BULETINUL INSTITUTULUI POLITEHNIC DIN IAŞI
Publicat de
Universitatea Tehnică „Gheorghe Asachi” din Iaşi
Tomul LVII (LXI), Fasc. 2, 2011
Secţia
ELECTROTEHNICĂ. ENERGETICĂ. ELECTRONICĂ

USING OF A HYBRID METHOD IN THE LOADING PROFILES DETERMINATION OF A HYDROPOWER CASCADE

BY

GH. GRIGORAŞ[1,*], DANIELA COMĂNESCU[2] and GH. CÂRŢINĂ[1]

[1]“Gheorghe Asachi” Technical University of Iaşi
Faculty of Electrical Engineering, Energetics and Applied Informatics,
[2]Hidraulica S.A., Subsidiary “Bistriţa”, Piatra Neamţ, Romania

Received: May 23, 2011
Accepted for publication: June 24, 2011

Abstract. The problem of optimal management of hydropower cascade includes determination, for each hydropower plant, of the operating regime in which it operates. The analysis of loading profiles corresponding to a hydro cascade can represent the first step that electrical companies must to perform for evaluate the daily power reserve**.** Thus, in the paper, an approach to loading profiles determination of a hydropower cascade from Romania is proposed. For this purpose, a hybrid method based on clustering techniques, conjunctively with fuzzy modeling, is applied to classify loading profiles of the hydropower cascade into coherent groups – typical loading profiles (TLP).

Key words: loading profile; hydro cascade; hydropower plant; clustering techniques; fuzzy model.

1. Introduction

For optimal operating of a hydropower cascade, a strategy that can be implemented is based on the typical loading profile (TLP) of the cascade and each hydropower plant. This approach is efficient, convenient, and available for practical system. But for implementation of this strategy it is very important to

[*] Corresponding author: *e-mail*: ggrigor@ee.tuiasi.ro

know loading profiles both the hydropower cascade and for each hydropower plant, because a demand by the dispatcher, regarding electricity generation, is defined for the cascade, while the distribution of the demand over the particular plants is performed according to the defined rules, in accordance with a series of conditions and limitations. Knowing typical loading profile on the cascade, electrical companies can estimate the power reserve available on each power plant and on the whole cascade. Thus they can provide better bidding and improve efficiency marketing strategies in what concern technological system services (Grigoraş *et al.*, 2011; Stojanović *et al.*, 2009; Vucosavić *et al.*, 2009).

In this paper, a cascade containing three small hydropower plants on the Bistriţa river, from Romania, was analysed. The data correspond for the year 2008, when the hydrological regime was a normal one. For these hydropower plants and total cascade were determined the typical loading profiles using the *K*-means clustering method conjunctively with Fuzzy Technique. Obtained results demonstrate the ability of the proposed method to become first step in evaluating power reserve in small hydropower plants which now are not dispatch units.

2. The Loading Profiles Model of a Hydropower Cascade

The loading diagram of a hydropower plant is reconstructed using the normalized loading profile and their daily (monthly, yearly, depending the case) energy. The time interval of sampling load curve data is one hour. The type loading profile is represented by 24 load values throughout of the day.

The shape of load profiles is influenced by the type of the hydropower plant, and on the other hand, by the type of day or season of the year (Grigoraş *et al.*, 2011). Because a large number of loading profiles create unnecessary problems in handling them, they could be grouped into coherent groups, seeing that some similarities exist between loading profiles. For each coherent group a typical loading profile (TLP) is determined.

In the first step of the loading profile determination process, all gathered measurements have to be preprocessed by arranging them and normalize using a suitable normalizing factor (average power, peak power or energy over the surveyed period), (Cârţină *et al.*, 2005; Gasperic *et al.*, 2002):

$$z_{ij} = \frac{x_{ij}}{\sum_i x_{ij}}, \tag{1}$$

where: z_{ij} is the normalized value, x_{ij} – actual value and $\sum_i x_{ij}$ – the energy over the surveyed period.

It is very important to underline that since the classification of the loading profiles through the visual comparison of the graphics is subjective and impractical, the cluster analysis method was applied to solve this problem. Clustering represents the technique of grouping rows together that share similar values across a number of variables. It is a wonderful exploratory technique to help you understand the clumping structure of your data.

The main purpose of clustering method is to compare units that represent loading profiles, and to gather them progressively in coherent groups in a way that the profiles in the same group are similar and the profiles in different groups are distinct. There are two major methods of clustering: hierarchical clustering and *K*-means clustering (Cârţină *et al*., 2005; Jain *et al.*; JMP…Guide, 1998).

a) *Hierarchical clustering* is subdivided into agglomerative methods, which proceed by series of fusions of the *n* objects into groups, and scattering methods, which separate *n* objects successively into finer groupings. Agglomerative techniques are more commonly used. Hierarchical clustering may be represented by a two dimensional diagram, known as *dendrogram*, which illustrates the fusions or divisions made at each successive stage of analysis. Hierarchical clustering is appropriate for small tables. Up to several hundred rows, you can choose the number of clusters you like after the tree is built.

b) *The K-means clustering* is an algorithm to classify or to group the objects based on attributes/features into *K* number of group (*K* is positive integer number). The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid

$$\min(E) = \min\left(\sum_{i=1}^{K}\sum_{x\in C_i} d(x, z_i)\right), \tag{2}$$

where z_i is the center of cluster C_i, while $d(x, z_i)$ is the Euclidean distance between a point x and z_i.

Thus, the criterion function E attempts to minimize the distance of each point from the center of the cluster to which the point belongs. More specifically, the algorithm begins by initializing a set of K cluster centers. Then, it assigns each object of the dataset to the cluster whose center is the nearest, and recomputed the centers. The process continues until the centers of the clusters stop changing.

3. The Algorithm for Loading Profiles Determination

The analysis, based on the *K*-means clustering method, was performed for a data base corresponding to a normal hydrological year, 2008. The data base contain operational recording for the three hydropower plants forming a cascade. The period of sampling load curve data is 1 h. Diagram for determination process of the typical loading profiles is presented in Fig. 1.

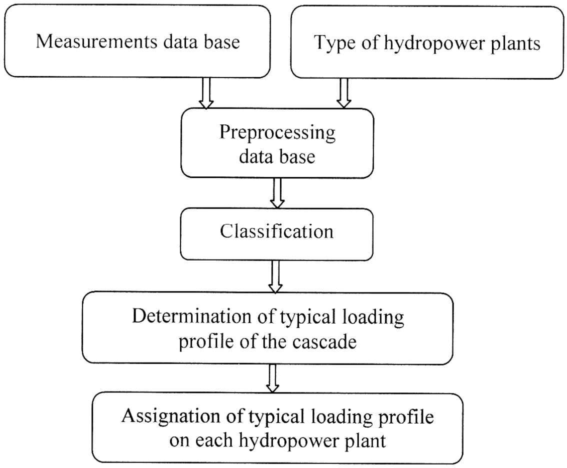

Fig. 1 – Diagram for determination of the typical loading profiles of a hydropower cascade.

Active power profiles, corresponding to the considered hydropower cascade, were normalized relatively to the energy delivered on the cascade, during the day when the load was recorded. For this purpose, the following relation was used:

$$p_i^h = \frac{P_i^h}{E_i}; \; (h = 1, ..., 24; \; i = 1, ..., 366), \qquad (3)$$

where: p_i^h are the normalized values of the active power, [MW/MWh], P_i^h – the active power, [MW], generated by all three hydropower plants at h hour, and E_i – the active energy, [MWh], delivered by the hydropower cascade during the day i.

In the next step it was applied the algorithm for determination of the optimal number of clusters (Grigoraş *et al.*, 2011; Yatskiv & Gosarova, 2005; Ray & Turi, 1999). Getting started, the maximum of clusters, $K_{\max}$, was calculated ($K_{\max} = \sqrt{n} = 19$, where n = 366). Then, for the set of normalized active power profiles, the K-means clustering method with given K, ($2 \le K \le$ $\le K_{\max}$), is used. Finally, the silhouette global coefficient (Grigoraş *et al.*, 2011; Yatskiv & Gosarova, 2005; Ray & Turi, 1999; Rousseeuw, 1987) is calculated to assess the partition quality. The used criterion leads to the result $K_{opt} = 5$, for which SC coefficient's value is maximum (Fig. 2).

Each of these clusters is a daily way of exploiting the water on the cascade and thus a certain power reserve.

After aggregation of the normalized active power profiles of each cluster, the typical loading profiles were determined.

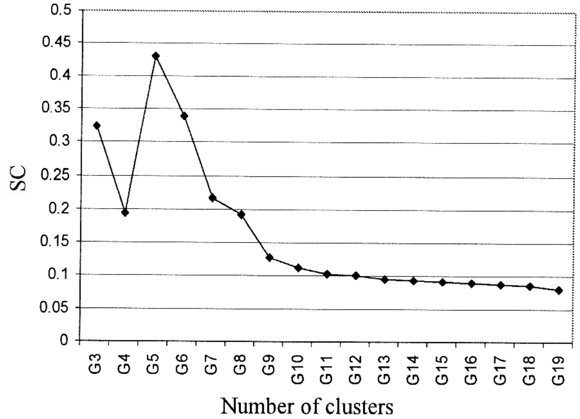

Fig. 2 – Values of the SC coefficients.

The typical profile for each cluster is obtained by averaging the values for each hour

$$m_{P_i}^h = \frac{\sum_{i=1}^{N_D} p_i^h}{N_D}; \; (h=1,...,24; \; i=1,...,N_D)\,, \tag{4}$$

where N_D represents the total number of days from each cluster obtained.

In Figs. 3,…,7 are shown the typical loading profiles corresponding to the five obtained clusters.

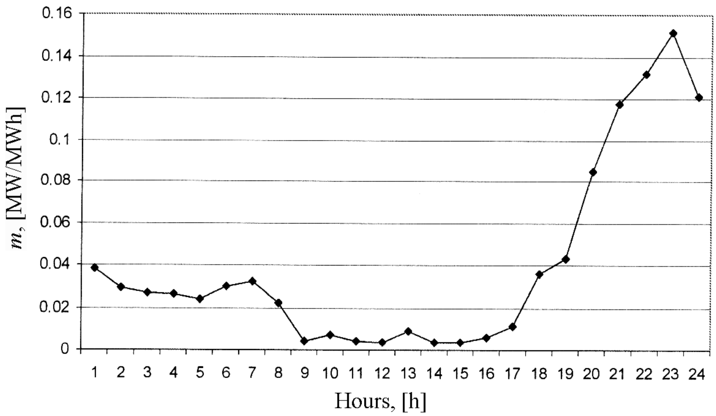

Fig. 3 – Typical loading profile for $G1$ cluster.

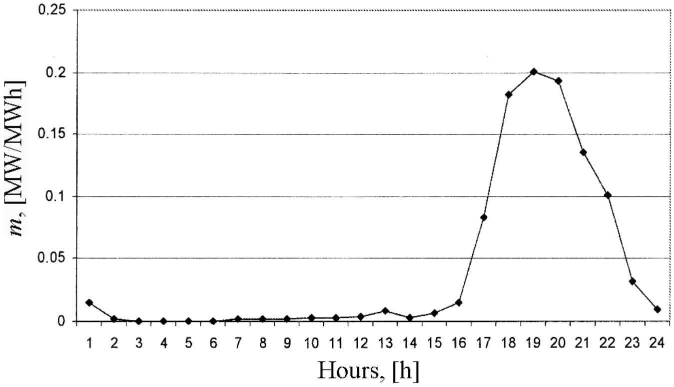

Fig. 4 – Typical loading profile for *G*2 cluster.

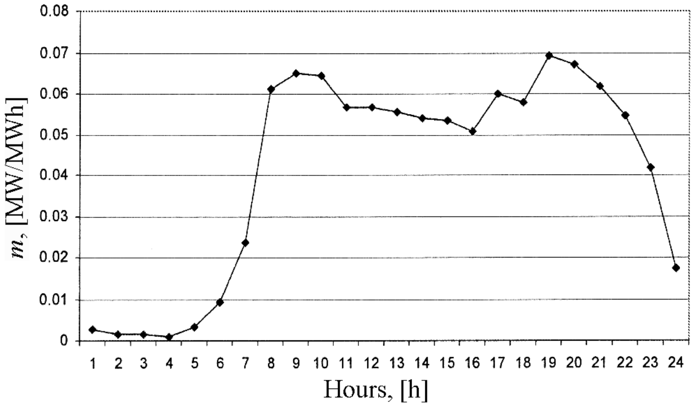

Fig. 5 – Typical loading profile for *G*3 cluster.

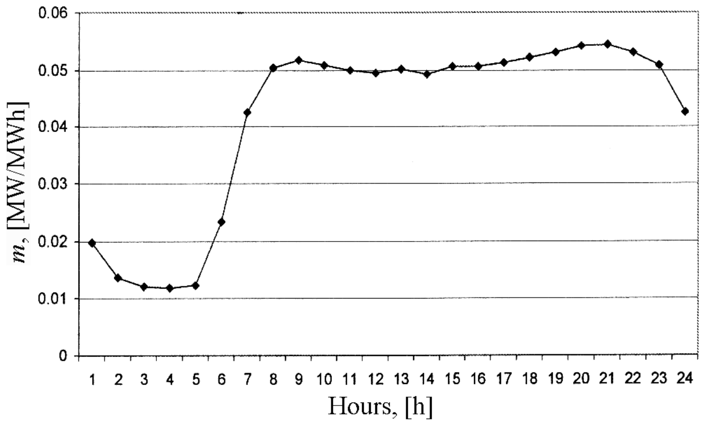

Fig. 6 – Typical loading profile for *G*4 cluster.

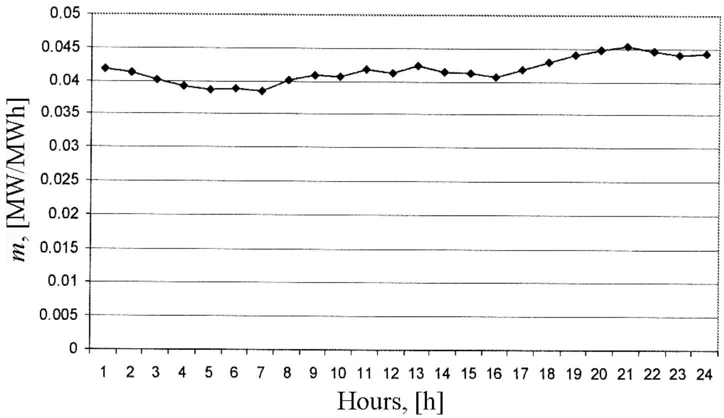

Fig. 7 – Typical loading profile for *G*5 cluster.

In the Table 1 are indicated the number of the representative days from every cluster for which may be similar typical loading profiles obtained. Thus, it can be seen that the most consistent clusters are *G*4 and *G*5, which together accounted for about 80% from total operating days of the hydropower cascade.

Table 1
Centralized Results of Data Analyse

Month	*G*1	*G*2	*G*3	*G*4	*G*5	Total
January	–	–	–	25	6	31
February	4	–	–	17	8	29
March	5	2	4	17	3	31
April	5	1	10	13	1	30
May	4	–	–	14	13	31
June	5	–	–	21	4	30
July	4	–	–	19	8	31
August	–	–	–	1	30	31
September	–	–	–	2	28	30
October	2	–	1	9	19	31
November	1	1	2	14	12	30
December	1	11	10	8	1	31
Total	31	15	27	160	133	366
Total, [%]	8.47	4.10	7.38	43.72	36.34	100

4. Fuzzy Modeling

Starting from the statistical model and using coefficients computed with relation (3) a fuzzy model for loading of a hydro cascade can be used (Fig. 8, Table 2).

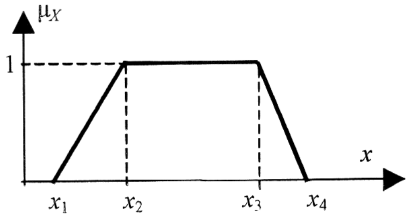

Fig. 8 – Fuzzy trapezoidal model for active power.

Table 2
Breaking Points for Hourly Coefficients of Fuzzy Models

Breaking points	Cluster				
	*G*1	*G*2	*G*3	*G*4	*G*5
X_1	$m_{P_1}^h - k_{11}^h s_{P_1}^h$	$m_{P_2}^h - k_{21} s_{P_2}^h$	$m_{P_3}^h - k_{31} s_{P_3}^h$	$m_{P_4}^h - k_{41} s_{P_4}^h$	$m_{P_5}^h - k_{51} s_{P_5}^h$
X_2	$m_{P_1}^h - k_{12}^h s_{P_1}^h$	$m_{P_2}^h - k_{22} s_{P_2}^h$	$m_{P_3}^h - k_{32} s_{P_3}^h$	$m_{P_4}^h - k_{42} s_{P_4}^h$	$m_{P_5}^h - k_{52} s_{P_5}^h$
X_3	$m_{P_1}^h + k_{13}^h s_{P_1}^h$	$m_{P_2}^h + k_{23} s_{P_2}^h$	$m_{P_3}^h + k_{33} s_{P_3}^h$	$m_{P_4}^h + k_{43} s_{P_4}^h$	$m_{P_5}^h + k_{53} s_{P_5}^h$
X_4	$m_{P_1}^h + k_{14} s_{P_1}^h$	$m_{P_2}^h + k_{24} s_{P_2}^h$	$m_{P_3}^h + k_{34} s_{P_3}^h$	$m_{P_4}^h + k_{44} s_{P_4}^h$	$m_{P_5}^h + k_{54} s_{P_5}^h$

Table 3
Breaking Points of the Fuzzy Model Corresponding to Typical Loading Profiles of G4 and G5 Clusters

h	Breaking points for fuzzy model of G1 cluster				Breaking points for fuzzy model of G2 cluster			
	X_1 MW/MWh	X_2 MW/MWh	X_3 MW/MWh	X_4 MW/MWh	X_1 MW/MWh	X_2 MW/MWh	X_3 MW/MWh	X_4 MW/MWh
1	0.002	0.006	0.033	0.037	0.024	0.028	0.055	0.059
2	0.002	0.005	0.023	0.025	0.025	0.028	0.054	0.058
3	0.004	0.006	0.018	0.020	0.029	0.032	0.048	0.051
4	0.004	0.006	0.018	0.020	0.028	0.030	0.048	0.051
5	0.003	0.005	0.019	0.021	0.028	0.030	0.047	0.049
6	0.005	0.007	0.047	0.054	0.023	0.027	0.051	0.054
7	0.018	0.023	0.062	0.067	0.026	0.029	0.048	0.051
8	0.032	0.036	0.065	0.069	0.028	0.031	0.049	0.052
9	0.035	0.039	0.065	0.069	0.030	0.032	0.049	0.052
10	0.033	0.037	0.065	0.069	0.029	0.032	0.050	0.052
11	0.037	0.040	0.060	0.063	0.024	0.028	0.055	0.059
12	0.034	0.038	0.061	0.065	0.023	0.027	0.056	0.060
13	0.036	0.039	0.061	0.065	0.023	0.027	0.057	0.062
14	0.033	0.037	0.062	0.065	0.023	0.027	0.056	0.060
15	0.037	0.040	0.061	0.064	0.023	0.027	0.056	0.059
16	0.036	0.039	0.062	0.065	0.028	0.031	0.051	0.053
17	0.037	0.041	0.062	0.065	0.029	0.032	0.052	0.055
18	0.038	0.042	0.063	0.066	0.031	0.033	0.053	0.055
19	0.040	0.043	0.063	0.067	0.033	0.035	0.053	0.055
20	0.041	0.044	0.064	0.067	0.033	0.035	0.054	0.057
21	0.043	0.045	0.064	0.066	0.033	0.036	0.055	0.058
22	0.041	0.044	0.062	0.065	0.033	0.035	0.054	0.056
23	0.037	0.041	0.061	0.064	0.032	0.035	0.053	0.056
24	0.022	0.026	0.059	0.064	0.035	0.037	0.051	0.053

In the Table 2, coefficients k_{ij}, (i = 1, N_G, j = 1, 4), were determined for each hour, *h*, depending on the results of a statistical calculation performed and the experience of the authors. Thus, in the Table 3, the breaking points of the fuzzy models corresponding to typical loading profiles of the *G*4 and *G*5 clusters are presented as examples.

In the Figs. 9,…,13 the variation of all fuzzy typical loading profiles are shown.

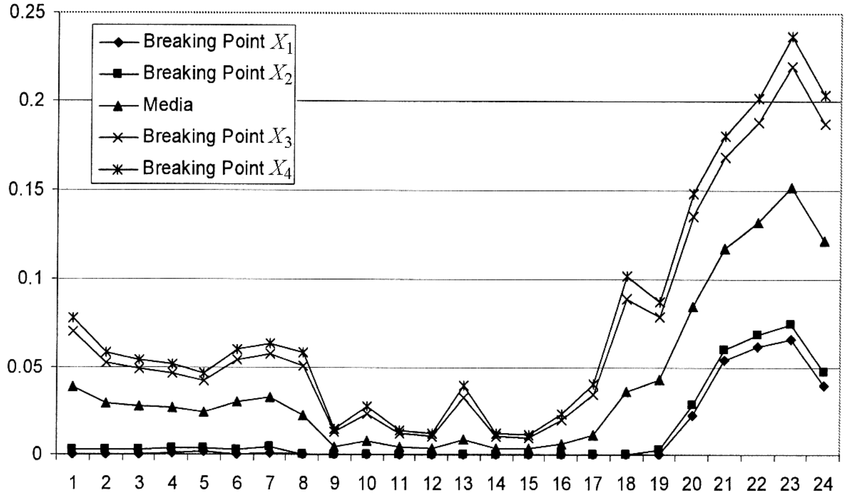

Fig. 9 – Fuzzy model of TLP for *G*1 cluster.

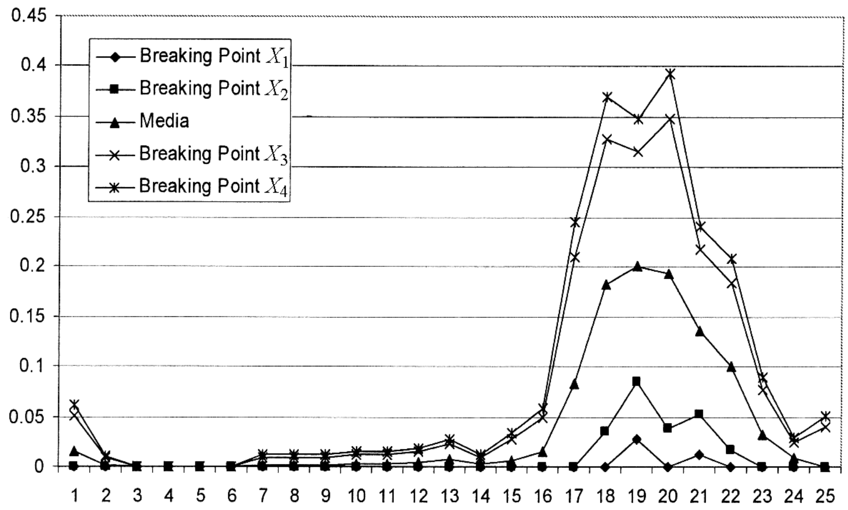

Fig. 10 – Fuzzy model of TLP for *G*2 cluster.

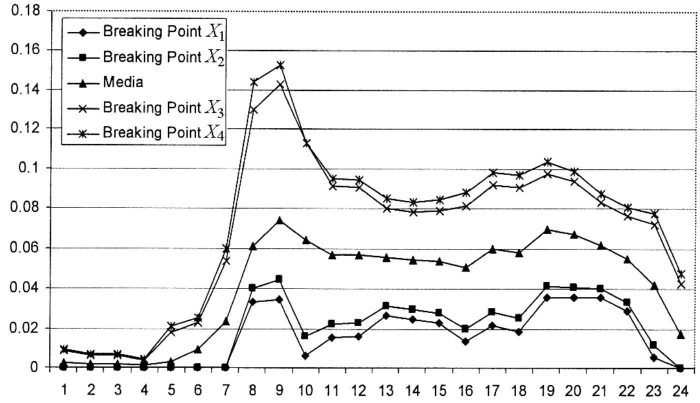

Fig. 11 – Fuzzy model of TLP for *G*3 cluster.

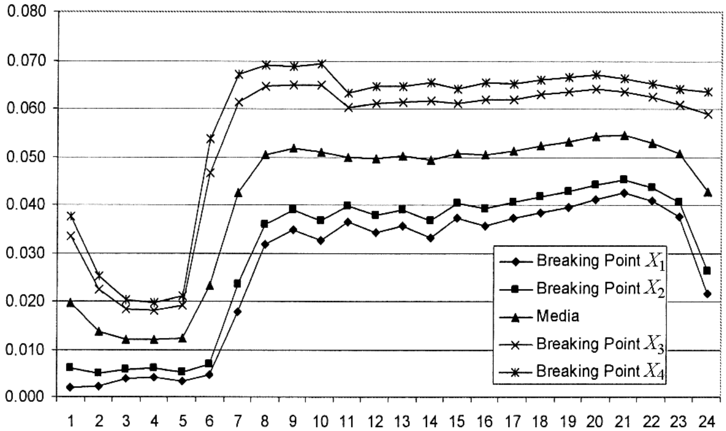

Fig. 12 – Fuzzy model of TLP for *G*4 cluster.

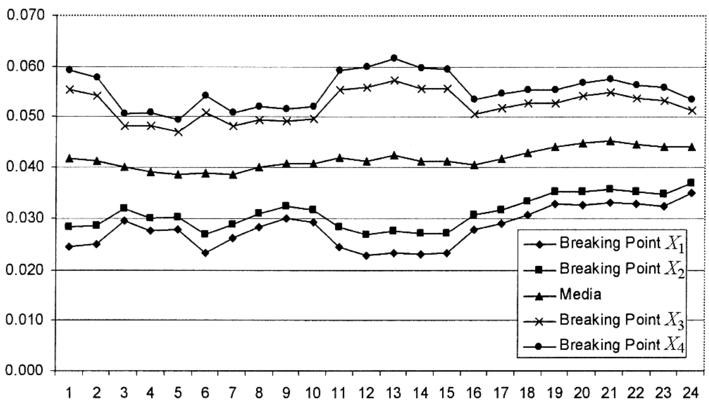

Fig. 13 – Fuzzy model of TLP for *G*5 cluster.

5. Conclusions

A hybrid method, based on the *K*-means clustering algorithm conjunctively with fuzzy modeling, is proposed for determination of the Typical Loading Profiles of a hydropower cascade consisting of three small hydropower plants. Obtained results demonstrate the ability of the proposed method to become first step in evaluating power reserve in small hydropower plants, which now are not dispatch units.

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FOLOSIREA UNEI METODE HIBRIDE ÎN DETERMINAREA PROFILURILOR DE ÎNCĂRCARE ALE UNEI AMENAJĂRI HIDROENERGETICE

(Rezumat)

Se propune o abordare relativ nouă a determinării profilurilor tip de încărcare aferente unei amenajări hidroenergetice formată din trei hidrocentrale, pentru care s-au folosit tehnicile de grupare in corelaţie cu tehnicile fuzzy. Rezultatele obţinute demonstrează capacitatea acestor tehnici de a depăşi problemele privitoare la alcătuirea profilurilor tip de încărcare pentru o amenajare hidroenergetică.