Impact on the fuzzy modeling in operation of electric distribution systems

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Abstract: - Estimation of the load, particularly of the peak load, is basis for the system state estimation, and for technical, and economic calculations. This makes possible improvement in economic operation, maintenance of electrical equipment, and optimal planning and operating of electrical distribution systems. In the paper, starting from a fuzzy correlation model of the loads, a power flow analysis from an electric distribution system with the 20 kV voltage level is presented. The results showed that using a fuzzy correlation model for the loads from the 20 kV nodes puts a new quality into the electric distribution system analysis in uncertain conditions.

Key-Words: - fuzzy model, correlation loads, peak load, electric distribution system, power flow analysis.

1 Introduction

Information plays a very important role in electric distribution systems. Thus, estimation of the loads represents basis for the system state estimation for technical and economic calculations, [1]–[5].

The limited sources and the growing request of electric energy, together with the impact of power generation, transportation, distribution and usage on the environment and the eco-system, motivates the research on techniques to optimize the energy utilization in cyber-physical energy systems, [6], [7]. Cyber-physical systems (CPS) represent an emerging technology that aims to integrate embedded processing devices to monitor and control physical processes, [6]–[10]. Cyber-Physical Energy Systems (CPES) are a dedicated case of CPS dealing with electric power systems. In Cyber-Physical Energy Systems, the "physical" process is made by a network of electric devices that are controlled by a complex set of interconnected embedded systems. In these systems, embedded computing is integrated within the electric power system to gather information about the most relevant parameters, such as voltage, current, phases, consumed energy and power, [6], [7]. Acquired data are then combined and processed to generate suitable control commands to achieve the desired application goal. Typical goal is the estimation of the state corresponding to the electric power system.

But the problem of generating a coherent information set is critical in electric distribution systems, because, except the usual measurements from substations, there are few information about the state of network, [1]. The continuous measurement of the loading of network elements is only carried out in particular places. In the remaining part of the network load conditions are only measured infrequently. With load modeling based on power system elements it is possible to get detailed information of the development of the loads on elements such as transformers, lines, cable links and this is used to support the planning and operation of distribution systems, [11]-[13]. As a result, there is at any moment a generalized uncertainty about the power demand conditions and therefore about the network loading, voltage level and power losses. The effects of the load uncertainties will propagate to calculation results, affecting the state estimation and the optimal solutions of the various problems concerning the operation control and development planning, [1].

The complexity of the problem increased with the size of the electric distribution system. In this situation, different technologies such as fuzzy logic, neural networks, and expert systems have been developed to manage the large amount of data available and to best utilize the information provided in the data. One of immediate challenges is what type of technology is suitable for us to appropriately process the information to improve our applications, [1]–[3], [5], [11], [20], [21].

In this paper, starting from a fuzzy correlation model for the loads from 20 kV nodes of the electric distribution system, a power flow analysis is made. The obtained results are compared with values from real case. The analysis revealed that the use of these fuzzy models leads to satisfactory results regarding to the state estimation of the electric distribution system at the peak load.

2 Aspects about Fuzzy Modeling

The notion of modeling is essential to modern techniques of process control. Developing a control process in fact means developing a model that allows one to predict the action and reduce the amount of feedback required. An important point that needs to be made is that the model does not represent reality, but is a projection of it in a simplified space, whose dimensions were chosen depending on the problem to be solved. The model cannot be good or bad as such, but only adapted or not to the prediction requirements of the process.

Modeling can be performed in numerous ways. Not long ago, modeling meant systems of differential equations, transfer functions, and so on. The introduction of computers was perceived as a powerful means of computation and of pushing the limits of model complexity and process control.

Since its first presentation in 1965 by L. A. Zadeh, the Fuzzy Techniques (FT) had an unexpected growth and success. The broad development of mathematical theory especially in areas of Fuzzy Control, Neural Networks, and Pattern Recognition provided the basis for different applications. They finally became the driving force of Fuzzy Techniques that today is reflected in many different software and hardware products, [26].

The basic idea of FT is to model and to be able to calculate with uncertainty. Mathematical models and algorithms in electric power system theory aim to be as close to reality as possible. The required human observations, descriptions, and abstractions during the modeling process are always a source of imprecision. A way to classify this imprecision is depicted in Fig. 1, [26].

While the two sources of imprecision have long since led to suitable mathematical models, the last one came in our mind only a few decades ago, although we use it instinctively in our everyday life the linguistic descriptions such as Small, Medium, High [5], [11], [26]. These vague descriptions are as well part of modeling process and the algorithm.

Uncertainty in fuzzy logic is a measure of nonspecifically that is characterized by possibility distributions. This is, somewhat similar to the use of probability distributions, which characterize uncertainty in probability theory.

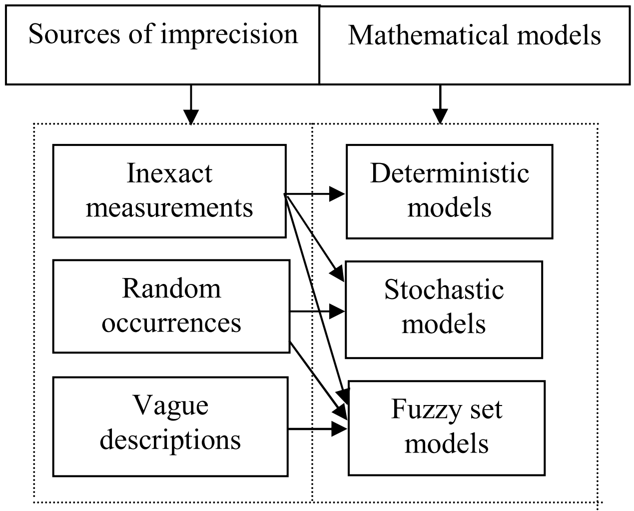

Fig. 1. Mathematical models for imprecision

Linguistic terms used in our daily conversation can be easily captured by fuzzy sets for computer implementations. A fuzzy set is a set containing elements that have varying degrees of membership in the set. Even though the choices of membership function are subjective, there are some rules for membership function selection that can produce good results. The membership values of each function are normalized between 0 and 1.

There are different ways to derive membership functions. Subjective judgment, intuition and expert knowledge are commonly used in constructing membership function. Even though the choices of membership function are subjective, there are some rules for membership function selection that can produce well the results. The membership values of each function are normalized between 0 and 1.

The uncertain of the load level, reliability indices and the length of the feeders and so on can be represented as fuzzy numbers, with membership functions over the real domain $\Re$. A fuzzy number can have different forms: linear, piecewise-linear, hyperbolic, triangular, trapezoidal or gaussian, Figs. 2 – 7. Generally, the fuzzy numbers are represented as trapezoidal or triangular fuzzy number.

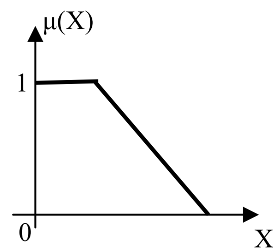

Fig. 2. Linear membership function

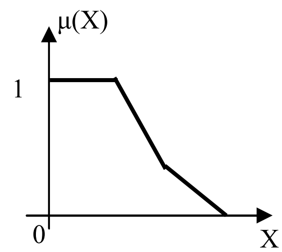

Fig. 3. Piecewise-linear membership function

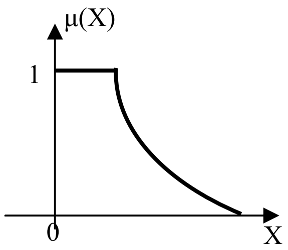

Fig. 4. Hyperbolic membership function

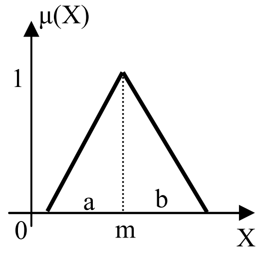

Fig. 5. Triangular membership function

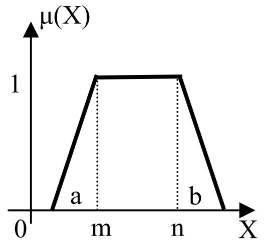

Fig. 6. Trapezoidal membership function

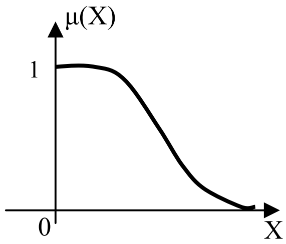

Fig. 7. Gaussian membership function

In the case of triangular and trapezoidal representations, a fuzzy number $\widetilde{A}$ is usually represented by its breaking points, Fig. 5, Fig. 6:

$$\widetilde{A} \Leftrightarrow (x_1, x_2, x_3) = [m, a, b] \tag{1}$$

$$\widetilde{A} \Leftrightarrow (x_1, x_2, x_3, x_4) = [m, n, a, b] \tag{2}$$

3 Fuzzy Modeling of the Nodal Loads Using Correlation Theory

The knowledge of loads at system buses is one of the most important requirements, for efficient operation of power systems. Estimation of the load, particularly of peak loads, allows improvement in operation and maintenance of electrical equipment and in planning of network operating configuration, [1], [12]. The main difficulties in modeling of peak loads at receiving buses in distribution systems result from the random nature of loads, diversification of load shapes on different parts of the systems, the deficiency of measured data and the fragmentary and uncertain character of information on loads and customers, [3]-[5].

The basic constraints of the general model are:

- It must represent flows at given time, compatible with the Kirchhoff laws.
- It must present coherency between estimated loads and measurements.
- The load allocation must be independent of the network topology under operation.

The last point is important: it would be unacceptable, from an operator point of view that the established load for a given node would "magically" chance, if he performed some switching or load transfer simulation.

Many factor such loads and voltages at system buses, energy consumption, and parameters of equivalent circuits are included in power distribution calculations. These data is loaded with different errors arising from the inaccuracy of measuring instruments and deficiency of measurements, [3]-[5], [13]. The theory, which enables efficient description on unreliable and inaccurate data, and relationship between them, is fuzzy set theory. This theory was introduced to various engineering problems in which uncertainties were represented as intrinsic ambiguities. In this paper, the fuzzy numbers associated to a trapezoidal membership function, Fig. 8, are used to represent a vague knowledge about the load behavior, [2]-[5].

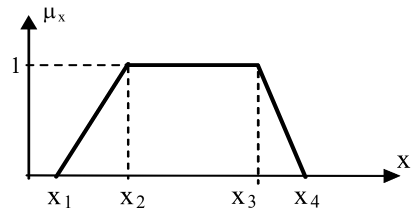

Fig. 8. Trapezoidal fuzzy load

This kind of models can be used to represent the uncertain knowledge about load behavior either for active and reactive powers.

Thus, if for some substations there are sufficient database, for a good forecasting of the load, for the other substations of the power system, the forecasting of the load can be make using the correlation study. Fig. 9 presents an uncorrelated fuzzy load characterized by its active and reactive membership functions expressed by trapezoidal fuzzy numbers, [2].

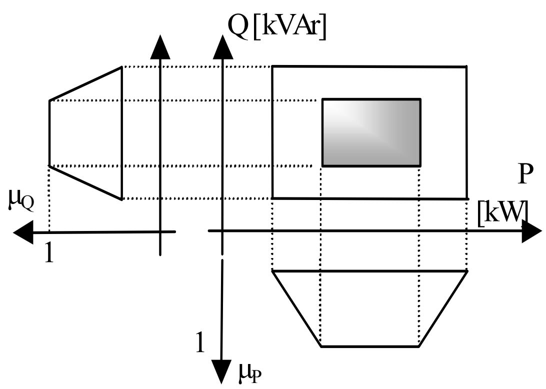

Fig. 9. Uncorrelated P, Q fuzzy loads

This representation allows concluding that, assuming such a model, all possible combinations of active and reactive powers values are possible. Therefore, this model will certainly be far from reality and another can be used, Fig. 10.

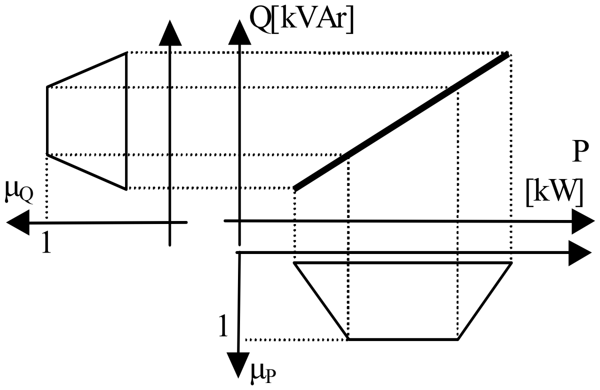

Fig. 10. Correlated P, Q fuzzy loads

Based on the correlation theory, the fuzzy models of the loads can be obtained using the algorithm presented below. The starting point of the algorithm is statistical analysis of the active and reactive curves of the substations and utilization of a linear regression model. This can be made for different time windows (window 24h, window 7h etc). The window 24h can be used successfully to estimate the hourly load on any substation. The other time windows 7h can be used in the peak load estimation of the substations, using the maximum value of the active power recorded in a reference substation.

The steps of the algorithm [11], [13]:

- Select of a reference for the correlation study. The reference is chosen the active power curve of the main injection point (usually the connecting power station to a higher voltage level grid);
- Calculation of the k_{PrPi} and k_P:

$$k_{P_rP_i} = \rho_{P_rP_i} \cdot \frac{\sigma_{P_i}}{\sigma_{P_r}}; \qquad (3)$$

$$k_P = \sum_{j=1}^{h} (P_{ij} - k_{P_rP_i} \cdot P_{rj}) / L_h \qquad (4)$$

where:

P_r - the reference active power;

P_i – the active power on the i substation (i = 1, 2, …, n, n is total number of the 20 kV substations from the analysis system);

ρ_{PrPi} – the correlation coefficient between the active powers of the substation i and reference r;

σ_{Pi}, σ_{Pi} – the standard deviations for $P_i(t)$, $P_r(t)$;

L_h – analysis window dimension (24, 7, etc);

h – hours number of the analysis windows.

- Determination the active powers of substations at the peak load hour of the system with the linear regression model:

$$P_i = k_{P_rP_i} \cdot P_r + k_P \qquad (5)$$

- Determination the fuzzy models for active powers of substations at the peak load hour. Thus, for the maximum values of the reference, a fuzzy trapezoidal model can be chosen, Fig. 8.

If the type reactive power curves from the 20 kV distribution substations are known, for determination of the relationship between the active and reactive powers, same algorithm is used.

In this situation, the reference for the correlation study is same, so the reactive powers could be determined:

$$Q_i = k_{P_rQ_i} \cdot P_r + k_Q \qquad (6)$$

where coefficients k_{PrQi} and k_Q are same purport with the coefficients k_{PrPi} and k_P.

In contrary case, for estimation of the fuzzy reactive powers from the distribution substations the following fuzzy variables are used: the fuzzy active powers determined with the fuzzy model above described and power factor $\cos\varphi$, considered as fuzzy variable with the trapezoidal membership function having the following breaking points:

x_1=0.85; x_2=0.88; x_3=0.92; x_4=0.95.

The fuzzy model used for the $\cos\varphi$ corresponds to urban residential loads. Also, fuzzy variables P and $\cos\varphi$ must be correlated as it is shown in Fig. 11.

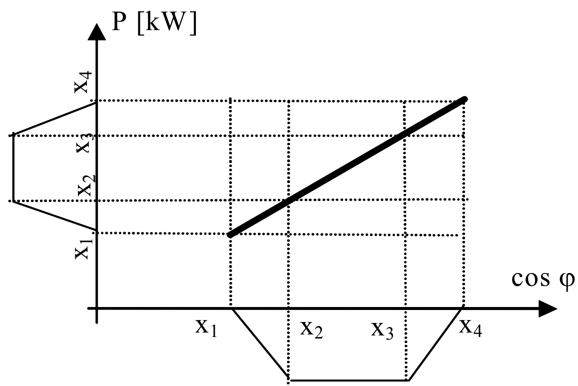

Fig. 11. Correlation between fuzzy variables P and $\cos\varphi$

Finally, reactive powers result from relation:

$$Q = P \cdot \tan\varphi \qquad (7)$$

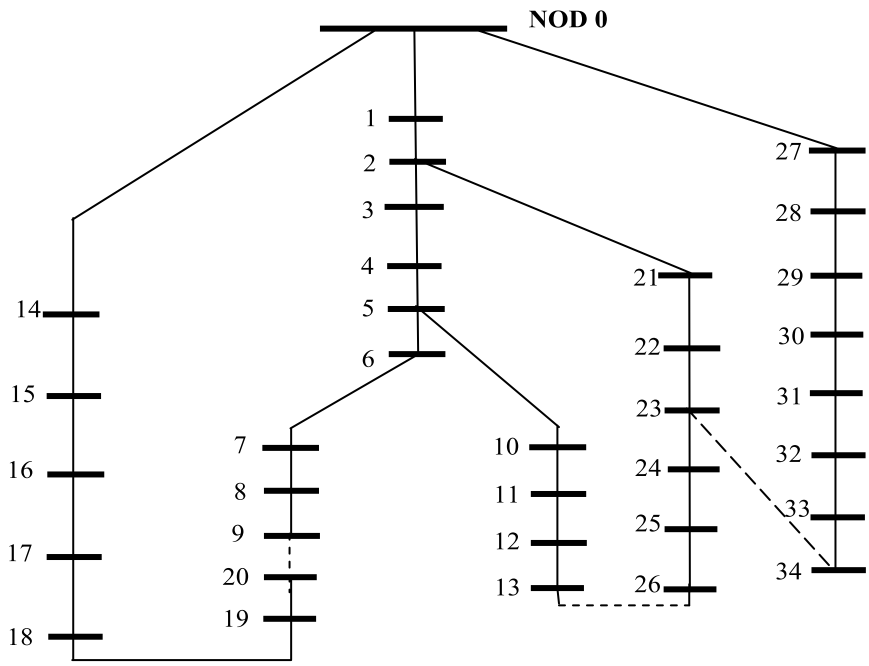

Fig. 12. The 20 kV test electric distribution system

4 Study Case

A study case based on a 20 kV test electric distribution system (34 substations) is used to illustrate fuzzy power flow models, Fig. 12. The distribution substations are equipped with one transformer with the nominal power by 400 kVA, 630 kVA and 1000 kVA. The results of study are obtained for the loading system at the peak load.

4.1 Estimation of the nodal loads

The starting point for the proposed method based on fuzzy modeling of the nodal load is statistical analysis of the active and reactive power curves.

For example, in the Figs. 13 – 16, four analysis windows for variation of active powers from the substation no. 28 are represented: window 24h, window 7h (t_{PL} ± 3h), 7h (t_{PL}-3h; t_{PL}+3h), 7h (t_{PL}-4h; t_{PL}+2h) and 7h (t_{PL}-5h; t_{PL}+1h) (where t_{PL} represents the hour when it registered the system peak load).

In the Table 1, the estimated values of the active powers from the all electric substations, at the peak load, for the different time windows are presented. For a better interpretation of the results, the estimation errors are shown in the Fig. 17. The lowest estimation errors were obtained for the time window 7h (t_{PL}-5; t_{PL}+1).

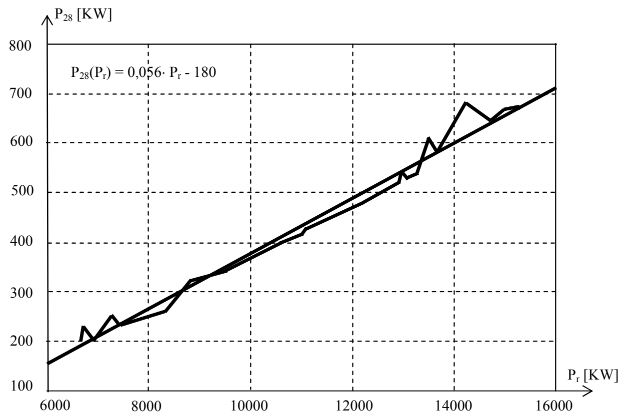

Fig. 13. The variation P_{28} (P_r), window 24 h

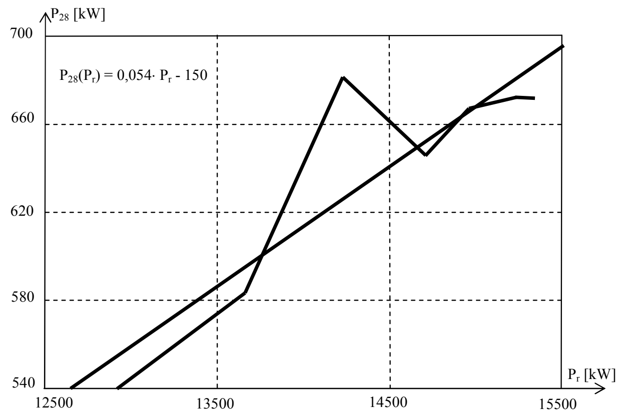

Fig. 14. The variation $P_{28}(P_r)$, window 7h (t_{PL}–3h; t_{PL}+3h)

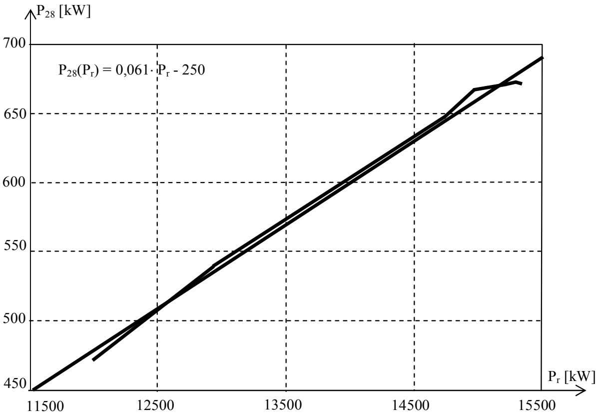

Fig.15. The variation $P_{28}(P_r)$, window 7h (t_{PL}–4h; t_{PL}+2h)

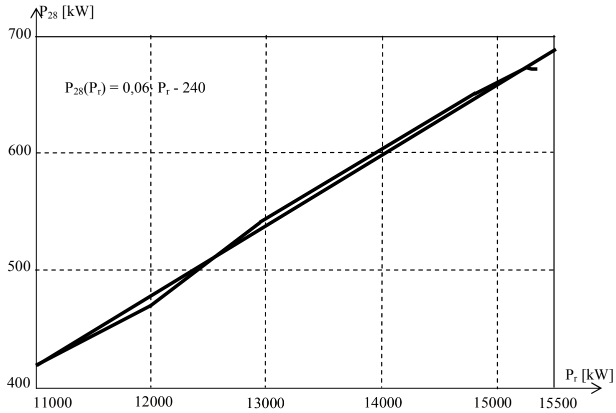

Fig.16. The variation $P_{28}(P_r)$, window 7h (t_{PL}–5h; t_{PL}+1h)

Table 1. The obtained results with the statistical model at the peak load hour of the distribution system

DS	P_m [kW]	Window 24h		Window 7h (t_{PL}-3; t_{PL}+3)		Window 7h (t_{PL}-5; t_{PL}+1)	
		P_e [kW]	Err_P [%]	P_e [kW]	Err_P [%]	P_e [kW]	Err_p [%]
1	240.50	239.87	-0.25	242.91	1.00	239.18	-0.54
2	216.30	224.75	3.90	221.72	2.50	214.72	-0.73
3	311.10	346.66	11.43	325.90	4.75	315.86	1.53
4	436.00	397.62	-8.80	448.77	2.92	430.60	-1.23
5	410.70	381.80	-7.03	404.67	-1.46	422.27	2.81
6	420.30	422.38	0.49	415.96	-1.03	407.03	-3.15
7	600.60	614.11	2.24	597.28	-0.55	610.54	1.65
8	617.70	609.06	-1.39	605.77	-1.93	622.15	0.72
9	561.20	560.48	-0.12	553.07	-1.44	567.94	1.20
10	208.70	213.18	2.15	211.44	1.31	200.76	-3.80
11	617.00	607.32	-1.56	598.10	-3.06	626.26	1.50
12	588.10	562.06	-4.42	593.15	0.86	586.35	-0.29
13	404.90	408.13	0.79	378.81	-6.44	406.06	0.28
14	357.20	397.83	11.37	362.83	1.57	359.61	0.67
15	360.40	384.70	6.74	354.75	-1.56	363.06	0.73
16	365.60	371.42	1.59	388.43	6.24	356.33	-2.53
17	545.70	596.06	9.22	596.63	9.33	543.04	-0.48
18	254.90	257.03	0.83	257.09	0.86	260.77	2.30
19	191.30	213.61	11.66	202.63	5.92	191.78	0.25
20	168.10	196.46	16.87	183.60	9.22	162.46	-3.35
21	667.50	622.26	-6.77	618.86	-7.28	662.08	-0.81
22	421.40	409.54	-2.81	414.28	-1.68	428.87	1.77
23	440.40	388.90	-11.69	411.62	-6.53	436.36	-0.91
24	637.00	642.21	0.81	633.43	-0.56	619.42	-2.75
25	452.30	444.02	-1.82	459.63	1.62	448.10	-0.92
26	623.70	534.84	-14.24	615.64	-1.29	616.91	-1.08
27	402.20	392.49	-2.41	394.50	-1.91	408.35	1.53
28	671.80	677.40	0.83	686.71	2.21	679.72	1.18
29	634.10	643.68	1.51	640.00	0.93	628.87	-0.82
30	594.20	569.71	-4.12	613.92	3.32	594.83	0.10
31	388.10	437.63	12.76	386.38	-0.44	399.55	2.95
32	329.80	341.49	3.54	332.31	0.76	330.87	0.32
33	571.00	568.94	-0.36	563.85	-1.25	549.30	-3.80
34	635.40	667.39	5.03	630.39	-0.78	655.06	3.09

The errors were calculated with the relation:

$$Err = \frac{P_{e\,i} - P_{m\,i}}{P_{m\,i}} \cdot 100 \quad (\%) \qquad (8)$$

where:

P_{mi} – real value for active power from electric substation i;

P_{ei} – estimated values for active power from electric substation i.

But, because of the difficulties in the modeling of peak load from the electric distribution system, in the following fuzzy techniques are used.

The uncertain of the peak load was represented as fuzzy number with a trapezoidal membership function. The breaking points (x_1, x_2, x_3 and x_4) of the fuzzy trapezoidal numbers, corresponding to the active and reactive powers from substations at the peak load of analyzed electric distribution system, window 7h(t_{PL}-5; t_{PL}+1), are presented in Table 2.

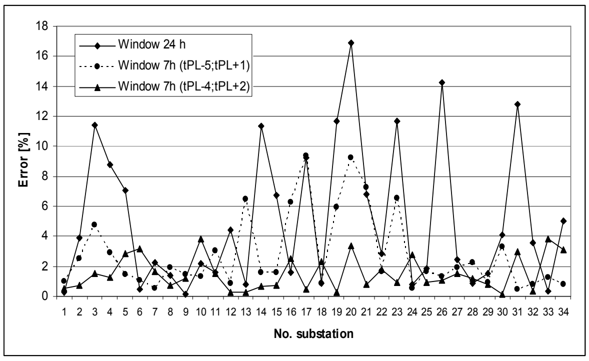

Fig. 17. The estimation errors obtained with the statistical model for different time windows

Table 2. Breaking points for the fuzzy trapezoidal models, window 7h (t_{PL}-5h; t_{PL}+1h)

DS	Active Power					Reactive Power				
	x_1 [kW]	x_2 [kW]	x_3 [kW]	x_3 [kW]	$Crisp_P$ [kW]	x_1 [kVAr]	x_2 [kVAr]	x_3 [kVAr]	x_4 [kVAr]	$Crisp_Q$ [kVAr]
1	203.97	221.57	239.18	256.78	230.37	126.41	119.59	101.89	84.40	108.07
2	181.20	197.96	214.72	231.47	206.34	112.30	106.85	91.47	76.08	96.68
3	262.84	289.35	315.86	342.37	302.61	162.90	156.18	134.56	112.53	141.54
4	331.89	381.24	430.60	479.95	405.92	205.69	205.78	183.44	157.75	188.16
5	396.70	409.48	422.27	435.05	415.88	245.85	221.02	179.89	143.00	197.44
6	364.66	385.85	407.03	428.22	396.44	226.00	208.26	173.40	140.75	187.10
7	563.46	587.00	610.54	634.07	598.77	349.21	316.83	260.09	208.41	283.63
8	553.52	587.83	622.15	656.46	604.99	343.04	317.28	265.03	215.77	285.28
9	521.49	544.71	567.94	591.16	556.32	323.19	294.01	241.94	194.31	263.36
10	162.19	181.47	200.76	220.05	191.12	100.52	97.95	85.53	72.33	89.08
11	570.93	598.59	626.26	653.93	612.43	353.83	323.09	266.79	214.94	289.66
12	532.85	559.60	586.35	613.10	572.98	330.23	302.04	249.79	201.52	270.90
13	411.23	408.65	406.06	403.48	407.35	254.86	220.57	172.98	132.62	195.26
14	316.62	338.11	359.61	381.10	348.86	196.23	182.50	153.19	125.26	164.30
15	334.89	348.97	363.06	377.14	356.01	207.55	188.36	154.66	123.96	168.63
16	301.29	328.81	356.33	383.84	342.57	186.73	177.48	151.80	126.16	160.54
17	439.03	491.04	543.04	595.04	517.04	272.09	265.04	231.34	195.58	241.01
18	216.96	238.86	260.77	282.67	249.82	134.46	128.93	111.09	92.91	116.85
19	169.93	180.85	191.78	202.70	186.32	105.32	97.62	81.70	66.63	87.82
20	145.98	154.22	162.46	170.70	158.34	90.47	83.24	69.21	56.11	74.76
21	626.18	644.13	662.08	680.03	653.11	388.08	347.67	282.05	223.52	310.33
22	419.03	423.95	428.87	433.79	426.41	259.69	228.83	182.70	142.58	203.45
23	390.01	413.19	436.36	459.54	424.77	241.71	223.02	185.89	151.04	200.42
24	549.63	584.52	619.42	654.31	601.97	340.63	315.50	263.87	215.06	283.77
25	395.52	421.81	448.10	474.39	434.96	245.13	227.67	190.89	155.92	204.90
26	544.85	580.88	616.91	652.94	598.90	337.67	313.53	262.81	214.61	282.16
27	401.53	404.94	408.35	411.76	406.65	248.85	218.57	173.96	135.34	194.18
28	587.35	633.54	679.72	725.91	656.63	364.01	341.95	289.56	238.60	308.53
29	590.84	609.85	628.87	647.89	619.36	366.17	329.17	267.90	212.95	294.05
30	518.79	556.81	594.83	632.85	575.82	321.52	300.54	253.40	208.01	270.87
31	391.53	395.54	399.55	403.56	397.55	242.65	213.49	170.21	132.64	189.75
32	306.86	318.86	330.87	342.87	324.87	190.18	172.11	140.95	112.70	153.98
33	480.38	514.84	549.30	583.75	532.07	297.72	277.88	234.00	191.87	250.37
34	626.36	640.71	655.06	669.41	647.89	388.19	345.82	279.06	220.03	308.27

The values for active powers were obtained using the correlation/linear regression model (5), for which the fuzzy model of the reference has the following values of the breaking points: $x_1=0.9\cdot P_r$; $x_2=0.95\cdot P_r$; $x_3 = P_r$ and $x_4 = 1.05\cdot P_r$. The results for the reactive powers were obtained using model (6), using same reference.

The crisp values ($Crisp_P$ and $Crisp_Q$) from the Table 2 represent values obtained from defuzzification process using the centroid method.

The estimation errors for the active powers from electric distribution substations are shown in the Fig. 18.

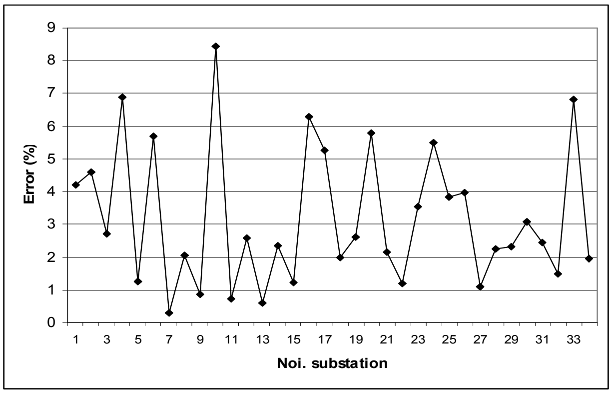

Fig. 18. The estimation errors for active powers obtained with the fuzzy model

The numerical data show that the fuzzy correlation model can be used with very good results for determination of the peak load of different distribution substations.

4.2 Power flow analysis using fuzzy correlation loads

Using the results obtained in the above paragraph, a fuzzy power flow analysis is made. Thus, the calculations must be carried out in every break-point of fuzzy numbers corresponding to nodal loads.

Therefore, all state variables (node voltages, power flow, power losses and so on) will be calculated as fuzzy numbers. The results of study are obtained for the loading network at the peak load.

The signification of the calculated variables that described network state at the peak load is:

- P_s, Q_s – active and reactive power injected by the bulk system;
- ΔP_L, ΔQ_L – total active and reactive losses of the lines;
- ΔP_{Tr}, ΔQ_{Tr} – total active and reactive losses of the transformers;
- ΔP_T, ΔQ_T – total active and reactive losses of the distribution system;
- Q_{CL} - total reactive power of the lines.

In the Table 3 the most important steady state variables are presented. The crisp values of these variables are compared with the real values, and the conclusion is that the proposed method leads to encouraging results.

From the Figs. 19 – 20 it can observe that after steady state calculations, the membership functions for power losses are approximately triangular (x_3 is very close x_4).

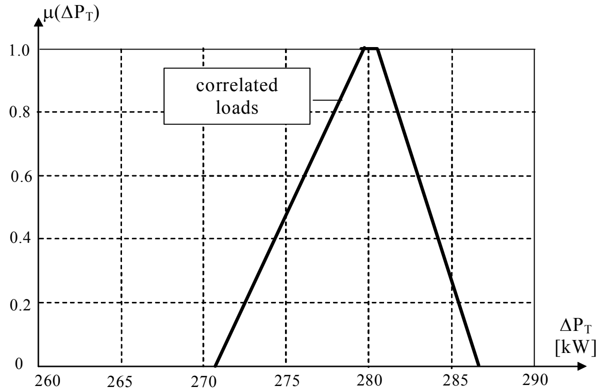

Fig. 19. Membership function of the total active losses

Table 3. State variables obtained using fuzzy model with correlated loads

State quantities	x_1	x_2	x_3	x_4	Crisp	Real Case	Err [%]
P_s [kW]	14081.67	14856.06	15397.45	16397.45	15183.16	15550.04	-2.36
Q_s [kVAr]	9321.84	8562.00	7324.74	6102.63	7827.80	8004.18	-2.20
ΔP_L [kW]	86.50	89.30	89.60	91.80	89.30	90.08	-0.87
ΔP_{Tr} [kW]	186.30	190.50	191.10	194.80	190.68	193.10	-1.25
ΔP_T [kW]	272.78	279.76	280.70	286.65	279.97	284.19	-4.83
ΔQ_L [kVAr]	57.70	59.60	59.80	61.30	59.60	63.40	-5.99
ΔQ_{Tr} [kVAr]	1208.60	1228.00	1231.40	1249.10	1229.28	1269.68	-3.18
ΔQ_T [kVAr]	1266.30	1287.60	1291.20	1310.40	1288.88	1333.08	-3.32
Q_{CL} [kVAr]	502.28	502.25	502.23	502.21	502.24	502.18	0.01

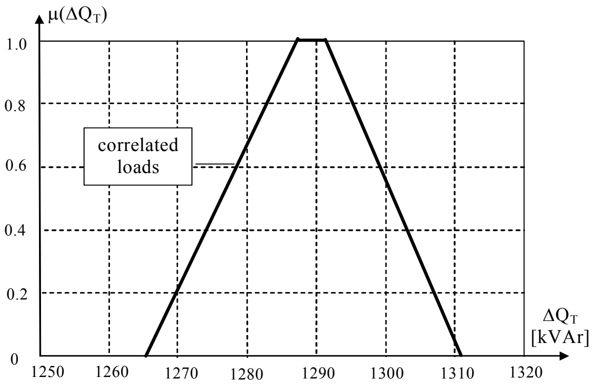

Fig. 20. Membership function of the total reactive losses

5 Conclusions

Starting from the statistical analysis, a method based on the fuzzy modeling of active and reactive powers from the substations corresponding to an electric distribution system is proposed. The numerical results show that the fuzzy correlation models can be used with very good results for determination of the peak load corresponding distribution substations, and further with the state estimation of the system.

Generally, if the time window is less and correlated with the overall loads then, the obtained results are better.

Combination of the fuzzy approach with the expert systems leads to an efficient and robust tools.

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