Model–Free Control or Active Disturbance Rejection Control? On Different Approaches for Attenuating the Perturbation

Rafał Madoński and Przemysław Herman

Abstract— **This paper is focused on a comparison between Model–Free Control and Active Disturbance Rejection Control methods. These two techniques do not require a detailed mathematical description of the system, since they base on the on-line estimation and rejection of the unmodeled elements of the dynamics. Robustness of the closed-loop control system (against external perturbation) and its relation to energy consumption is discussed here. A model of a planar manipulator is used in the conducted case study as an exemplary plant. Conclusions are supported with results obtained with numerical simulations.**

I. INTRODUCTION

"Building reliable systems from unreliable parts" – this statement was pointed out in [10] as one of the key challenges facing the field of control. Almost ten years later, the need of providing satisfactory control quality, even in the presence of nonlinear, time-varying and disturbed phenomena, is still up-to-date. However, some significant input was made since then by the growth of various control techniques that try to estimate the unknown disturbance. These methods usually do not need a precise mathematical model of the process, since the unmodeled dynamics can be treated as a part of the acting perturbation and eventually decoupled from the system. As a result, the disturbance-rejection techniques allow user to treat complex systems (i.e. nonlinear, time-varying, etc.) with simpler models, thus facilitating the control task greatly.

This approach is not novel and has been of interest to researches for years. However, some interesting analytical techniques were developed recently that combine elements known from the classic control theory with the latest achievements in the field. Active Disturbance Rejection Control (ADRC) and Model–Free Control (MFC) are examples of such approaches.

The ADRC method ([3], [6]) assumes that a resultant of the modeling uncertainty and external disturbances can be considered as one of the states of the system. An estimate of this state, provided by a state observer, can be further used in the control signal to compensate for the real perturbation in the plant.

On the other hand, the MFC technique ([1], [2]) uses a particular mathematical model of the system, based on its input-output behavior, which is only valid within a short period of time (in literature it is referred to as "*local* modeling"). Hence, the assumed model has to be continuously updated to provide a reliable information about the plant. The influence of unmodeled dynamics and external disturbances on the considered system can be partially canceled by using the above information in the control signal.

Hence, it is difficult to unanimously classify ADRC and MFC methods within the frames of modern control theory, since the on-line rejection of the system uncertainties makes them both robust and adaptive frameworks. The ADRC and MFC have already been proven to be efficient solutions in practical applications (ADRC: [7], [8], MFC: [5], [11]). Even though they represent different approaches for working with complex systems (in ADRC it is the state observer, in MFC it is the *local* modeling), their common ground is that they allow to work on simplified models of the real processes. They also have similar implementation and tuning complexity[1].

An intriguing questions thus arises for the potential system operators: which of these control methods is more efficient in terms of disturbance rejection? Hence, this paper is trying to tackle this problem. The comparison is made using a model of an one degree-of-freedom system with unbalanced rotating mass (we will denote it as PM1R), described in the next section.

II. SYSTEM DESCRIPTION

The PM1R is a laboratory testbed with a rotating link driven with a DC motor with reduction gear (see Fig. 1). Base of the system is fixed to the wall and the angular position sensor is attached directly to the drive rotor. The nonlinear dynamics model of the PM1R, based on [9], is presented below:

$$J\ddot{q}_m + \tau_f + \eta\tau_g = \tau_m - \eta\tau_d, \tag{1}$$

where $J[kgm^2] = J_m + \eta^2 J_l$ is the combined moment of inertia (with $J_m[kgm^2]$ denoting the moment of inertia of the motor shaft, $J_l[kgm^2]$ standing for the moment of inertia of the manipulator link, and η being the gear ratio), $q_m[rad]$ denotes the angular position of the motor shaft, $\tau_g[Nm] = MGL\sin(\eta q_m)$ is the moment of gravity influence (with $M[kg]$ being the mass of the link, $L[m]$ its length, and $G[m/s^2]$ denoting the gravity acceleration), $\tau_m[Nm]$ and $\tau_d[Nm]$ are the driving and disturbance torques respectively, and $\tau_f[Nm]$ denotes the moment of friction. The model of

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[1]This claim is more of a subjective one, but it should not be underestimated, since it comes from the experience gained from numerous simulation and experimental studies conducted by the first author on various types of systems with different levels of control difficulty.

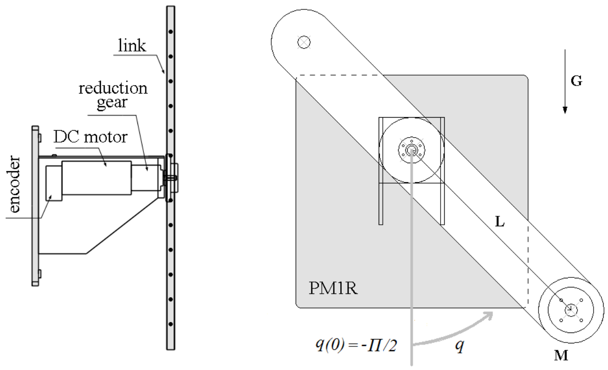

Fig. 1. Scheme of the PM1R system with the assumed notation.

friction torque is a combination of Coulomb and viscous terms:

$$\tau_f = f_c sign(\dot{q}_m) + f_v \dot{q}_m, \tag{2}$$

where $f_c[Nm]$ and $f_v[sNm/rad)]$ are the friction parameters.

Following assumptions were made during proposing the above model:

- **Input signal**
  If the armature induction of the motor can be neglected, we obtain the formulation of driving torque with respect to the motor input voltage ($u[V]$, which is the input signal for the whole system) in a following form:
  $$\tau_m = \frac{k_i u + k_i k_e \dot{q}_m}{R}, \tag{3}$$
  where $k_i[Nm/A]$ is the torque constant, $k_e[sV/rad]$ is the current constant, and $R[\Omega]$ is the circuit resistance.
- **Output signal**
  The model from (1) is in relation to the motor since the measured signal is the angular position of the shaft. However, in our research we are more interested in the position of the manipulator link ($q[rad]$). Hence, the output of the PM1R system in the considered scenario is the angular position of the link, denoted as:
  $$q = \eta q_m \overset{\frac{d}{dt}}{\Longrightarrow} \dot{q} = \eta \dot{q}_m \overset{\frac{d}{dt}}{\Longrightarrow} \ddot{q} = \eta \ddot{q}_m. \tag{4}$$

A. Active Disturbance Rejection Control

The main idea of ADRC method is to reduce the unknown or hard to model phenomena to a resultant disturbance (in literature also known as *total disturbance*). This perturbation is treated as an additional state variable of the system. This fictitious state is estimated on-line by an Extended State Observer (ESO) and then incorporated in the control signal to compensate for the real disturbance acting on the plant. With an intuitive algorithm and wide range of parameter adaptability, the ADRC is a method for dealing with nonlinearities, parameters uncertainties, external disturbances, and coupling issues (for examples visit [6] and references therein).

Let us consider PM1R system from (1) (with respect to (4)) as a partially unknown second order system (i.e. $m = 2$), as seen below[2]:

$$q^{(m=2)} = \ddot{q} = D + \beta u_{ADRC}, \tag{5}$$

where $u_{ADRC}[V]$ is the input signal (DC motor input voltage), $D \in \mathbb{R}$ is the sum of internal (e.g. unmodeled or unknown dynamics) and external disturbances, and $\beta \in \mathbb{R}$ stands for the system parameter. By rewriting the above relation in state space, we obtain:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= D + \beta u_{ADRC}, \\ q &= x_1, \end{aligned} \tag{6}$$

where $x_1[rad]$ and $x_2[rad/s]$ are the chosen phase state variables (angular position and velocity of the manipulator link, respectively).

The state space model from (6) can be extended with an additional, fictitious state x_3^{Δ}, representing the resultant disturbance of the whole system:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= x_3^{\Delta} + \beta u_{ADRC}, \\ \dot{x}_3^{\Delta} &= \dot{D}. \end{aligned} \tag{7}$$

Now, all three states can be estimated with a linear ESO[3], which is defined as:

$$\begin{aligned} \dot{\hat{x}}_1 &= \hat{x}_2 + L_1 \epsilon, \\ \dot{\hat{x}}_2 &= \hat{x}_3^{\Delta} + L_2 \epsilon + \hat{\beta} u_{ADRC}, \\ \dot{\hat{x}}_3^{\Delta} &= L_3 \epsilon, \end{aligned} \tag{8}$$

where $\epsilon := q - \hat{x}_1$ is the estimation error of state x_1; $\hat{\beta}$ denotes the constant value (approximation of term β from equation (5)); L_1, L_2, and L_3 are the observer gains; $\hat{x}_1$, $\hat{x}_2$, $\hat{x}_3^{\Delta}$ are estimations of the states x_1, x_2, x_3^{Δ} respectively, where the last state variable estimates the resultant disturbance (i.e. $\hat{x}_3^{\Delta} \equiv \hat{D}$).

The control signal in ADRC is defined as:

$$u_{ADRC} = -\frac{\hat{D}}{\hat{\beta}} + \frac{1}{\hat{\beta}} \overbrace{(\ddot{q}_{ref} + u^{**})}^{FF+FB}, \tag{9}$$

where $u^{**}[V]$ is the feedback controller (FB) chosen by the user and $\ddot{q}_{ref}[rad/s^2]$ is the additional (and optional) feedforward term (FF). The first component of the above equation is suppose to cancel the *total disturbance* (D) and the second component is responsible for tracking the reference signal.

Assuming that (5) represents the actual PM1R system accurately, as well as $(\epsilon \to 0) \Rightarrow (\hat{D} \to D)$ and $\hat{\beta} \approx \beta$, we may substitute u_{ADRC} in (5) with the one from (9) to obtain following relation:

$$\ddot{q} = D + \beta \left(-\frac{\hat{D}}{\hat{\beta}} + \frac{\ddot{q}_{ref} + u^{**}}{\hat{\beta}} \right) \approx \overbrace{\ddot{q}_{ref} + u^{**}}^{FF+FB}, \tag{10}$$

[2]The input signal u from (3) will be now denoted as u_{ADRC} i.e. $(u \equiv u_{ADRC})$ to avoid confusion with governing signals of other control methods considered in this work.

[3]In its linear variant, ESO takes the form of a classic Luenberger observer.

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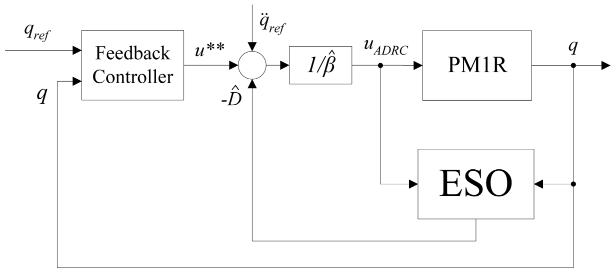

Fig. 2. Block diagram of the ADRC method for PM1R system.

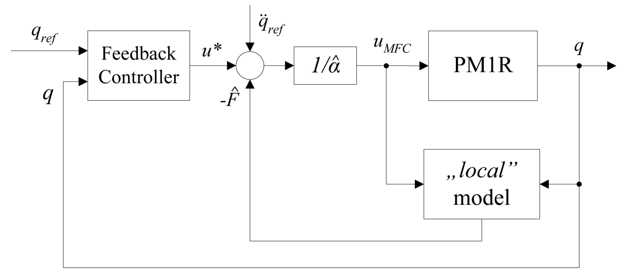

Fig. 3. Block diagram of the MFC method for PM1R system.

which idealistically reduces the nonlinear and mostly unknown PM1R plant model to just a set of integrators with feedback controller and a feed-forward term. A block diagram of the ADRC method for PM1R system is presented in Fig. 2, where $q_{ref}[rad]$ is the reference signal.

B. Model–Free Control

In the MFC approach, a *local* model of the considered plant is constructed. Proposed model, which is prepared regardless of the system physical considerations, is purely a numerical one. It consists of minimum amount of parameters, where one of them, usually denoted as $F \in \mathbb{R}$, represents everything that user does not include in the mathematical model of the system, e.g. unmodeled dynamics, external and unmeasured disturbances. Thus, the main idea of MFC is to identify the unknown term F and compensate in the control signal for its negative effects.

Let us consider for a while an exemplary SISO plant which can be described by a following input-output equation:

$$\Psi(t, y, \dot{y}, \ddot{y}, \ldots, y^{(\gamma)}, \mu, \dot{\mu}, \ddot{\mu}, \ldots, \mu^{(\phi)}) = 0, \quad (11)$$

where Ψ is the function of input (μ) and output (y) signals. Now, assume that $\exists\, n \in \mathbb{Z}^+, n \leq \gamma : \frac{\delta \Psi}{\delta y^{(n)}} \neq 0$. By using the multivariable calculus we can rewrite (11) as a following equation:

$$\Psi^*(t, y, \dot{y}, \ddot{y}, \ldots, y^{(n-1)}, y^{(n)}, y^{(n+1)}, \ldots \\ \ldots, y^{(\gamma)}, \mu, \dot{\mu}, \ddot{\mu}, \ldots, \mu^{(\phi)}) = 0, \quad (12)$$

from which the system output signal can be derived as presented below:

$$\Psi^*(t, y, \dot{y}, \ddot{y}, \ldots, y^{(n-1)}, y^{(n+1)}, \ldots \\ \ldots, y^{(\gamma)}, \mu, \dot{\mu}, \ddot{\mu}, \ldots, \mu^{(\phi)}) = y^{(n)}. \quad (13)$$

Thus, a *local* model of the system from (11) can be defined as:

$$\Psi^*(\cdot) = y^{(n)} = F + \alpha\mu. \quad (14)$$

where $\alpha \in \mathbb{R}$ denotes the constant design parameter (to be chosen in a way that F and αu are of the same magnitude [1]).

By using the same methodology, the *local* model of a partially unknown PM1R plant from (1) (including relation (4)) can be written as follows[4,5]:

$$q^{(m=2)} = \ddot{q} = F + \alpha u_{MFC}, \quad (15)$$

where $u_{MFC}[V]$ is the input signal (DC motor input voltage). According to (15), the estimation of term F uses only the information about the system input and output, as presented below:

$$\hat{F} = \ddot{q} - \hat{\alpha} u_{MFC}. \quad (16)$$

The control signal u_{MFC} is as follows[6]:

$$u_{MFC} = -\frac{\hat{F}}{\hat{\alpha}} + \frac{1}{\hat{\alpha}} \overbrace{(\ddot{q}_{ref} + u^*)}^{FF+FB}, \quad (17)$$

where $u^*[V]$ is the feedback controller (FB) chosen by the operator and $\ddot{q}_{ref}[rad/s^2]$ is the additional feed-forward term (FF). The first component of the above equation is suppose to cancel the resultant disturbance (F) and the second component is responsible for tracking the desired signal.

Assuming that (15) represents the actual PM1R system accurately, as well as $\hat{F} \to F$ and $\hat{\alpha} \approx \alpha$, we may substitute u_{MFC} in (15) with u_{MFC} from (17) to obtain following relation:

$$\ddot{q} = F + \alpha \left(-\frac{\hat{F}}{\hat{\alpha}} + \frac{\ddot{q}_{ref} + u^*}{\hat{\alpha}} \right) \approx \overbrace{\ddot{q}_{ref} + u^*}^{FF+FB}, \quad (18)$$

which, like in the case of ADRC from (10), theoretically reduces the nonlinear and mostly unknown PM1R plant model to a set of two, "pure" integrating actions with feedback controller and a feed-forward term. A block diagram of the MFC method for PM1R system is depicted in Fig. 3.

III. SIMILARITIES BETWEEN ADRC AND MFC

- **Idea**
  The main idea behind ADRC and MFC is that they try to estimate everything user does not include in the mathematical description of the plant. By acquiring this knowledge one can partailly cancel the effects of

[4]Here, similarly to considerations in II-A, the only thing that is assumed to be known is the relative order of the system, i.e. $m = 2$.

[5]The input signal u from (3) will be now denoted as u_{MFC} i.e. ($u \equiv u_{MFC}$) to avoid confusion with governing signal u_{ADRC} seen in prior sections of this paper.

[6]Please visit section IV-C to find information how to implement the control rule without problems with algebraic loop.

unmodeled dynamics in each sampling period, thus making the system inherently robust to unknown phenomena acting on the plant. In ADRC and MFC, an assumption is made, that as long as terms D or F are estimated closely in real-time, analytical expression of the resultant disturbance is not required.

- **Sampling time**
The ADRC method uses the observer to continuously reconstruct the states of the system. The MFC estimates the *local* model of the process in order to poses a precise information about its behavior. Both of these approaches are working on-line, thus their efficiency depends substantially on the sampling time. The rule of thumb is that the less sampling time of the system, the better results can be obtained by ADRC and MFC.
- **Feedback controller**
Two main loops can be distinguished in both ADRC and MFC, i.e. compensation loop and output feedback control loop. The former is related to the design of the control signal, either including element $\hat{D}$ in the ADRC or element $\hat{F}$ in the MFC. The latter is connected to a type of controller, which in both of the considered control approaches is arbitrary but should be related to a given task.
- **Customization**
The advantage of both ADRC and MFC is that they can be tailored to a particular system (but not to all systems). Usually, the relative order of the plant in these techniques is the minimum information needed to formulate a control rule (along with the availability of input and output signals). However, one has to have in mind, that the order of the system has significant influence on the design complexity. In ADRC, the higher order of the plant, the more states user has to estimate, which causes additional tuning and computation problems. In MFC, high order plants face the requirement of computing higher derivatives of output signals.
- **Scalability**
Elements $\hat{\beta}$ and $\hat{\alpha}$, in ADRC and MFC respectively, are the estimates of system constant parameters, as seen in (8) and (16). They can be also considered as scaling parameters of the control signals, since they directly affect their denominators. Hence, $\hat{\beta}$ and $\hat{\alpha}$ influence and enhance the dynamic behavior and disturbance rejection of the closed loop system. From a practical point of view, their derivation is crucial, but unfortunately nontrivial and time-consuming.
- **Error convergence**
Contrarily to the classic feedback control, once the considered control frameworks are tuned properly, there is no need to add integrators to the stabilization controller to ensure the convergence of the position error to zero, as the integral effect is already included in $\hat{D}$ (in ADRC) or $\hat{F}$ (in MFC).

IV. STUDY PREPARATION

A. Controller design and tuning

For both of the tested control algorithms, the same standard PD feedback controller was used, defined as:

$$u^{**} = u^{*} = k_p e + k_d \dot{e}, \tag{19}$$

where $e := q_{ref} - q$ is the tracking error and $k_p > 0$ and $k_d > 0$ are the proportional and derivative gains, respectively. The error dynamics for this particular controller is obtained by applying (19) and the definition of tracking error to equation (10) (or (18)). The result is as follows:

$$\ddot{e} + k_d \dot{e} + k_p e = 0. \tag{20}$$

Proper tuning of the PD controller gains can guarantee an exponential convergence of the tracking error to zero (i.e. $e \to 0$) for any initial conditions. For our research tuning was done empirically with aim to provide minimum tracking error with no significant overshoot.

B. Observer tuning

In order to propose a pole-placement tuning method for the ESO (based on [4]) let us first rewrite equation (8) in the following form:

$$\begin{aligned} \dot{\underline{\hat{x}}} &= \underline{A}\underline{\hat{x}} + \underline{B} u_{ADRC} + \underline{L}\epsilon, \\ \hat{y} &= \underline{C}\underline{\hat{x}}, \end{aligned} \tag{21}$$

where $\underline{\hat{x}} = \left[\hat{x}_1 \ \hat{x}_2 \ \hat{x}_3^{\Delta}\right]^T$, $\underline{L} = [L_1 \ L_2 \ L_3]^T$, $\underline{C} = [1 \ 0 \ 0]$,

$$\underline{A} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \underline{B} = \begin{bmatrix} 0 \\ \hat{\beta} \\ 0 \end{bmatrix}.$$

By setting:

$$\lambda(s) = |sI - (\underline{A} - \underline{LC})| = (s + \omega)^3, \tag{22}$$

the gains of ESO are chosen as:

$$\underline{L} = \left[3\omega \ \ 3\omega^2 \ \omega^3\right]^T, \tag{23}$$

where $\omega[rad/s]$ is the observer bandwidth (tuning parameter). Coefficients in $\underline{L}$ are selected such that the roots of characteristic polynomial $s^3 + 3s^2 + 3s + 1 = 0$ are all placed in one pole location (ω) in the open left-half of the complex plane. Choosing ω should be a compromise between estimation quality and noise sensitivity.

C. Implementation remarks

In order to avoid computational problems (like algebraic loop), the control signal in MFC from (16) should be implemented in a following discrete form:

$$\hat{F}(n) = \ddot{q}(n) - \hat{\alpha} u_{MFC}(n-1), \tag{24}$$

where $n = \frac{t}{T_s}$ is the current sample (with $t[s]$ standing for the current simulation time and $T_s[s]$ being the sampling time), $u_{MFC}(n-1)$ is the control signal applied to the system in previous sampling cycle.

One should also remember that when it comes to ADRC, user should tune the observer loop first before trying to find feedback controller gains.

TABLE I
PARAMETERS USED IN THE CONDUCTED SIMULATIONS

Element	Value	Unit	Element	Value	Unit
L	0.25	m	f_v	0.001	sNm/rad
G	9.81	m/s^2	R	2.23	Ω
M	0.5	kg	β	1	–
η	$1:21$	–	α	1	–
k_i	0.241	Nm/A	ω	300	rad/s
k_e	0.024	sV/rad	k_p	6	–
J	0.083	kg/m^2	k_d	3	–
f_c	0.003	Nm	T_s	0.001	s

D. Simulation settings

The tests were performed in Matlab/Simulink environment with solver set to ODE5 and fixed sampling time $T_s = 0.001s$.

Table I presents the parameters chosen for the conducted simulation tests. Most of the values in the provided table resemble real parameters from the PM1R system described in Section II. The limitations of the system were also taken under consideration, like the saturation of the control signal which is $\pm 12V$.

The same sinusoidal reference signal $q_{ref} = \sin(t)$ was used in all of the performed simulations. The *a priori* knowledge about the reference signal was used to calculate the noise-free derivatives of the desired trajectory, required in the control signals in (9) and (17).

Integral criteria, like IAE (which was calculated from the tracking error) and ISE (which was calculated from the control signal), were also used in the tests to support the conclusions.

V. NUMERICAL SIMULATIONS

The test was divided into three following cases:

C1: Both ADRC and MFC were tuned first to provide similar control quality (in terms of trajectory tracking). No external disturbance was applied to the system in this case. In Fig. 4 no significant differences between results obtained with ADRC and those for MFC can be seen. This observation is confirmed by the benchmark indices in Table II. Figure 5 presents the control signals generated by each controller.

C2: In this case, a significantly large perturbation $d = const = 10$ was added to the system output. It should be highlighted that no retuning have been done after test C1. In the case of MFC, noticeable (however temporary) oscillations can be seen during the first seconds of the study. This effect, seen in Fig. 6, is in consequence of the estimation phase as the controller needs time to react to the changes applied to the system (in our case - the external disturbance). Similar estimation takes place in ESO, however thanks to the high gains of the observer, its estimates converge rapidly and therefore the system adapts to the new situation faster. The unwanted oscillatory behavior of the MFC has its direct effect on the control signal, depicted in Fig. 7. The above remarks are backed up with integral criteria in Table II.

TABLE II
INTEGRAL CRITERIA FOR ADRC AND MFC (C1-C3)

Case C1:		
—	ADRC	MFC
IAE	1.33	1.32
ISE	133.8	136.8
Case C2:		
—	ADRC	MFC
IAE	49.76	89.45
ISE	124.5	168.6
Case C3:		
—	ADRC	MFC
IAE	3.43	1.43
ISE	145.8	148.4

C3: Again, with no extra retuning after C1 (or C2), the system output was disturbed with a sinusoidal signal $d = 0.05\sin(12t)$. Despite the perturbation acting on the plant, the MFC method managed to deliver satisfactory tracking quality, as seen in Fig. 8. The ADRC, on the other hand, had problems with estimating and canceling the sinusoidal-type signal. From analyzing the control signals in Fig. 9 one can notice that the MFC approach paid the price of being superior solution in this case. Similar conclusions can be derived from ISE values in Table II.

The obtained results provided some interesting insight into the advantages and disadvantages of the considered control strategies. Following observations can be made. Both ADRC and MFC, in spite of the fundamental differences in dealing with the unmodeled dynamics, deliver similar control quality (in terms of trajectory tracking and energy efficiency) for case C1.

Case C2 pointed out the fact that the ADRC method, by the use of tunable observer, can be adjusted to a given situation. High gains provide faster convergence of the states (including state $\hat{x}_3^{\Delta}$ representing the resultant disturbance).

In contrary to the previous point, the ADRC did not perform well in case C3. The proposed structure of ESO provides a full disturbance rejection only for constant perturbation ($\dot{D} = 0$). The quality of ADRC could be improved by extending the observer with more virtual states, representing the estimates of consecutive derivatives of the resultant disturbance.

VI. CONCLUSIONS

Two control strategies based on cancellation of the system unknown and unmodeled elements were tested. The ADRC and MFC methods were compared with respect to the robustness against various external disturbances. Advantages, as well as drawbacks of the considered approaches, were pointed out by an illustrative case study. Main conclusion from the conducted simulation study is that ADRC and MFC are effective solutions for dealing with unpredictable phenomena. However, the numerical examples showed that

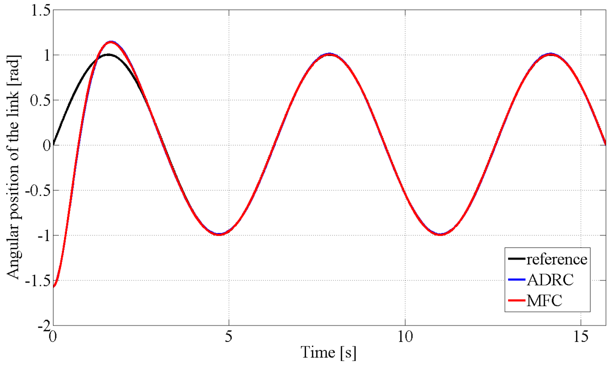

Fig. 4. C1: output signals in the case of no external disturbance.

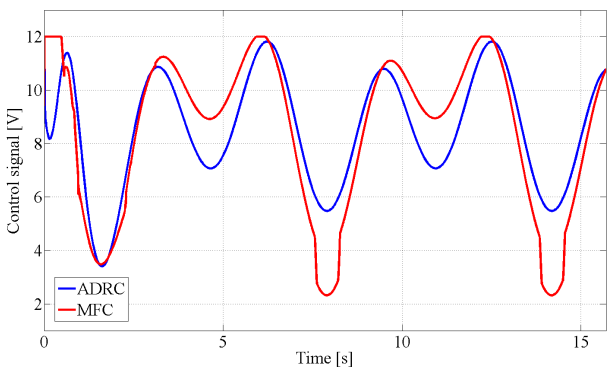

Fig. 5. C1: control signals in the case of no external disturbance.

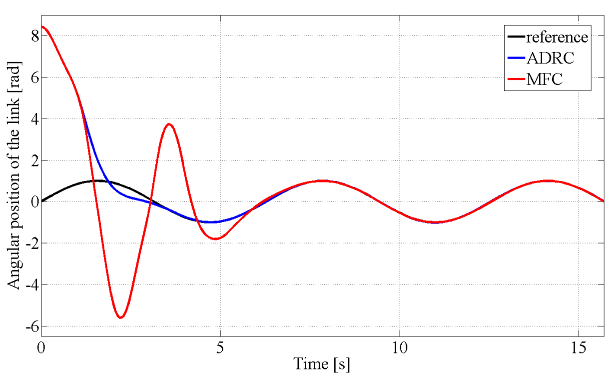

Fig. 6. C2: output signals in the case of external disturbance $d = 10$.

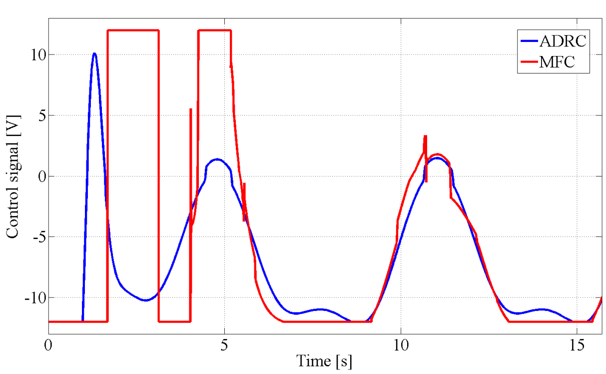

Fig. 7. C2: control signals in the case of external disturbance $d = 10$.

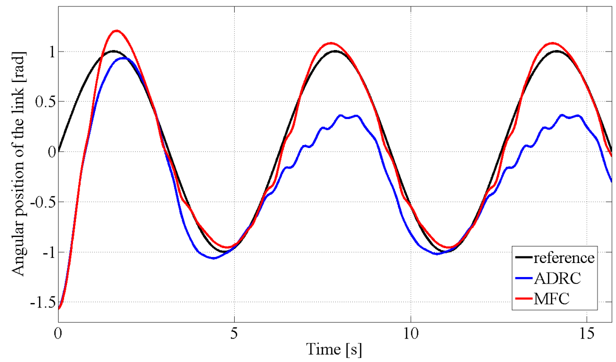

Fig. 8. C3: output signals in the case of ext. dist. $d = 0.05\sin(12t)$.

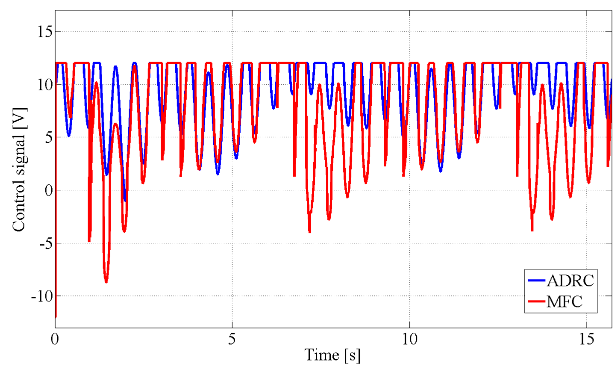

Fig. 9. C3: control signals in the case of ext. dist. $d = 0.05\sin(12t)$.

these two approaches are not all-purpose solutions and need to be tailored to a given situation in order to work properly.

REFERENCES

[1] M. Fliess, C. Join, "Model–Free Control and Intelligent PID Controllers: Towards a Possible Trivialization of Nonlinear Control?", *IFAC Symposium on System Identification*, Saint-Malo, 2009

[2] M. Fliess, C. Join, "Intelligent PID Controllers", *Mediterranean Conference on Control and Automation*, pp. 326–331, Ajaccio, 2008

[3] Z. Gao, "Active Disturbance Rejection Control: A Paradigm Shift in Feedback Control System Design", *American Control Conference*, pp. 2399–2405 , Minneapolis, 2006

[4] Z. Gao, "Scaling and Parameterization Based Controller Tuning", *American Control Conference*, pp. 4989-4996, Denver, 2003

[5] P. Gedouin, E. Delaleaua, J. Bourgeot, C. Join, S. A. Chirani, S. Calloch, "Experimental Comparison of Classical PID and Model–Free Control: Position Control of a Shape Memory Alloy Active Spring", *Control Engineering Practice*, 19(5), pp. 433-441, 2011

[6] J. Han, "From PID to Active Disturbance Rejection Control", *IEEE Transactions on Industrial Electronics*, 53(3), pp. 900–906, 2009

[7] M. Kordasz, R. Madoński, M. Przybyła, P. Sauer, "Active Disturbance Rejection Control for a Flexible-Joint Manipulator", *Springer's Lecture Notes in Control and Information Sciences*, Volume 422, pp. 247–256, 2012

[8] R. Madoński, P. Herman, "An Experimental Verification of ADRC Robustness on a Cross-coupled Aerodynamical System", *International Symposium on Industrial Electronics*, pp. 859–863, Gdańsk, 2011

[9] M. Michałek. Sterowanie robotow manipulacyjnych, internal report (in Polish). *Chair of Control and Systems Engineering*, Poznań University of Technology, 2010.

[10] R. M. Murray, K. J. Aström, S. P. Boyd, R. W. Brockett, G. Stein, "Future Directions in Control in an Information-Rich World", *IEEE Control Systems Magazine*, 23(4), pp. 20–33, 2003

[11] J. Villagra, B. D'Andrea-Novel, S. Choi, M. Fliess, H. Mounier, "Robust Stop-and-Go Control Strategy: an Algebraic Approach for Nonlinear Estimation and Control", *International Journal of Vehicle Autonomous Systems*, 7(3/4), pp. 270–291, 2009