adding and removing clouds), and identifying the parameters of the consequent part.

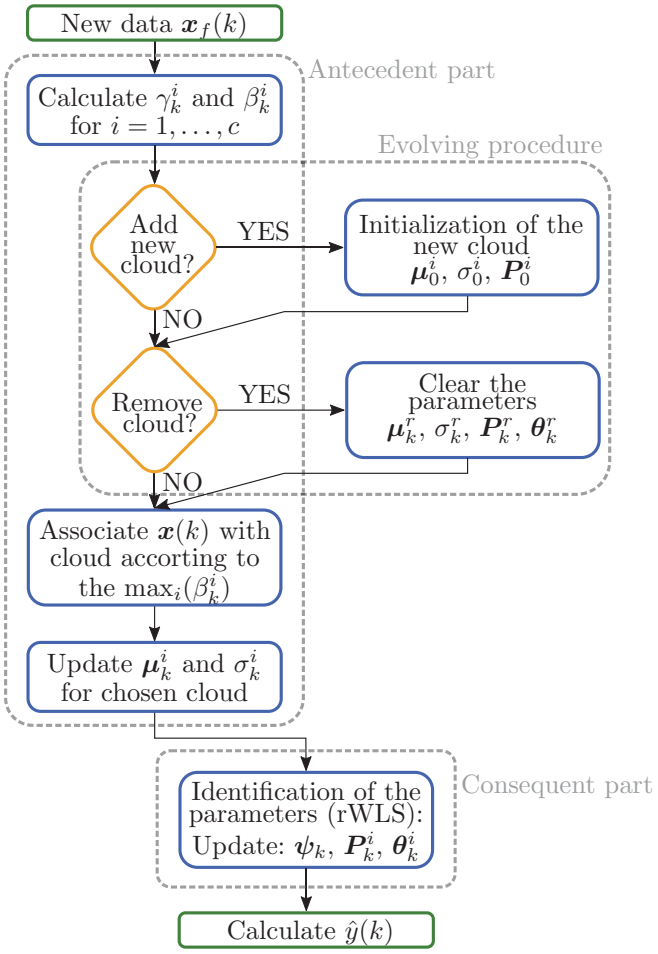

Fig. 2. Cloud-based identification procedure (flowchart for one data sample).

4. SIMULATION EXAMPLE

To evaluate the proposed method three sets of input/output signals were acquired with simulation of the TE process model. The first set of signals is called TRAIN and it is used for acquiring the models for each output. The other two sets (VAL1 and VAL2) were used for validation (4-step prediction) of the obtained models. Furthermore, the estimated output $\hat{y}(k)$ was compared to the original output signal $y(k)$ and evaluated using the Mean Square Error (MSE) which is defined as follows:

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(\hat{y}(k) - y(k))^2 \qquad (11)$$

where N is the number of samples in the output signals.

Four different experiments were provided for testing the new evolving mechanisms proposed in Section 3, as follows: OEM (original evolving mechanism, without C_2^{add} and removing), ADM (adding new clouds with delay C_2^{add}), ERM (removing mechanism) and NEM (new evolving mechanism). All these experiments were compared to well-established technique eFuMo proposed by Dovzan et al. (2015). The parameters chosen for eFuMo are presented in Table 2. The same parameters were used for identifying all three models (*Cost*, *Production*, and *Quality*).

Table 2. Chosen parameters of eFuMo method

γ_c	γ_v	λ_r	τ	c_{max}	N_{out}	k_n
0.9999	0.9999	0.9999	80	20	50	3

For more appropriate and honest comparison of cloud-based method and eFuMo, the parameters that have the same meaning were chosen the same (e.g. $\gamma_c = \lambda_r = 0.9999$, $\tau = n_{add} = 80$ and $c_{max} = c_{max} = 20$). The evolving parameter of the cloud-based method was defined bigger as the default value ($\gamma_{max} = 0.85$).

For both methods, eFuMo and cloud-based, the same regression vectors $\boldsymbol{x}_f(k)$ were used. The proposed regressors by Glavan et al. (2013a) were selected for each output (model) as follows:

$$\begin{aligned} Cost &: \boldsymbol{x}_f(k) = [y(k-1), y(k-2), F_p(k-1), \\ &\quad F_p(k-2), F_p(k-4), R_4(k-1), R_7(k-1), \\ &\quad R_7(k-5), R_9(k-1), R_9(k-5), r_2(k-1), \\ &\quad r_2(k-4), r_2(k-5)]^T \\ Production &: \boldsymbol{x}_f(k) = [y(k-1), y(k-2), F_p(k-1), \\ &\quad F_p(k-5), R_4(k-1), R_4(k-4), R_7(k-1), \\ &\quad r_2(k-5)]^T \\ Quality &: \boldsymbol{x}_f(k) = [y(k-1), y(k-2), F_p(k-1), \\ &\quad R_4(k-1), r_2(k-5)]^T \end{aligned}$$

The results of the validation are shown in Tables 3, 4, and 5, for each output *Cost*, *Production* and *Quality*, respectively. We can notice that on-line identification improves the performance of the cloud-based algorithm in comparison with the off-line mode. Moreover, the cloud-based method performs better than eFuMo for modeling the *Cost* and the *Production*, while in case of the *Quality* eFuMo provides better results. Furthermore, we can compare the results between the different evolving mechanisms proposed in the paper. In some cases they improve the performance of the algorithm, but unfortunately, in other cases they provide worse results.

5. CONCLUSION

In this paper we focused on implementing new evolving mechanisms for improving the performance of the cloud-based identification method. These mechanisms protect adding new clouds (rules) based on outliers and remove existing ones which are not active or they do not obtained enough information from the data. The proposed evolving procedure was tested on sets of signals acquired from the Tennessee Eastman process model. Three different models were identified and evaluated using 4−step prediction in on-line and off-line manner. Moreover the results were compared with well established identification method eFuMo. From the obtained results we can conclude that the new evolving mechanisms in some cases are able to improve the overall performance of the algorithm.

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Table 3. Validation based on the 4-step-ahead prediction for the first output (*Cost*).

	OEM	OEM+ADM	OEM+ERM	NEM	OEM	OEM+ADM	OEM+ERM	NEM
	VAL1				VAL2			
Cloud based (on-line)	4.9654	4.8923	4.9654	4.8923	7.1088	7.0964	7.1088	7.0964
Cloud based (off-line)	5.1641	5.1478	5.1641	5.1478	7.4398	7.4436	7.4398	7.4436
eFuMo (off-line)	8.5618				13.0917			

Table 4. Validation based on the 4-step-ahead prediction for the the second output (*Production*).

	OEM	OEM+ADM	OEM+ERM	NEM	OEM	OEM+ADM	OEM+ERM	NEM
	VAL1				VAL2			
Cloud based (on-line)	0.1761	0.1788	0.1761	0.1788	0.1642	0.1659	0.1642	0.1659
Cloud based (off-line)	0.1964	0.2006	0.1964	0.2006	0.1639	0.1664	0.1639	0.1664
eFuMo (off-line)	0.2074				0.2006			

Table 5. Validation based on the 4-step-ahead prediction for the third output (*Quality*).

	OEM	OEM+ADM	OEM+ERM	NEM	OEM	OEM+ADM	OEM+ERM	NEM
	VAL1				VAL2			
Cloud based (on-line)	0.1123	0.1387	0.1203	0.1466	0.0687	0.0687	0.0684	0.0682
Cloud based (off-line)	0.2310	0.2302	0.2853	0.2729	0.0683	0.0682	0.0694	0.0688
eFuMo (off-line)	0.0715				0.0881			

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