Robust Adaptive Control with the Use of DACDM Algorithm – Impact of Settings on Tracking Quality

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***Abstract*—In this paper a new, discrete, robust adaptive control algorithm (DACDM) and research results on tracking quality improvement and on the increase of control system robustness to parametric uncertainty were presented. The proposed control algorithm permits to obtain the desired output signal courses at the *apriori* declared time regime with the save of control system stability in the presence of control signal constraint by the proper modification and integration of so far applied algorithms of continuous time control which makes possible the triple level monitoring of system robustness in discrete control – through the use of coefficient diagram, through the introduction of an additional filter to the control system (which parameters are by the *J* function reflected) as well as the use of the adaptive algorithm with parameters estimation of discrete model by recursive least squares (RLS) method. The influence of various settings of algorithm parameters on a tracking quality, was considered. Simulations results confirm the efficiency of DACDM algorithm in the context of considered classes of plants.**

***Index Terms*—adaptive control, DACDM algorithm, robust control, tracking quality, parametric uncertainty**

I. Introduction

In the modern computer science there are number of control methods classifications due to their target and applications. From many types of control techniques, robust and adaptive *control* methods may be selected. Among others, robust control methods includes H_∞ method [1], *Quantitative* Feedback Theory [2] and less common Coefficient Diagram Method (CDM) [3]. The well known adaptive control methods are most of all: Pole Placement Adaptive Control (PP) [4], Model Reference Adaptive Control [5], Linear-Quadratic-Gaussian Control [6], Predictive Control [7] and others. The analysis of advantages and disadvantages of various types of them, highlights the possibility and the need of connection of robust and adaptive techniques. Basically, there are two approaches, namely: robust adaptive control and adaptive robust control [8]. In the analysis of this issue, it should be considered that in most of the literature by robust adaptive control is understood the increase of adaptive control robustness for model errors or disturbances. The incomplete information about non-modeled part of the plant's dynamics is often a source of modeling errors. Adaptive robust control is a technique to obtain of adaptive controller by applying mechanisms of adaptation in the robust controller. It is then possible to improve the control and tracking quality (the robust stability of the closed-loop system is then provided). From the perspective of robust control, the adaptive control is therefore a method of reduction of plant model uncertainty level with the use of proper identification – implemented in a closed-loop system.

In this paper a new, complex method of discrete robust adaptive control (DACDM) with control signal constraint and with optimization of robustness index *J*, is presented. The proposed algorithm formulates an answer to the question how to place the poles of characteristic equation of closed-loop system in specific system realizations and at the presence of disturbances. Other, present applied algorithms and methods do not specify where place the poles. A proposed DACDM algorithm – which is based on the CDM algorithm, pole placement method and on estimation of delta model parameters [9], includes tools, which optionally enable to determine the optimal poles placement (with the lowest robustness index value *J*) of the particular control system. It is described in detail, *e.g.* in [10]. In the classic PP algorithm the choice of the stable characteristic polynomial is not specified and this is its weakest point, what determines directly the obtained control quality, because for example in the case, when placed poles are not selected in accordance with the frequency response of the plant – control signal may have then large values – significantly exceeding the permitted constraint of control signal amplitude. The use of the CDM algorithm proposed in this article (in discrete robust adaptive control with the parameter estimation of continuous model with the use of delta discretization method), allows to decrease the impact of parametric uncertainty on the quality of control in the presence of control signal constraint and disturbances.

In the proposed DACDM algorithm, the synthesis of the control system in accordance with the CDM algorithm is conducted for the continuous time description and adaptive mechanisms are performed for the discrete system. It should be noted, that the parametric estimation of model uses RLS algorithm for the discrete model, while parametric estimation of delta model is applied for the continuous time model.

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This paper is organized as follows. Section 2 introduces and describes terminology and mechanisms used in DACDM algorithm, as well as the same algorithm. Section 3 describes experimental tests used to evaluate the performance of the DACDM algorithm. Finally, Section 4 presents conclusions and further work.

II. DACDM Algorithm

The robust adaptive control system from Fig. 1 is considered, where *r(t)* – reference signal, r_t – discrete reference signal, *y(t)* – output signal, y_t – discrete output signal, v_t – discrete unconstraint control signal, *u(t)* – constraint control signal, u_t – discrete constraint control signal, T_p – sampling period. The DACDM algorithm [11] from Fig. 2 allows in a complex way (three stage of robustness control) to perform the control system synthesis and in the effect to designate the control law of robust adaptive controller for a particular plant model (in the presence of the control signal amplitude constraint and disturbances).

The representation of nominal linearized plant model with the use of transfer function *G(s)* is a starting point for the synthesis of discrete control system. The accepted simplification enforces the description of model parametric uncertainties. Values of particular elements of parametric uncertainty vector $\underline{q}$ are defined authoritatively - in DACDM algorithm it is recommended to accept wide ranges of parameter values changes in the initial phase of control system synthesis and their gradual decrease after the averaged model obtainment in the next iteration of the algorithm.

To compute the nominal poles placement defined by target characteristic polynomial $P_T(s)$ and transfer function $G_{reg}(s)$ of the controller, the CDM algorithm is performed (in the offline version with or without optimization of the robustness index *J* [10]) for continuous plant model. This method enables the control of robustness, stability and system dynamics with the use of coefficient diagram (CD). A detailed description of this useful tool may be found in [3], [12], [13].

The key role in the CDM algorithm (determining the obtainment of nominal poles placement and in result –the tracking quality) plays the choice of expected design specifications – expressed by the equivalent of time constant τ (it specify the desired dynamics of system step response) and by the vector of s tability indices $\underline{\gamma}_i$. These indices specify desired limits of stability – given by stability limits vector γ^*_i – after exceeding these vector values, system may lose stability [3]. The choice of equivalent of time constant (1) should be based on the expected settling time (t_s) of step response:

$$\tau = t_s / (2{,}5 \sim 3) \qquad (1)$$

The choice of stability indices γ^*_i may be based on values of standard Manabe form (2) [14]. This form ($\underline{\gamma}_i$ vector) provides that the declared by the value of τ dynamics requirements of the implemented system, will be fulfilled already in the first iteration of the DACDM algorithm.

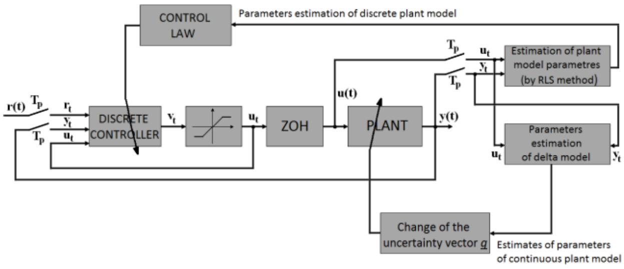

Figure 1. Block diagram of robust adaptive control system.

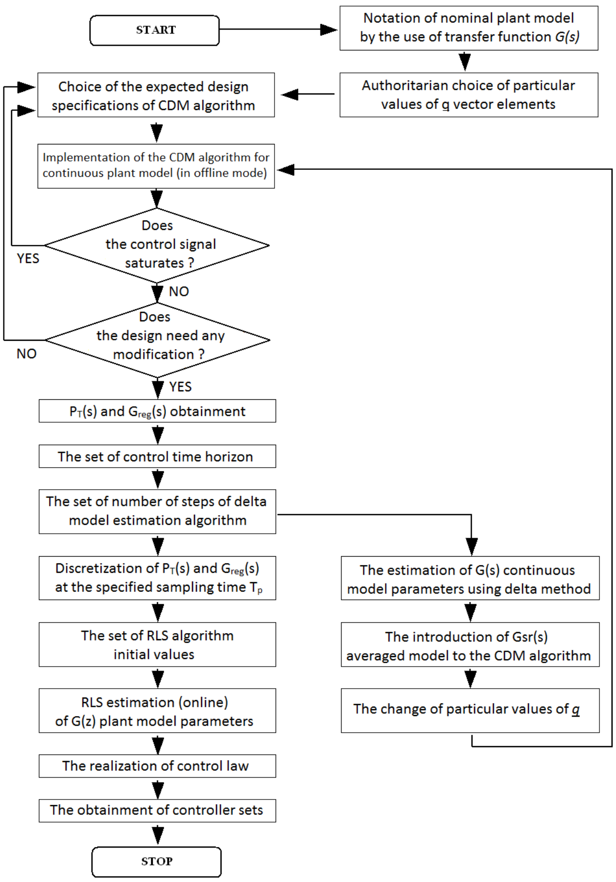

Figure 2. DACDM algorithm.

Standard forms should therefore be considered as initial settings values of particular index of stability. They may be tuned in the following iterations of the algorithm – more details are presented in [3].

$$\underline{\gamma}_i = [2{,}5 \quad 2 \quad 2 \quad \ldots \quad 2]^T \qquad (2)$$

for $i=1, \ldots, n-1$, $\gamma_0 = \gamma_n = \infty$, where n is the degree of target characteristic polynomial.

The controller structure is chosen based on the Table I after taking into account the expected type of disturbance.

In the DACDM algorithm, in order to use of robust control advantages in the adaptive control, the notation of system model transfer function is converted into its equivalent in the discrete form (characteristic polynomial and the plant model are discretized). The adaptive pole placement method enables the estimation of model parameters using recursive least squares algorithm in DACDM algorithm in each discrete moment of time. The improvement of tracking quality follows due to the modification of current control according to the implemented control law from the standard CDM algorithm. The target characteristic polynomial specify the expected poles placement and together with the characteristic polynomial (obtained from the plant model and controller), creates the diophantine equation. From this equation, current controller set values for current estimates of model parameters, may be calculated.

TABLE I. THE CHOICE OF $G_{REG}(S)$ POLYNOMIALS DEGREES DUE FOR THE EXPECTED TYPE OF DISTURBANCE

Type of disturbance	Degree of A(s)	Degree of B(s)	Degree of P(s)	Condition
Without	m-1	m-1	2m-1	-
Step type	m	m	2m	$l_0 = 0$
Growing linearly	m+1	m+1	2m+1	$l_0 = l_1 = 0$
Impulse/ Sinusoidal	m+1	m-1	m-1	-

*m – degree of denominator' polynomial of the plant model transfer

Apart from the estimation of discrete model parameters by the RLS method, in proposed DACDM algorithm, takes place the estimation of continuous delta model parameters. These estimates for a small sampling period, are close to continuous model parameters [9]. After declared number of estimation steps of delta model parameters, the model described by transfer function $G_\delta(s)$ is obtained (created from estimates of $G_\delta(\gamma)$ delta model) and compared to the nominal model *G(s)*. Through the proposed averaging (with appropriate weights) of the particular, corresponding values of nominal model parameters and delta model parameters, the transfer function $G_{sr}(s)$ of the averaged model is obtained and introduced to the CDM algorithm in the next iteration of the DACDM algorithm [11].

This step is also the third stage of the system robustness control (after analysis of the CD and the optional step of robustness index *J* optimization in the first iteration of the CDM algorithm), because it enables the change of particular values of parametric uncertainty vector $\underline{q}$ without the change of design specifications. The choice of new (smaller) parametric uncertainty ranges has an authoritarian character and involves the decision of reiteration (or not) of the optional step of the *J* index optimization. It is recommended to use the optimization only, when the system is still characterized by low robustness to parametric uncertainty.

After the resumption of CDM algorithm for the averaged model (which replaces the nominal plant model) in a given iteration, new polynomials values of the continuous controller (without change of the target characteristic equation), are obtained. In the following steps of the DACDM algorithm, the discretization of control system (with the averaged plant model) allows for the implementation of adaptive PP method.

III. SIMULATIONS

From the simulation tests one can see the impact of control signal constraint on tracking quality in discrete robust adaptive control systems with nominal plant models: stable minimum phase oscillatory (SMPO), stable minimum phase non-oscillatory (SMPNO), unstable minimum phase (UMP), stable non-minimum phase (SNMP), with random parameters from Table II [11].

TABLE II. TRANSFER FUNCTIONS OF PLANT MODELS

SMPO	SMPNO	UMP	SNMP
Transfer function *G(s)*			
$\dfrac{1}{s^2+0{,}2s+1}$	$\dfrac{1}{s^2+2s+0{,}5}$	$\dfrac{1}{s^2+10s}$	$\dfrac{-2s+1}{s^2+2s+0{,}5}$

For the synthesis of control system, characteristic polynomials obtained from the CDM algorithm without optimization of robustness index *J* (for SMPO, SMPNO, SNMP model), as well as with optimization (for UMP model), were used. Low robustness of system from the standard CDM algorithm for UMP model, forces the introduction of an additional filter *K(s)* and the use of optional optimization procedure of the DACDM algorithm. Discrete control systems were obtained based on the step-invariant transformation and presented in detail in [11].

Five integral quality indices (3)-(7) [15] to comparative assess of the tracking quality in robust adaptive control systems based on DACDM and PP methods were introduced. They both inform about the tracking quality, as well as the model parametric estimation with the use of RLS algorithm:

– I1 – The sum of normalized errors of parameter estimation:

$$I1=\frac{1}{n\theta}\sum_{i=1}^{n\theta}\sum_{t=0}^{t_h}\left|\frac{\theta_i-\hat{\theta}_{i,t}}{\theta_i}\right| \tag{3}$$

where $n\theta$ is the number of estimated parameters, and t_h is a simulation horizon,

– I2 – The sum of squared errors of prediction:

$$I2=\sum_{t=0}^{t_h}\varepsilon_t^2 \tag{4}$$

where ε_t is a prediction error: $\varepsilon_t = y_t - \underline{\varphi}_t^T \underline{\hat{\theta}}_{t-1}$,

– I3 – The sum of tracking squared errors for the last positive half period of the reference signal simulation horizon under consideration:

$$I3=\frac{1}{t_2-t_1+1}\sum_{t=t_1}^{t_2}(r_t-y_t)^2 \tag{5}$$

– I4 – The sum of squared errors of control signal u_t for the last positive half period of the reference signal simulation horizon under consideration:

$$I4=\frac{1}{t_2-t_1+1}\sum_{t=t_1}^{t_2}(u_t-u_{00})^2 \tag{6}$$

– I5 – Mean squared error of tracking:

$$I5 = \frac{1}{t_h + 1} \sum_{t=0}^{t_h} (r_t - y_t)^2 \qquad (7)$$

In discussed below, tracking simulations of the specified rectangular signal with amplitude equal to ±1, period to 40 [s] and in the control time horizon of 150 [s], 10 steps of parameters estimation of the continuous plant model *G(s)* by delta discretization method were set. After that time, to the CDM algorithm, a new model $G_{sr}(s)$ was introduced. The estimation of model parameters was performed with the use of RLS method.

Tracking in systems with control signal constraint and at disturbance

The efficiency of disturbances damping in DACDM systems with control signal constraint ($u_t=90\%v_t$) was considered. In Fig. 3 values of quality integral indices, are given – for signals from Fig. 4. After a disturbance in the 45th second (within 10 seconds) with amplitude equal to 0,5, each of designed robust adaptive control systems provides the resumption of reference signal tracking. Systems with SMPNO, UMP and SNMP models provide the resumption of tracking after similar times, while the system with SMPO model needed twice more time to damped arising oscillations. In each of the recorded signals, tracking quality is very high (low values of quality indices from Fig. 3).

Impact of weights changes of the averaged model on system robustness

The impact of weights changes of the averaged model on system robustness and tracking quality [11], was studied. Two cases were considered:

- Because of the convergence of delta model parameters to continuous model parameters (high certainty of continuous model parameters after the parametric estimation with a large number of steps), weights of estimated delta model were increased in relation to the nominal model – initially marked by wide range of parametric uncertainty $\underline{q}$ (±0,3) – for which, accordingly, weights values in averaged model calculation, were reduced.
- The range of parametric uncertainty $\underline{q}$ of nominal plant model has been reduced (weights values were increased), in accordance with the thinking that discrete control system calculated on the basis of CDM algorithm provide a high robustness, so weights assigned from parametric estimation are less important (accordingly weights values were reduced).

The effectiveness of solutions in both cases were tested in robust adaptive control systems with control signal constraint and at disturbance. It has been considered an example in which for the first of present case, in order to assess the system robustness to parametric uncertainty, values of all of model parameters were changed due to +0,2. In the second case, robustness was tested in the system, where all of model parameters values were changed due to +0,2 and to +0,1.

Simulation parameters	*Initial values of discrete model RLS estimation*	*Initial values of delta model RLS estimation*	*Disturbance*
- type of set-point signal: rectangular, - amplitude: ±0,1, - period: 40 [s], - control horizon: 150 [s]	$\hat{\underline{\theta}}_0 = 0{,}5\underline{\theta}$, $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ=20 (SMF1), 30 (SMF2), 10 (NSMF), 40 (SNMF) λ=0,4 (SMF1), 0,3 (SMF2), 0,6 (NSMF), 0,3 (SNMF) Tp=0,5 (SMF1), 0,6 (SMF2), 0,4 (NSMF), 0,5 (SNMF)	$\hat{\underline{\theta}}_0 = 0{,}5\underline{\theta}$ $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ=30, λ=0,9, Tp=0,01	*Step type* *Control signal constraint* $90\%v_t$

Model	*Integral quality indices values*				
	I1	*I2*	*I3*	*I4*	*I5*
SMF1	114,3343	989,7946	1,3799	3,5422	0,6003
SMF2	208,0924	3,8824	0,5383	0,0632	0,9311
NSMF	923,9421	1,8209	0,5501	3,4503	39,3581
SNMF	141,0911	91,2038	1,0810	0,0384	1,3641

Figure 3. Simulation parameters and integral quality indices values for the rectangular signal tracking in DACDM systems at constraint of control signal and at disturbance.

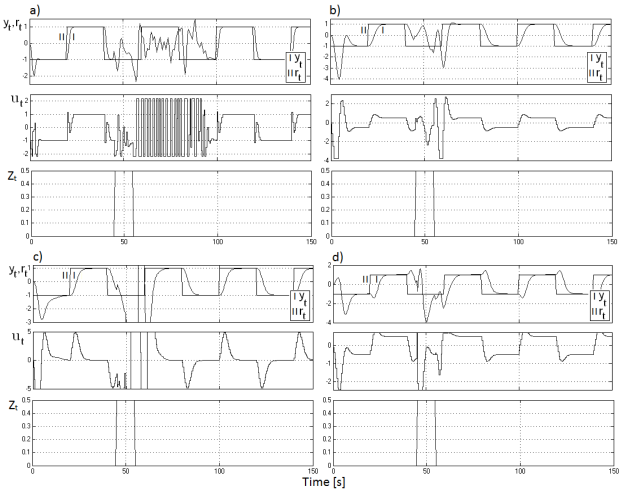

Figure 4. The rectangular signal tracking in DACDM systems with SMPO (a), SMPNO (b), UMP (c), SNMP (d) models at constraint of control signal and at disturbance.

Simulation parameters	*Initial values of discrete model RLS estimation*	*Initial values of delta model RLS estimation*	*Disturbance*
- type of set-point signal: rectangular, - amplitude: ±0,1, - period: 40 [s], - control horizon: 150 [s]	$\hat{\underline{\theta}}_0 = 0{,}5\underline{\theta}$, $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ=20 (SMF1), 30 (SMF2), 10 (NSMF), 40 (SNMF) λ=0,4 (SMF1), 0,3 (SMF2), 0,6 (NSMF), 0,3 (SNMF) Tp=0,5 (SMF1), 0,6 (SMF2), 0,4 (NSMF), 0,5 (SNMF)	$\hat{\underline{\theta}}_0 = 0{,}5\underline{\theta}$ $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ=30, λ=0,9, Tp=0,01	*Step type* *Control signal constraint* $90\%v_t$ *$\underline{q}$ vector* $\underline{q} = [0{,}2 \quad 0{,}2 \quad 0{,}2]^T$

Model	*Weight of estimated delta model / nominal model*	*Integral quality indices values*				
		I1	*I2*	*I3*	*I4*	*I5*
SMF1	0,5/0,5	117,1935	2.0530e+003	0,9038	5,5209	0,4862
	0,6/0,4	101,3242	1847,3498	0,7839	5,1294	0,4103
	0,7/0,3	98,3232	1739,3830	0,6920	5,0201	0,3829
SMF2	0,5/0,5	365,2527	16,7527	0,5079	0,0838	0,7762
	0,6/0,4	360,9288	16,1392	0,4839	0,0793	0,7632
	0,7/0,3	357,3992	16,0210	0,4782	0,0732	0,7329
NSMF	0,5/0,5	101,4689	2,2035	0,5923	4,3881	0,7168
	0,6/0,4	98,9300	2,0193	0,5492	4,0382	0,6929
	0,7/0,3	92,2910	1,9382	0,5129	4,0193	0,6582
SNMF	0,5/0,5	285,4290	121,9326	18,3740	37,0560	15,1534
	0,6/0,4	279,1000	111,1499	16,3909	36,2001	14,2993
	0,7/0,3	268,3829	109,2947	16,2918	35,2987	13,5828

Figure 5. Simulation parameters and integral quality indices for the tracking in DACDM systems at constraint of control signal and at disturbance for the $G_\delta(s)$ model weights analysis.

Simulation parameters	Initial values of discrete model RLS estimation	Initial values of delta model RLS estimation	Disturbance
- type of set-point signal: rectangular, - amplitude: ±0,1, - period: 40 [s], - control horizon: 150 [s]	$\underline{\hat{\theta}}_0 = 0{,}5\underline{\theta}$, $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ= 20 (SMF1), 30 (SMF2), 10 (NSMF), 40 (SNMF) λ= 0,4 (SMF1), 0,3 (SMF2), 0,6 (NSMF), 0,3 (SNMF) Tp= 0,5 (SMF1), 0,6 (SMF2), 0,4 (NSMF), 0,5 (SNMF)	$\underline{\hat{\theta}}_0 = 0{,}5\underline{\theta}$ $\underline{\varphi}_0 = [0{,}1 \quad 0{,}1 \quad 0{,}1 \quad 0{,}1]^T$ ρ=30, λ=0,9, Tp=0,01	Step type **Control signal constraint** $90\% v_t$ **$\underline{q}$ vector** $\underline{q}$= var

Model	Weight of estimated delta model / nominal model	Integral quality indices values				
		$I1$	$I2$	$I3$	$I4$	$I5$
SMF1	0,5/0,5($\underline{q}$=0,3)	49,6968	268,1143	0,2288	0,0854	0,2492
	0,4/0,6($\underline{q}$=0,2)	117,1935	2,0530e+003	0,9038	5,5209	0,4862
	0,3/0,7($\underline{q}$=0,1)	92,8349	27,1041	0,7171	2,7575	0,5524
SMF2	0,5/0,5($\underline{q}$=0,3)	273,0765	68,1902	1,0988	0,2578	1,4313
	0,4/0,6($\underline{q}$=0,2)	365,2527	16,7527	0,5079	0,0838	0,7762
	0,3/0,7($\underline{q}$=0,1)	111,8002	17,6085	0,5189	0,0720	1,0803
NSMF	0,5/0,5($\underline{q}$=0,3)	137,5139	4,7358	0,6289	4,8991	32,0842
	0,4/0,6($\underline{q}$=0,2)	101,4689	2,2035	0,5923	4,3881	0,7168
	0,3/0,7($\underline{q}$=0,1)	147,3430	3,9400	0,7756	4,9562	5,8944
SNMF	0,5/0,5($\underline{q}$=0,3)	335,4099	138,9663	21,1770	47,0680	17,1528
	0,4/0,6($\underline{q}$=0,2)	285,4290	121,9326	18,3740	37,0560	15,1534
	0,3/0,7($\underline{q}$=0,1)	245,4099	111,9369	16,1597	33,0658	14,1384

Figure 6. Simulation parameters and integral quality indices for the tracking in DACDM systems at constraint of control signal and at disturbance for the *G(s)* model weights analysis.

As a reference point in assess of results, the tracking quality for systems with nominal model and estimated delta model (both weights equal to 0,5), was assumed. The recorded values of integral quality indices *I1-I5* are given in detail in Fig. 5 and Fig. 6.

Analysis of quality integral indices from the Fig. 5 shows that for implementation of the DACDM algorithm, after the correctly performed estimation of delta model parameters, is preferred to introduce the averaged model with changed nominal weights values in the case, when initially was assumed a wide range of elements values of the $\underline{q}$ vector. For SMPO model (oscillatory nature) was obtained the largest improvement in tracking quality for specified $\underline{q}$ (smaller values of *I1* and *I2* indices inform that estimation of discrete model parameters in the initial phase of tracking occurs faster, which is reflected in smaller values of indices *I3-I5* – directly assess the quality of tracking). In the case of SMPNO model (inert nature), in relation to other models, changes of quality indices values are the smallest - what in terms of weights selection allows for more radical introduction of assessments used to determine the averaged model without worrying about deterioration of tracking results. In all studied cases, it is preferred to increase weights values of estimated delta model in relation to weights values of the nominal model.

In the second case (Fig. 6), in which impact of model *G(s)* weights selection was considered due to the change of estimation of parametric uncertainty values (weights of the nominal model were raised for smaller values of $\underline{q}$ vector) without analysis of results of delta model parameters estimation (which weights were reduced accordingly to the growth of the *G(s)* model weights values), the absence of any further regularity may be observed. Differences of quality integral indices does not allow to clarify rules of judgment (weights assignment) for the averaged model construction.

The numerical analysis of both presented methods of weights selection shows that the rule of weights assignment in the construction of robust adaptive control system (DACDM) should be based on results of estimation of delta model parameters which determine the obtained knowledge about parameters uncertainty of the continuous model. Weights assignment proportional to the change of parameters uncertainty vector values is incorrect, because it is performed at the expense of weights values changes of the estimated delta model (sum of the nominal model weight and the estimated delta model weight is equal to 1).

IV. CONCLUSIONS

The DACDM method in relation to tested models, provides a high robustness to parametric uncertainty, disturbance and constraint of the control signal.

The appropriate choice of sampling time T_P adjusted to a particular plant and the choice of initial parameters of estimation algorithm, as well as the constraint of control signal, determine mainly the tracking quality in robust adaptive control systems. Selection of number of DACDM algorithm steps depends on the choice of the RLS algorithm initial parameters at the specified reference signal.

In order to provide the maximum robustness of system, weights selection of the averaged model should be based on delta model estimation results, which determine the obtained knowledge about the uncertainty of continuous plant model parameters.

In further work it is planned to develop the DACDM algorithm version for multi-dimensional robust adaptive control systems.

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