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A Fuzzy Model of Television Rating Control with Trend Rules Tuning based on Monitoring Results

Olexiy Azarov
Computer Facilities Department
Vinnytsia National Technical University
Vinnytsia, Ukraine
azarov2@vntu.edu.ua

Leonid Krupelnitsky
Computer Facilities Department
Vinnytsia National Technical University
Vinnytsia, Ukraine
krupost@gmail.com

Hanna Rakytyanska
Soft Ware Design Department
Vinnytsia National Technical University
Vinnytsia, Ukraine
h_rakit@ukr.net

***Abstract*—The problem of constructing the recommendation rules for the television rating control is considered. A hybrid approach combining the benefits of semantic training and fuzzy relational equations in simplification of the process of expert recommendation systems construction is proposed. The problem of retaining the television rating can be attributed to the problems of fuzzy resources control. The trends of demand-supply relationships are described by the primary fuzzy knowledge bases. Rules refinement by solving the primary system of fuzzy relational equations allows avoiding labor-intensive procedures for the generation and selection of expert rules.**

***Keywords*—TV channel rating, expert recommendation systems, fuzzy resources control, fuzzy classification knowledge bases, solving fuzzy relational equations**

I. Introduction

The top priority task of the personnel of TV companies is to control the ratio of programs of different genres when forming the broadcast grid in order to increase and maintain the rating of the channel [1]. The rating of a television channel is determined by specialized sociological services and directly affects the cost of advertising time. Content management is modeled by integrating trials, expert recommendations and users' preferences [2]. The recommendation accuracy strongly depends on the mechanisms of the supply and demand regulation [3, 4]. Parametric statistical models are widely used to evaluate the viewers' demand and the popularity of TV programs [5−7]. These models are adjusted to fit the distribution of user ratings in video on demand services dealing specifically with TV content [5]. To enhance the recommendation accuracy, the statistical models aim to learn audience preferences that follow from the rich user content generated in the social networks [6, 7]. The timing and item recommendations are generated via clustering the common interests of a group of people [8, 9]. Finally, the cognitive models describe the behavior of viewers when choosing a TV channel [10, 11]. Such models predict program commitments based on viewer-program emotional relationships reflecting satisfaction and perception toward alternative programs.

The problem of retaining the television rating can be attributed to the problems of fuzzy resources control [1, 12]. In such models, the "demand-supply" relationships are described by fuzzy IF-THEN rules. Experienced managers make effective administrative decisions based on a comparison of the viewers' demand for the programs of different genres with the rating of the programs offered at the given time [2]. Dependent upon this, a control action is formed, which consists of increasing or decreasing the rating of the programs in the channel broadcast grid. In works [12, 13], it is suggested to build the fuzzy resources control model on the grounds of the general method of nonlinear dependencies identification by means of fuzzy knowledge bases. The method [12, 13] implies the stage of tuning the fuzzy control model using "demand-supply" training data. The tuning stage consists of finding such fuzzy rules weights and such membership functions forms, which provide maximum proximity of the results of fuzzy logic inference to the correct managerial decisions.

The construction of expert recommendation systems is associated with computational costs. Constantly changing preferences of different categories of viewers require the selection and adjustment of the appropriate set of expert rules. At the same time, experts establish the trends of demand-supply relationships, which are subject to further refinement. Such trend dependencies are described by primary fuzzy knowledge bases. The solution to the problem of expert rules refinement may be the use of fuzzy relational equations [14−17], the solutions of which represent the linguistic modification of the primary terms. The obtained solutions can be considered as composite fuzzy rules that connect significance measures of the primary fuzzy terms [18, 19]. The number of rules in the class is determined by the number of solutions, and the form of the membership functions of the composite terms in the rule is determined by significance measures of the primary terms. Refinement of the rule set by solving the primary system of fuzzy relational equations allows avoiding labor-intensive procedures for the generation and selection of expert rules. Therefore, it is important to develop a hybrid approach combining the benefits of semantic training [12, 13] and fuzzy relational equations [14−17] in simplification of the process of expert recommendation systems construction. Following the approach proposed in [14−17], the genetic algorithm is used for tuning the primary fuzzy model and solving the primary system of fuzzy relational equations.

II. Structure of the TV Rating Control Model

The fuzzy model of resources management was constructed using the example of the Ukrainian television

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channel, presenting programs of such basic genres: political programs and news releases ($s=1$); TV serials ($s=2$); entertaining and sports programs ($s=3$) [20].

For the TV rating control problem, the monitoring and forecast window is a week. The analysis of the TV channel rating is carried out according to the results of monitoring of the TV programs ratings obtained for the previous week. The TV program is compiled for the forthcoming week. The structure of the TV rating control model corresponds to the following hierarchical tree of logic inference [12, 13]:

$$y_s(t,p) = f_s(x_s(t,p), z_s(t,p-1)),\ s=\overline{1,K}, \quad (1)$$

$$u(t,p) = f_0(z_1(y_1(t,p)),...,z_K(y_K(t,p))), \quad (2)$$

where $x_s(t,p)$ is the viewers' demand for the programs of the genre s at the time moment t of the p-th week; $z_s(t,p-1)$ is the rating of the offered programs of the genre s at the time moment t of the (p–1)-th week; $y_s(t,p)$ is a control action for the time moment t of the p-th week, consisting in increasing–decreasing the rating of the offered programs of the genre s; K is the number of genres of the proposed TV programs; $u(t,p)$ is the rating of the TV channel at the time moment t of the p-th week.

It is supposed that the control action is determined as the difference between the rating values before and after control, i.e. $y_s(t,p) = z_s(t,p) - z_s(t,p-1)$.

The proportion of TV viewers who watch TV at the time moment (t, p) determines the rating of the TV channel. In accordance with expert estimates, the range of the parameters $x_s(t,p)$, $z_s(t,p)$ and $u(t,p)$ is [0, 20] %. The parameter $y_s(t)$ range is [-20, 20] %.

We shall describe the trend dependencies with the help of the primary fuzzy terms: increased (decreased) (I, D) or stable (St) for $x_s(t,p)$, $z_s(t,p)$ and $u(t,p)$; increase (decrease) (I, D) or stay inactive (N) for $y_s(t,p)$. For the composite terms construction, we shall use the linguistic modifiers: sharply (sh), moderately (m), weakly (w). These modifiers describe the semantic intensity of the primary terms D and I [17].

Functional dependencies (1) and (2) are defined by the primary fuzzy relations and rules presented in Table I and Table II, respectively.

TABLE I. PRIMARY FUZZY RULES FOR CONTROL ACTIONS IN EACH GENRE CATEGORY

Primary rule	IF		THEN
	$x_s(t,p)$	$z_s(t,p-1)$	$y_s(t,p)$
H_1	D	I	D
H_2	D	St	
H_3	St	I	
H_4	D	D	N
H_5	St	St	
H_6	I	I	
H_7	St	D	I
H_8	I	St	
H_9	I	D	

It is necessary to transfer the primary fuzzy relations and rules into the composite ones for the modified decision classes of the variables $y_s(t,p)$ and $u(t,p)$.

TABLE II. PRIMARY FUZZY RELATIONS FOR TV RATING CLASSES

IF		THEN $u(t)$		
		D	St	I
$z_s(t,p)$	D	m–sh	w	-
	St	w	m–sh	w–m
	I	-	w–m	m–sh

III. THE PROBLEM OF TUNING THE FUZZY CONTROL MODEL

Correlations (1), (2) define the primary fuzzy control model in the form:

$$\boldsymbol{\mu}_y^s = f_s(\boldsymbol{\mu}_x^s, \boldsymbol{\mu}_z^s, \mathbf{W}_s), \quad (3)$$

$$\boldsymbol{\mu}_u = f_0(\boldsymbol{\mu}_Z^1,...,\boldsymbol{\mu}_Z^K, \mathbf{R}), \quad (4)$$

where $\boldsymbol{\mu}_x^s = (\mu_x^{s,D}, \mu_x^{s,St}, \mu_x^{s,I})$, $\boldsymbol{\mu}_z^s = (\mu_z^{s,D}, \mu_z^{s,St}, \mu_z^{s,I})$, $\boldsymbol{\mu}_y^s = (\mu_y^{s,D}, \mu_y^{s,N}, \mu_y^{s,I})$ are the vectors of significance measures of the primary fuzzy terms of the variables x_s, z_s and y_s in correlation (1); $\boldsymbol{\mu}_Z^s = (\mu_Z^{s,D}, \mu_Z^{s,St}, \mu_Z^{s,I})$ and $\boldsymbol{\mu}_u = (\mu^D, \mu^{St}, \mu^I)$ are the vectors of significance measures of the primary fuzzy terms of the variables z_s and u in correlation (2); $\mathbf{W}_s = (w_1^s,...,w_9^s)$ is the primary rules weights vector in correlation (1); $\mathbf{R} = (r_{11}^s,...,r_{13}^s,...,r_{31}^s,...,r_{33}^s)$ is the primary fuzzy relational matrix for genre preferences in correlation (2).

We use a bell-shaped membership function model of variable v to arbitrary term T in the form [12, 13]:

$$\mu^T(v) = 1\big/\left(1+((v-\beta)/\sigma)^2\right),$$

where β is a coordinate of function maximum, $\mu^T(\beta)=1$; σ is a parameter of concentration.

In this case, correlations (3), (4) take the form [14–17]:

$$\boldsymbol{\mu}_y^s(y_s, \mathbf{B}_y^s, \boldsymbol{\Omega}_y^s) = f_s(x_s, z_s, \mathbf{W}_s, \mathbf{B}_x^s, \boldsymbol{\Omega}_x^s, \mathbf{B}_z^s, \boldsymbol{\Omega}_z^s), \quad (5)$$

$$\boldsymbol{\mu}_u(u, \mathbf{B}_u, \boldsymbol{\Omega}_u) = f_0(\boldsymbol{\mu}_Z^1,...,\boldsymbol{\mu}_Z^K, \mathbf{R}), \quad (6)$$

where $\mathbf{B}_y^s = (\beta_y^{s,D}, \beta_y^{s,N}, \beta_y^{s,I})$, $\boldsymbol{\Omega}_y^s = (\sigma_y^{s,D}, \sigma_y^{s,N}, \sigma_y^{s,I})$, $\mathbf{B}_x^s = (\beta_x^{s,D}, \beta_x^{s,St}, \beta_x^{s,I})$, $\boldsymbol{\Omega}_x^s = (\sigma_x^{s,D}, \sigma_x^{s,sT}, \sigma_x^{s,I})$, $\mathbf{B}_z^s = (\beta_z^{s,D}, \beta_z^{s,St}, \beta_z^{s,I})$, $\boldsymbol{\Omega}_z^s = (\sigma_z^{s,D}, \sigma_z^{s,sT}, \sigma_z^{s,I})$, $\mathbf{B}_u = (\beta_u^D, \beta_u^{sT}, \beta_u^I)$, $\boldsymbol{\Omega}_u = (\sigma_u^D, \sigma_u^{sT}, \sigma_u^I)$ are the vectors of membership functions parameters of the primary fuzzy terms of the variables x_s, z_s, y_s and u.

It is assumed that some training data sample in the form of P pairs of experimental data can be obtained on the ground of successful managerial decisions $\langle\ \hat{x}_s^l$, $\hat{z}_s^l$, $\hat{y}_s^l$,

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$\hat{u}^l \rangle$, $l=\overline{1,P}$, where $\hat{x}_s^l$ and $\hat{z}_s^l$ are the control system state parameters in the experiment number *l*; $\hat{y}_s^l$ and $\hat{u}^l$ are the control action and TV rating in the experiment number *l*. The essence of the fuzzy model (5), (6) tuning is as follows. It is necessary to find the relation matrix **R**, the rules weights vector **W** and the vectors of the membership functions parameters $\mathbf{B}_x^s$, $\boldsymbol{\Omega}_x^s$, $\mathbf{B}_z^s$, $\boldsymbol{\Omega}_z^s$, $\mathbf{B}_y^s$, $\boldsymbol{\Omega}_y^s$, $\mathbf{B}_u$, $\boldsymbol{\Omega}_u$, which provide the minimum distance between theoretical and experimental data:

$$\sum_{l=1}^{P}[f_s(\hat{x}_s^l,\hat{z}_s^l,\mathbf{W}_s,\mathbf{B}_x^s,\boldsymbol{\Omega}_x^s,\mathbf{B}_z^s,\boldsymbol{\Omega}_z^s)-\hat{\boldsymbol{\mu}}_y^s(\hat{y}_s^l,\mathbf{B}_y^s,\boldsymbol{\Omega}_y^s)]^2=\min_{\mathbf{W},\mathbf{B},\boldsymbol{\Omega}} \qquad (7)$$

$$\sum_{l=1}^{P}[f_0(\hat{\boldsymbol{\mu}}_Z^1,...,\hat{\boldsymbol{\mu}}_Z^K,\mathbf{R})-\hat{\boldsymbol{\mu}}_u(\hat{u}^l,\mathbf{B}_u,\boldsymbol{\Omega}_u)]^2=\min_{\mathbf{R}}. \qquad (8)$$

We shall denote: $\{D_1,...,D_M\}$ and $\{d_1,...,d_m\}$ are the modified decision classes of the variables $u(t,p)$ and $y_s(t,p)$, respectively. Given the primary fuzzy model and qualitative output values, the problem of tuning the composite fuzzy model is formulated as follows [14–17]. For each output class D_J, $J=\overline{1,M}$, the fuzzy causes vector $\boldsymbol{\mu}_{Z,J}^s$ should be found which provides the least distance between observed and model fuzzy effects vectors in correlation (4), and for each output class d_j, $j=\overline{1,m}$, the fuzzy causes vectors $\boldsymbol{\mu}_{x,j}^s$, $\boldsymbol{\mu}_{z,j}^s$ should be found which provide the least distance between observed and model fuzzy effects vectors in correlation (3):

$$[f_0(\boldsymbol{\mu}_{Z,J}^1,...,\boldsymbol{\mu}_{Z,J}^K,\mathbf{R})-\boldsymbol{\mu}_u(D_J)]^2=\min_{\boldsymbol{\mu}_{Z,J}^1,...,\boldsymbol{\mu}_{Z,J}^K}, \qquad (9)$$

$$[f_s(\boldsymbol{\mu}_{x,j}^s,\boldsymbol{\mu}_{z,j}^s,\mathbf{W}_s)-\boldsymbol{\mu}_y^s(d_j^s)]^2=\min_{\boldsymbol{\mu}_{x,j}^s,\boldsymbol{\mu}_{z,j}^s}. \qquad (10)$$

The genetic algorithm is used for solving the optimization problems (7)–(10) of tuning the primary fuzzy model and rule-based solutions of primary fuzzy relational equations.

IV. SOLVING FUZZY RELATIONAL EQUATIONS

Let us consider the construction of composite rules for the rating $u(t,p)$ and control action $y_s(t,p)$, $s=1$. The primary system of fuzzy relational equations after tuning has the form:

$$\mu^{E_1}=(\mu^{C_{11}}\wedge 0.90)\vee(\mu^{C_{12}}\wedge 0.30)\vee(\mu^{C_{21}}\wedge 0.70)\vee$$
$$\vee(\mu^{C_{22}}\wedge 0.28)\vee(\mu^{C_{31}}\wedge 0.67)\vee(\mu^{C_{32}}\wedge 0.26),$$
$$\mu^{E_2}=(\mu^{C_{11}}\wedge 0.30)\vee(\mu^{C_{12}}\wedge 0.93)\vee(\mu^{C_{13}}\wedge 0.46)\vee$$
$$\vee(\mu^{C_{21}}\wedge 0.25)\vee(\mu^{C_{22}}\wedge 0.86)\vee(\mu^{C_{23}}\wedge 0.45)\vee$$
$$\vee(\mu^{C_{31}}\wedge 0.29)\vee(\mu^{C_{32}}\wedge 0.62)\vee(\mu^{C_{33}}\wedge 0.45),$$
$$\mu^{E_3}=(\mu^{C_{12}}\wedge 0.50)\vee(\mu^{C_{13}}\wedge 0.96)\vee(\mu^{C_{22}}\wedge 0.50)\vee$$
$$\vee(\mu^{C_{23}}\wedge 0.78)\vee(\mu^{C_{32}}\wedge 0.48)\vee(\mu^{C_{33}}\wedge 0.81), \qquad (11)$$

$$\mu^{e_1}=(\mu^{H_1}\wedge 0.89)\vee(\mu^{H_2}\wedge 0.75)\vee(\mu^{H_3}\wedge 0.82)$$
$$\mu^{e_2}=(\mu^{H_2}\wedge 0.49)\vee(\mu^{H_3}\wedge 0.45)\vee(\mu^{H_4}\wedge 0.79)\vee$$
$$\vee(\mu^{H_5}\wedge 0.90)\vee(\mu^{H_6}\wedge 0.86)\vee(\mu^{H_7}\wedge 0.51)\vee(\mu^{H_8}\wedge 0.54)$$
$$\mu^{e_3}=(\mu^{H_7}\wedge 0.78)\vee(\mu^{H_8}\wedge 0.80)\vee(\mu^{H_9}\wedge 0.93), \qquad (12)$$

$$\mu^{H_1}=\mu^{c_{11}}\wedge\mu^{c_{23}},$$
$$\mu^{H_2}=\mu^{c_{11}}\wedge\mu^{c_{22}},$$
$$\mu^{H_3}=\mu^{c_{12}}\wedge\mu^{c_{23}},$$
$$\mu^{H_4}=\mu^{c_{11}}\wedge\mu^{c_{21}},$$
$$\mu^{H_5}=\mu^{c_{12}}\wedge\mu^{c_{22}},$$
$$\mu^{H_6}=\mu^{c_{13}}\wedge\mu^{c_{23}},$$
$$\mu^{H_7}=\mu^{c_{12}}\wedge\mu^{c_{21}},$$
$$\mu^{H_8}=\mu^{c_{13}}\wedge\mu^{c_{22}},$$
$$\mu^{H_9}=\mu^{c_{13}}\wedge\mu^{c_{21}}, \qquad (13)$$

where variables $u(t,p)$ and $z_s(t,p)$ were described by fuzzy terms $E_1\div E_3$ and $C_{s1}\div C_{s3}$ (*D*, *St*, *I*); variables $y_s(t,p)$, $x_s(t,p)$ and $z_s(t,p-1)$ were described by fuzzy terms $e_1\div e_3$ (*D*, *N*, *I*), $c_{11}\div c_{13}$ and $c_{21}\div c_{23}$ (*D*, *St*, *I*).

The composite rules were built for the classes $D_1\div D_7$ (*shD*, *mD*, *wD*, *St*, *wI*, *mI*, *shI*) and $d_1\div d_7$ (*shD*, *mD*, *wD*, *N*, *wI*, *mI*, *shI*). Fuzzy effects vectors were defined with the help of the membership functions of the fuzzy terms $E_1\div E_3$, $D_1\div D_7$ in Fig. 1,a and $e_1\div e_3$, $d_1\div d_7$ in Fig. 1,b:

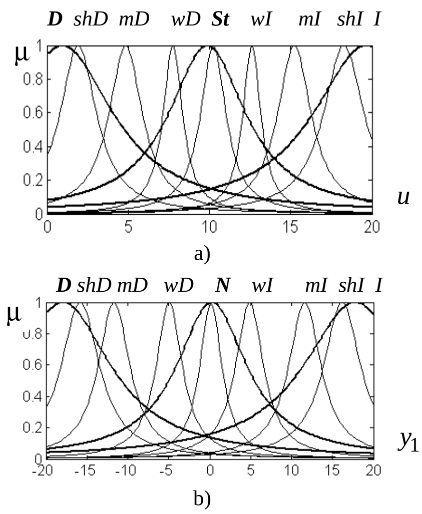

Fig. 1. Membership functions of the fuzzy terms for the variables *u*(*t*, *p*) (a) and $y_1(t,p)$ (b)

$\boldsymbol{\mu}^E(D_1)$ =(0.96, 0.22, 0.10); $\boldsymbol{\mu}^e(d_1)$ =(0.95, 0.20, 0.09);
$\boldsymbol{\mu}^E(D_2)$ =(0.63, 0.40, 0.11); $\boldsymbol{\mu}^e(d_2)$ =(0.68, 0.29, 0.10);

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$\mathbf{\mu}^E(D_3)$ =(0.30, 0.75, 0.14); $\mathbf{\mu}^e(d_3)$ =(0.33, 0.65, 0.16);
$\mathbf{\mu}^E(D_4)$ =(0.20, 0.99, 0.21); $\mathbf{\mu}^e(d_4)$ =(0.18, 0.99, 0.22);
$\mathbf{\mu}^E(D_5)$ =(0.12, 0.62, 0.30); $\mathbf{\mu}^e(d_5)$ =(0.14, 0.71, 0.37);
$\mathbf{\mu}^E(D_6)$ =(0.11, 0.37, 0.58); $\mathbf{\mu}^e(d_6)$ =(0.10, 0.31, 0.73);
$\mathbf{\mu}^E(D_7)$ =(0.10, 0.21, 0.94); $\mathbf{\mu}^e(d_7)$ =(0.08, 0.20, 0.98).

The solution set of the fuzzy relational equations (11) is presented in Table 3. The linguistic interpretation of the obtained solutions in the form of the "single input – single output" fuzzy rules is presented in Table 4 [18].

TABLE III. SOLUTIONS OF FUZZY RELATIONAL EQUATIONS FOR TV RATING CLASSES

IF	THEN $u(t)$						
	shD	*mD*	*wD*	*St*	*wI*	*mI*	*shI*
$\mu^{C_{11}}$	0.90–1	0.63	0.30	0.21	0.12	0.11	0.10
$\mu^{C_{12}}$	0.10	0.11	0.30–0.75	0.93–1	0.30–0.62	0.11	0.10
$\mu^{C_{13}}$	0.10	0.11	0.14	0.21	0.50	0.58	0.94
$\mu^{C_{21}}$	0.25–1	0.25–0.63	0.30	0.21	0.12	0.11	0.10
$\mu^{C_{22}}$	0.10	0.11	0.30–0.75	0.30–1	0.30–0.62	0.11	0.10
$\mu^{C_{23}}$	0.10	0.11	0.14	0.21	0.50	0.37–0.58	0.45–1
$\mu^{C_{31}}$	0.29–1	0.29–0.63	0.30	0.21	0.12	0.11	0.10
$\mu^{C_{32}}$	0.10	0.11	0.30–1	0.30–1	0.62–1	0.11	0.10
$\mu^{C_{33}}$	0.10	0.11	0.14	0.21	0.50	0.37–0.58	0.45–1

TABLE IV. COMPOSITE FUZZY RELATIONS FOR TV RATING CLASSES

IF		THEN $u(t)$						
		shD	*mD*	*wD*	*St*	*wI*	*mI*	*shI*
$z_1(t,p)$	*shD*	0.90	0	0	0	0	0	0
	mD	0	0.63	0.30	0	0	0	0
	wD	0	0	0.75	0.21	0	0	0
	St	0	0	0	0.93	0	0	0
	wI	0	0	0	0.21	0.62	0	0
	mI	0	0	0	0	0.50	0.58	0
	shI	0	0	0	0	0	0	0.94
$z_2(t,p)$	*shD*	1	0	0	0	0	0	0
	mD	0.70	0.63	0.30	0.30	0	0	0
	wD	0.25	0.25	0.75	0.50	0	0	0
	St	0	0	0	1	0	0	0
	wI	0	0	0	0.50	0.62	0.37	0
	mI	0	0	0	0.30	0.50	0.58	0.45
	shI	0	0	0	0	0	0	0.78
$z_3(t,p)$	*shD*	1	0	0	0	0	0	0
	mD	0.67	0.63	0.30	0.30	0	0	0
	wD	0.29	0.29	0.62	0.62	0.30	0	0
	St	0	0	1	1	1	0	0
	wI	0	0	0.30	0.62	0.62	0.37	0
	mI	0	0	0	0.30	0.50	0.58	0.45
	shI	0	0	0	0	0	0	0.81

The solution set of the fuzzy relational equations (12), (13) is presented in Table 5. The set of interval rules and linguistic interpretation of the obtained solutions in the form of the "multiple inputs – single output" fuzzy rules is presented in Table 6 [19].

TABLE V. SOLUTIONS OF FUZZY RELATIONAL EQUATIONS FOR CONTROL ACTIONS

IF						THEN
$x_1(t,p)$			$z_1(t,p-1)$			$y_1(t,p)$
$\mu^{c_{11}}$	$\mu^{c_{12}}$	$\mu^{c_{13}}$	$\mu^{c_{21}}$	$\mu^{c_{22}}$	$\mu^{c_{23}}$	
0.89–1	0–0.20	0–0.09	0.09	0–0.20	0.89–1	d_1
0.68–1 0.68–1 0–0.49	0.10 0.49 0.68–1	0–0.10 0–0.10 0.49	0.49 0.10 0–0.10	0–0.49 0.68–1 0.10	0.68–1 0–0.49 0.68–1	d_2
0.65–1 0.33 0–0.33	0.16 0.65–1 0.33	0–0.16 0–0.16 0.65–1	0.65–1 0.16 0–0.16	0.33 0.65–1 0.16	0–0.33 0–0.33 0.65–1	d_3
0.90–1 0–0.18 0–0.18	0.22 0.90–1 0.18	0–0.22 0–0.22 0.90–1	0.90–1 0–0.22 0–0.22	0.18 0.90–1 0.22	0–0.18 0–0.18 0.90–1	d_4
0.71–1 0–0.14 0–0.14	0.37 0.71–1 0.14	0–0.37 0.37 0.71–1	0.71–1 0–0.37 0–0.37	0.14 0.71–1 0.37	0–0.14 0.14 0.71–1	d_5
0.10 0–0.10 0–0.10	0.73–1 0.54 0.10	0–0.54 0.73–1 0.73–1	0.73–1 0–0.54 0.73–1	0.54 0.73–1 0–0.54	0–0.10 0.10 0.54	d_6
0–0.08	0–0.20	0.93–1	0.93–1	0–0.20	0.08	d_7

The lower and upper bounds of the interval rules were obtained with the help of the membership functions of the primary fuzzy terms. The membership functions of the primary and composite fuzzy terms for input variables are shown in Fig. 2.

The composite fuzzy rules for relations $y_2(t,p)$ and $y_3(t,p)$ were tuned in a similar way.

TABLE VI. COMPOSITE FUZZY RULES FOR CONTROL ACTIONS

Primary rule	IF		THEN
	$x_1(t,p)$	$z_1(t,p-1)$	$y_1(t,p)$
H_1	0–3.34, *shD*	16.35–20, *shI*	d_1
H_1 H_1 H_2 H_3	5.10, *mD* 0–5.10, *mD–shD* 0–5.10, *mD–shD* 8.00–12.57, *wD–wI*	14.60–20, *mI–shI* 14.60, *mI* 7.35–12.27, *wD–wI* 14.60–20, *mI–shI*	d_2
H_4 H_5 H_5 H_6	0–5.40, *mD–shD* 7.86–12.43, *wD–wI* 7.86, *wD* 14.35, *mI*	5.42, *mD* 12.43, *wI* 7.18–12.43, *wD–wI* 14.30–20, *mI – shI*	d_3
H_4 H_5 H_6	0–3.27, *shD* 9.20–11.43, *St* 16.45–20, *shI*	0–3.31, *shD* 8.63–11.00, *St* 16.40–20, *shI*	d_4
H_4 H_5 H_5 H_6	4.90, *mD* 8.16–12.45, *wD–wI* 12.45, *wI* 14.87–20, *mI – shI*	0–4.96, *mD–shD* 7.50, *wD* 7.50–12.10, *wD–wI* 14.79, *mI*	d_5
H_7 H_8 H_9 H_9	8.26–12.32, *wD–wI* 15.00–20, *mI–shI* 15.00, *mI* 15.00–20, *mI – shI*	0–4.76, *mD–shD* 7.61–12.00, *wD–wI* 0–4.76, *mD–shD* 4.76, *mD*	d_6
H_9	16.75–20, *shI*	0–3.05, *shD*	d_7

V. EXAMPLE OF THE TV CHANNEL RATING CONTROL

The values ⟨viewers' demand $\hat{x}_s(t,p)$, supply before and after control $\hat{z}_s(t,p-1)$, $\hat{z}_s(t,p)$, control action $\hat{y}_s(t,p)$ = = $\hat{z}_s(t,p)-\hat{z}_s(t,p-1)$, rating $\hat{u}(t,p)$ ⟩, corresponding to the experienced manager actions were taken as the training data sample. In this case, the TV rating was maintained at a

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consistently high level, and the unmet viewers' demand was reduced to a minimum.

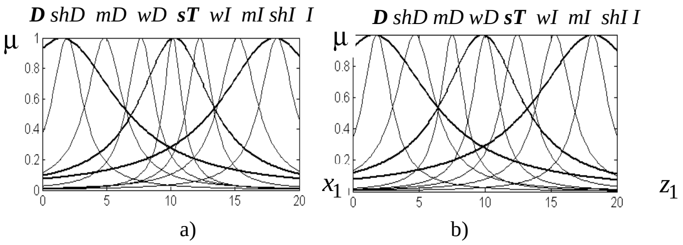

Fig. 2. Membership functions of the fuzzy terms for the input variables $x_1(t, p)$ (a) and $z_1(t, p)$ (b)

The unmet demand after control for each genre category can be defined as $\delta_s(t, p) = z_s(t, p) - x_s(t, p)$. The experimental value $\hat{x}_s(t, p)$ for each genre category is defined as the ratio of viewers who watch such programs broadcast by all TV channels at the time moment (t, p). Evaluation of the rating of TV programs in the channel broadcasting network is carried out with the help of the authors' monitoring system [21]. The experimental values $\hat{z}_s(t, p-1)$, $\hat{z}_s(t, p)$ and $\hat{u}(t, p)$ are determined on the basis of the weekly top 20 rating [20]. The sample includes data from 2015 to 2017. The training sample fragment is presented in Fig. 3 in the form of the dynamics of the demand and supply change for each genre during the day. Management is carried out at the level of each air-hour, i.e. $t \in [0...24]$. Comparison of the model and experimental control, as well as the unmet demand after control is presented in Fig. 4.

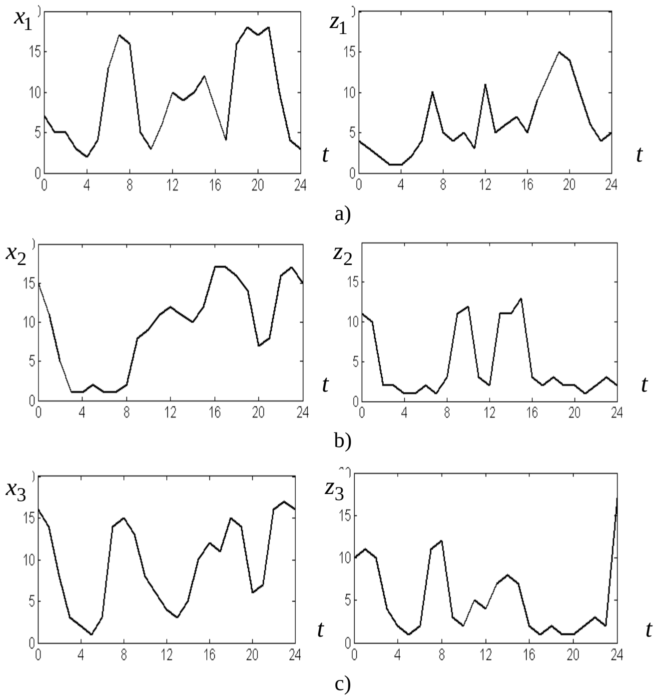

Fig. 3. The training sample fragment: the dynamics of the demand and supply change for genres s=1 (a); s=2 (b); s=3 (c)

For the political genre, the offered programs have balanced the viewers' demand (Fig. 4, a). The demand for the genre of television serials from 16 to 17 hours has been satisfied with the program of the sports and entertainment genre (Fig. 4, b). Some popular serials have been offered instead of the entertainment programs from 18 to 19 and from 22 to 23 hours (Fig. 4, c).

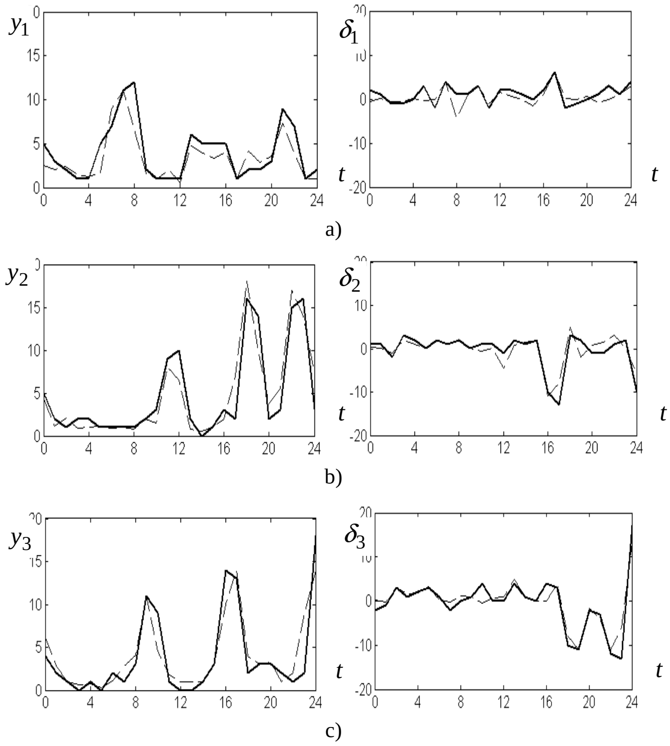

Fig. 4. The model (—) and experimental (—) control action and the unmet demand after control for genres s=1 (a); s=2 (b); s=3 (c)

Comparison of the model and experimental rating during the day is shown in Fig. 5,a. The dynamics of the average weekly rating change at the level of each air-hour for $p \in [1...14]$ weeks is shown in Fig 5,b. When compiling the average weekly rating, the time range is $t \in [8...23]$ hours, since the programs in the range $t \in [0...7]$ do not fall into the weekly top 20 rating.

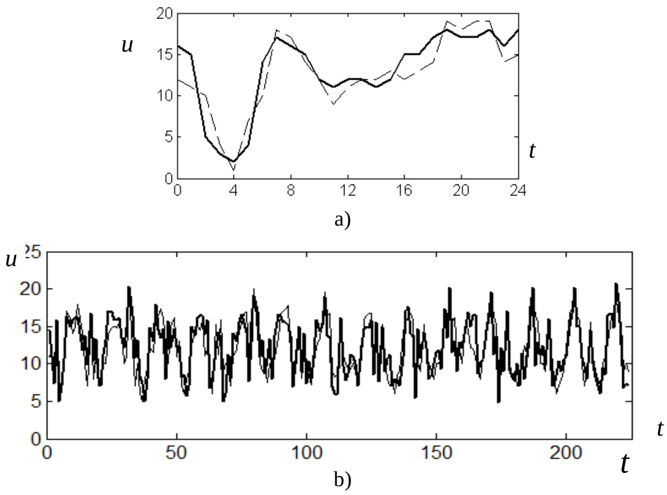

Fig. 5. The dynamics of the daily (a) and average weekly (b) TV rating change for the model (—) and experimental (—) control action

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VI. Conclusions

The proposed approach can find application in the automated recommendation systems in the TV domain. Further research is required to develop models, which are tuned to predict the TV programs popularity among different demographic groups. The policy of family channels with diversified content categories implies the balanced ratings for all social and age groups. In this case, the timing and item recommendations should be augmented by genre preference relationships based on viewers' demographics. Besides that, supplementary factors influencing the demand and supply values (collaborative filtering, items similarity, purchase prices of new programs, advertising revenue) can be taken into account with the help of the primary relations and rules.

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