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Fuzzy Modeling for an Anaerobic Tapered Fluidized Bed Reactor

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***Abstract* – Fuzzy modeling has great adaptability to the variations of system configuration and operation conditions. This paper investigates the fuzzy modeling of a laboratory scale system of anaerobic tapered fluidized bed reactor (ATFBR). The studied system is the anaerobic digestion of synthetic wastewater derived from the starch processing industries. The experiment was carried out in a mesophilic ATFBR reactor with mesoporous granulated activated carbon as bacterial support.**

The fuzzy system was generated and trained by a modified version of the Projection based Rule Extraction (PRE) method using the obtained experimental data, and it applies the inference technique Fuzzy Rule Interpolation based on Polar Cuts (FRIPOC).

The output parameters predicted by the tuned system have been found to be very close to the corresponding experimental ones and the model was validated by replicative testing.

***Keywords:* fuzzy modeling, FRIPOC, Anaerobic Tapered Fluidized bed Reactor, OLR, COD, BOD, pH.**

I. INTRODUCTION

The functional relationship between the input and output data of a system can be modeled in several ways. However, in case of multidimensional input and output the task becomes a bit complicated and therefore solutions based on fuzzy logic or neural networks gain a wide application area. The popularity of fuzzy systems in function approximation can be explained by the simple rule expression and the self explaining capability of fuzzy rules.

A. Sparse systems versus dense systems

Traditional fuzzy systems working with inference techniques like Zadeh's, Mamdani's or Takagi-Sugeno's determine the conclusion by means of rule-matching. Hereupon the conclusion is calculated as a weighted combination of rule consequents (fuzzy sets or the crisp consequent function) with non-zero matching, where the weights depend on the degree of matching. These methods require a dense (covering) character of the rule base in order to ensure a proper output in case of each input value. It means that for all the possible observations it should exist at least one fuzzy rule whose antecedent part overlaps the observation at least partially. For example Fig. 1 presents the antecedent space of a dense rule base with two input dimensions (A_1 and A_2). For simplicity all linguistic terms are trapezoid shaped and the partition is a Ruspini one. They ensure an $\varepsilon=0.5$ coverage of the input space.

The required dense character of the rule base can be ensured easily in case of a one or two dimensional input space with partitions containing a reduced number of fuzzy sets. However, increasing the number of input linguistic variables or/and the linguistic terms in the partitions the demanded coverage of the input space is realizable only at the expense of a huge number of rules. In the general case the number of required rules (N) can be calculated by the formula

$$N=\prod_{i=1}^{n_{in}} k_i \ , \qquad (1)$$

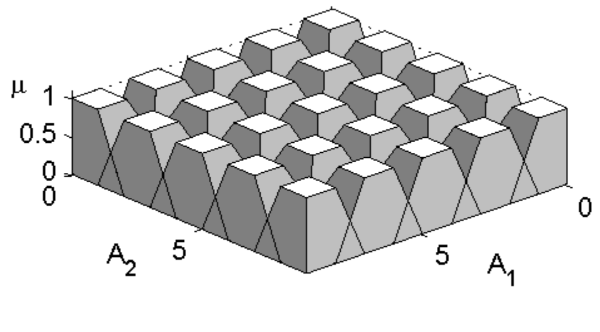

Fig. 1. Antecedent space of a dense rule base

where n_{in} denotes the number of input dimensions, and k_i is the number of linguistic terms in the i^{th} input dimension. Considering the same number of fuzzy sets in each dimension Fig. 2 demonstrates that even by relatively low values of both parameters the number of rules increases exponentially.

The rule number explosion leads to increased system complexity and results in grown storage demand and extended time consumption of the output calculation. The problem can be solved by applying sparse rule bases instead of using dense ones. A sparse rule base does not ensure a full coverage of the input space (see Fig. 3.) containing a reduced number of rules. Generally it can be generated in two ways.

The first approach [13] starts from a dense rule base and decreases the complexity by eliminating the rules considered as non relevant ones. The second approach suggests the generation of a sparse rule base straight from the available input-output data. These methods either intend the determination of the so-called "optimal fuzzy rules" [14] [15] or apply fuzzy clustering (e.g. [4] [18] [20] [21] [5]).

We followed the second approach by using a modified version of the Projection based Rule Extraction (PRE) [5] method for the generation of raw fuzzy systems that model the process being studied. Section II.B presents the applied technique shortly.

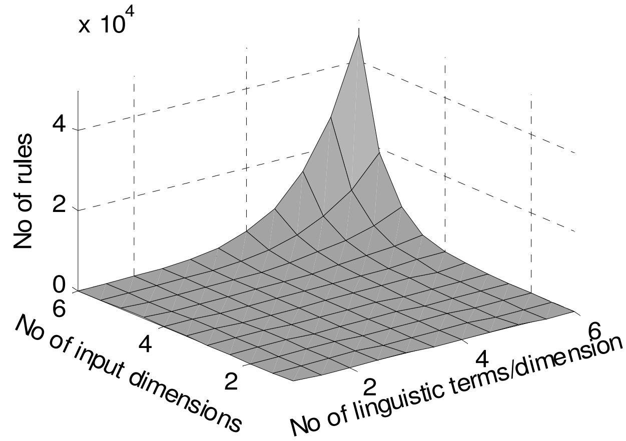

Fig. 2. Number of rules in a dense rule base depending on the number of input dimensions and the number of linguistic terms in a dimension

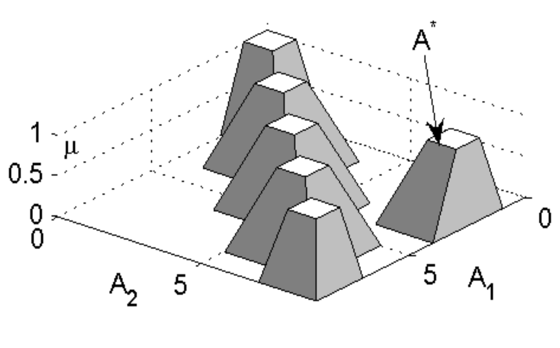

Fig. 3. Antecedent space of a sparse rule base

B. Fuzzy Rule Interpolation based Reasoning

In a sparse rule base there are no rules for a set of possible input values (observations). Fig. 3 presents the input space of a system applying a sparse rule base. There are two input dimensions and the rule base consists of five rules. In case of the observation A^* there is no rule whose antecedent part would overlap the observation at least partially. Therefore the classical compositional reasoning methods cannot afford an acceptable output and special approximate inference techniques are needed.

There are several such methods with more or less constrained field of application. Most of them are based on fuzzy rule interpolation. As first of its kind the KH method, introduced by Kóczy and Hirota [12], calculates the conclusion by its α-cuts using a linear interpolation based on the proportion, in which the observation divides the distance between the antecedents of the two neighboring rules (Fundamental Equation of Rule Interpolation - FERI). In spite of its drawbacks it became very popular due to its low computational complexity and easy implementability.

Later several other methods were developed aiming the extension of applicability of the KH method or the development completely new concepts. These techniques can be divided into two groups depending on whether they are producing the estimated conclusion directly or they are interpolating an intermediate rule first.

Relevant members of the first group are among others the KH method [12], the MACI [19], the FIVE [16] introduced by Kovács and Kóczy, the IMUL proposed by Wong, Gedeon and Tikk [22], the method based on the conservation of the fuzziness suggested by Gedeon and Kóczy and the interpolative reasoning based on graduality introduced by Bouchon-Meunier, Marsala and Rifqi [3]. The structure of the methods belonging to the second group can be described best by the generalized methodology (GM) defined by Baranyi et al in [1]. Typical members of this group are e.g. the technique family proposed by Baranyi et al. in [1], the IGRV [7] developed by Huang and Shen, the LESFRI [9] suggested by Johanyák and Kovács, the FRIPOC [8] proposed by Johanyák and Kovács, and the VEIN introduced in [11]. The main ideas of the method FRIPOC applied in course of the modeling are recalled in section 3.
The rest of this paper is organized as follows: Section II describes the applied rule base generation and parameter identification methods as well as the inference technique. Section III introduces briefly the modeled system. The results are presented and discussed in Section IV.

II. FUZZY SYSTEM GENERATION

A. Rule Base Generation and Parameter Identification

The applied rule base generation method follows the basic concepts of the method PRE [5]. It produces a Single Input Single Output (SISO) or a Multiple Input Single Output

(MISO) fuzzy system and creates a sparse rule base in most of the MISO cases. Thus it ensures a significant complexity reduction in comparison to the methods producing always a dense rule base. The method consists of six steps. They are the followings.

1) *Doing a one dimensional FCM clustering [2] in the current output dimension*. The optimal cluster number is determined by the minimal FS index [6]. In order to avoid the complexity explosion one should apply a maximum limit (e.g. 15 clusters).

2) *Generation of the output partition* by using trapezoidal shaped fuzzy sets and Ruspini partition. The core of the trapezoids is approximated from the clusters using the endpoints of the horizontal cut at $\alpha=0.85$ conform the suggestions in [5].

3) *Projection of the sets into the antecedent space*. For each consequent linguistic term one seeks those data points that have the maximal membership value in the linguistic term. Next in each input dimension a one dimensional FCM clustering of the input values is done corresponding to the found data points.

4) *Generation of the input partitions*. For each input dimension one collects the cluster centers obtained in the previous step and creates the linguistic terms similar to the case of step 2.

5) *Rule base creation*. The rules are determined from the relationship discovered by the projection in step 3. In case of a SISO system the rule base always will be dense. However in case of a MISO system the resulting rule base is sparse.

6) *Parameter identification*. Here first one has to select a parameter parameterization strategy. The comparative study in [10] shows that the use of the abscissas of the four characteristic points of a trapezoid gives the best results. The tuning is performed by an iterative gradient descent process where all parameters are adjusted individually repeatedly in order to increase the performance index of the system.

B. *Fuzzy Inference method*

We applied the method FRIPOC [8] as fuzzy inference technique. It belongs to the group of two-step fuzzy rule interpolation techniques. In the first step it determines a new rule whose antecedent sets are situated in the same position as the sets describing the observation, i.e. their reference point are identical in each antecedent dimension. The shape of the antecedent and consequent linguistic terms is calculated by a set interpolation technique that is based on the concept of linguistic term shifting and polar cuts. The position of the consequent sets is determined by an adapted version of the Sherpard interpolation [17].

The fuzzy sets representing the final conclusion are determined in the second step of FRIPOC applying a special single rule reasoning technique that is also based on polar cuts and which determines the shape of the new linguistic term going out from the differences between the antecedent sets of the interpolated rule and the sets that represent the observation.

III. ANAEROBIC TAPERED FLUIDIZED BED REACTOR

A. *Experimental Set up*

A schematic diagram of the experimental set up is shown in Fig. 4. The Anaerobic Tapered Fluidized Bed Reactor (ATFBR) consists essentially of conical shaped acrylic column of 5^0 taper angle with a total volume of 7.8 (l). A static bed volume of 500 (cm^3) of mesoporus Granulated Activated Carbon (GAC) was used as a biomass carrier. The effluent was recycled from the top to the bottom of the reactor using a magnetic driven polypropylene centrifugal pump operated at a constant rate enough to provide complete fluidization of the GAC. The recycle rate created essentially well mixed conditions in the reactor. The settlement zone of the reactor contained a conical gas liquid separator to allow venting of the biogas produced. Sampling ports were provided along the column length to obtain bed samples. Influent was pumped in continuously at the bottom of the reactor by means of a peristaltic pump and effluent was withdrawn from the top. Biogas produced from the reactor was collected by a 20 (l) displacement jar which contains 10 % sodium hydroxide solution.

B. *Reactor operation*

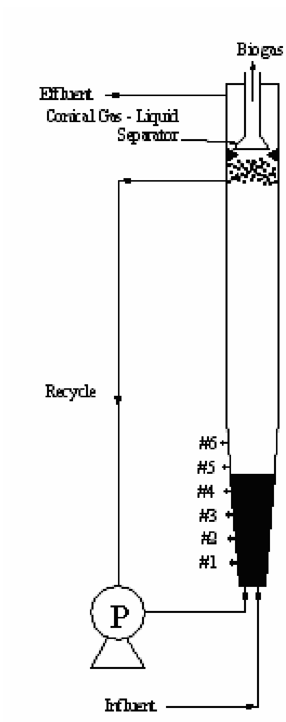

Fig. 4. Schematic diagram of an anaerobic tapered fluidized bed reactor

The experimental protocol was designed to examine the effect of the Organic Loading Rate (OLR) on the efficiency of the ATFBR. The ATFBR was subjected to a steady-state operation over a range of hydraulic retention time of 27 to 12 hours. The volumetric Chemical Oxygen Demand (COD) loadings were between 1.10 and 15.74 ($kg/m^3/d$). The reactor was operated for four different flow rates and five different concentrations with the optimum superficial velocity (2.5 U_{mf}) which gives the maximum COD removal.
The chosen flow rates were 7, 10, 13, and 16 (lpd) and COD concentrations of 1.1, 2.0, 3.0, 4.0 and 5.0 (kg/l). The reactor is operated initially for a flow rate of 7 (lpd) for the above different concentrations. Then for the particular COD concentration the reactor was operated for 5 days in order to study the performance. The attainment of the steady-state was verified after an initial period by checking whether the constant effluent characteristic values (COD removal and biogas generation) were the mean of the last measurements in each stage.
The COD removal efficiency was found to be 91-92% during the particular OLR. Then the COD concentration was increased to 10 – 15% daily till the next chosen COD concentration was reached. Again at that particular OLR the reactor is operated for 5 days. The experiment was repeated for the remaining three flow rates.
During the operation of the ATFBR, temperature, pH, COD and Biological Oxygen Demand (BOD) for influent and effluent waste water, biogas production rate, effluent total volatile fatty acids and alkalinity concentration were monitored daily. The volume of biogas produced in the reactor was directly measured in terms of the volume salt solution displaced from the gas. All analytical determinations were performed according to “Standard Methods”.

IV. FUZZY MODELING OF THE ATFBR SYSTEM

In course of the system training we used a data set of 78 points which were taken during the steady state operation of the reactor (when the efficiency of the reactor was 90 – 92%). Each of them was defined by 4 inputs (Flow rate, COD, pH and BOD) and 5 output (COD, Biogas, Volatile Fatty Acids, Alkalinity and BOD) values. Based on the above presented raw rule base generation and system identification methods the output dimensions were treated separately, practically we created five parallel MISO fuzzy systems each dealing with only one output dimension. The systems were tuned for the fuzzy reasoning method FRIPOC and the COG defuzzification was used.

TABLE 1. Results of the tuning process

	RMSE	RMSEP (%)
COD	27.7827	4.11
Biogas	0.8012	2.46
VFA	18.2828	7.75
Alkalinity	76.0786	9.67
BOD	88.4201	9.96

We used two performance indexes for the evaluation of the systems. The first of them is the root mean square (quadratic mean) of the error. We chose it owing to its comprehensibility and comparability to the range of the output linguistic variable. Its value is calculated by

$$RMSE = \sqrt{\frac{\sum_{j=1}^{M}\left(y_j - \hat{y}_j\right)^2}{M}} \qquad (2)$$

where M is the number of training data points, y_j is the output of the j^{th} data point in the current output dimension and $\hat{y}_j$ is the output calculated by the system. The second performance index was the relative value of *RMSE* to the range (*RMSEP*) expressed in percentage

$$RMSEP = \frac{RMSE}{DR} \cdot 100 \qquad (3)$$

where DR is the range of the output dimension. The values of the performance indexes at the end of the tuning are presented in table 1.

Each of the systems has four input dimensions; therefore the differences between the measured and calculated output values can be visualized only by 2D plots where the horizontal axis represents the ordinal number of data points. Figures 5-14 give a view of the results of the modeling. Each pair corresponds to an output dimension. The Fig. 5, 7, 9, 11, 13 represent the measured (circles) and the calculated (pentagrams) values. The Fig. 6, 8, 10, 12, 14 show the relative error for each data point calculated by

$$RE_j = \frac{\left|y_j - \hat{y}_j\right|}{DR} \cdot 100 \qquad (4)$$

In case of the linguistic variable effluent COD, the calculated values give a good approximation of the original ones achieving an *RMSEP*=4.11 % (Fig. 5 and 6). There are only a few points where a significant difference can be stated.
The system modeling the functional relationship between the input and biogas gave the best results (*RMSEP*=2.46 %). Both of the figures 7 and 8 show a very good approximation capability in this case.

In case of the third (*Volatile Fatty Acids*) and fourth (*Alkalinity*) dimensions we obtained moderate results. There are 3-4 peak points in the *RE* diagram in both cases. An improvement of the performance could be feasible by expanding the rule bases by some new rules and by enhancing the tuning algorithm.

Although the *RMSEP* of the linguistic variable (BOD) has a moderate value (9.96 %) one can observe clearly that the values calculated by the fuzzy system attain a very good coverage of the measured ones.

The biological system is a complex one and the repeatability of the system behavior is low. So the training based on certain selected points may not hold precisely for other data points. Even then the RMSEP % for all the output is quite reasonable.

V. CONCLUSIONS

In this paper, we have generated an aggregative fuzzy system – in fact five independent systems – in order to model the real system, which was described by 78 data points for the treatment of starch waste water using anaerobic tapered fluidized bed reactor. This is done by employing fuzzy modeling to identify the nonlinear relationship between the various experimental parameters.

We have validated our technique by replicative testing and had RMSEP % of 4.11 for effluent COD, 2.46 for Biogas, 7.75 for Volatile fatty acids, 9.87 for alkalinity and 9.96 for effluent BOD which is very much encouraging for further research in this area. Further no such work on fuzzy modeling using FRIPOC in the area of waste water treatment has been reported in the literatures.

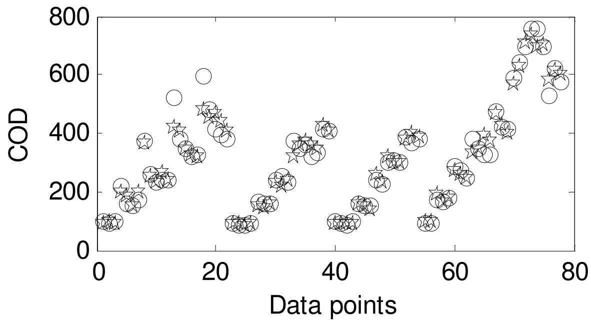

Fig. 5. Measured and calculated values in the effluent COD (output) dimension

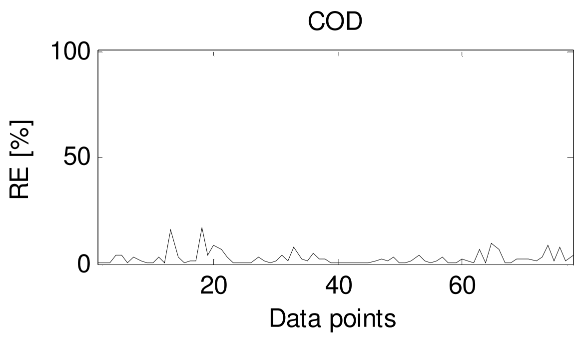

Fig.6. Relative error in the effluent COD (output) dimension

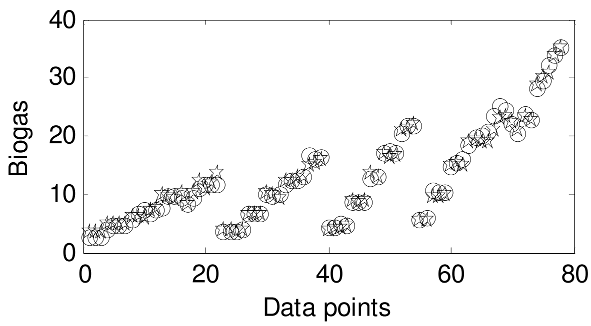

Fig. 7. Measured and calculated values in the Biogas output dimension

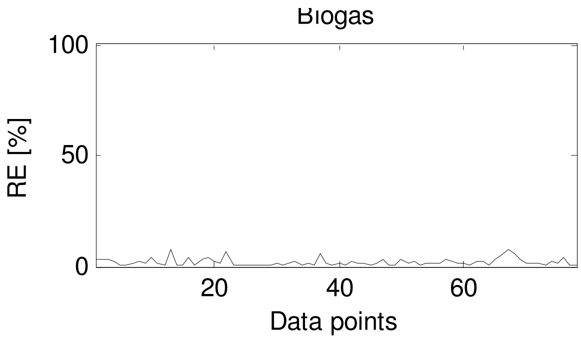

Fig. 8. Relative error in the Biogas output dimension

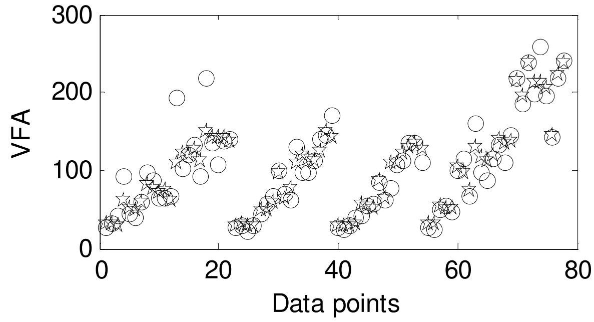

Fig. 9. Measured and calculated values in the volatile fatty acids output dimension

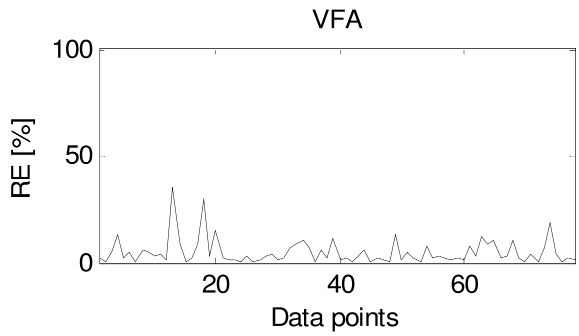

Fig. 10. Relative error in the volatile fatty acid output dimension

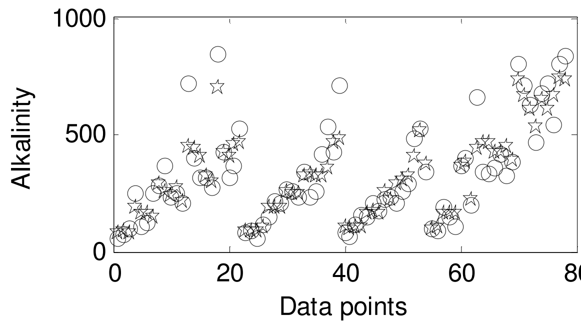

Fig. 11. Measured and calculated values in the alkalinity output dimension.

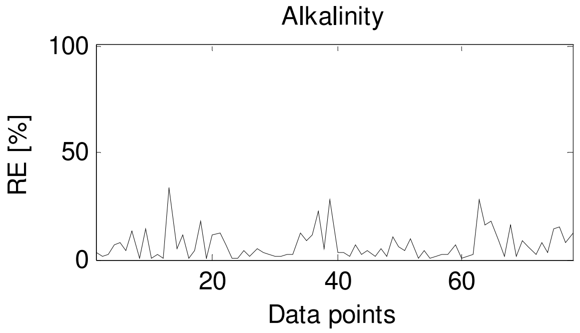

Fig. 12. Relative error in the alkalinity output dimension

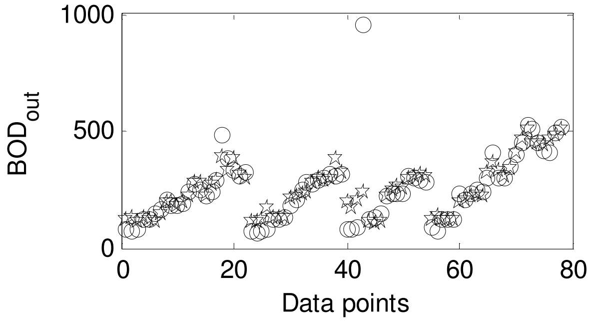

Fig. 13. Measured and calculated values of the BOD_{out} dimension

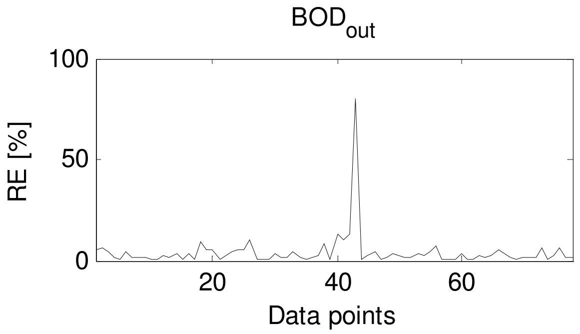

Fig. 14. Relative error of the BOD_{out} dimension

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