Towards a turnkey solution of industrial control under the active disturbance rejection paradigm

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Abstract: The potential of active disturbance rejection control (ADRC) as a viable solution to industrial control has become increasingly evident after the recent adoptions by major industrial concerns, chiefly because of its ability of disturbance rejection and its independence of a detailed mathematical model of the plant. With the controller and observer bandwidths in ADRC largely determined a priori by the design specifications, and with the order of the plant largely known for major classes of industrial processes, the only parameter the user needs is the gain in the input channel that characterizes the proportional relation between the input signal and the derivative of the process output of certain order. This normally slow changing process parameter is denoted here as the critical gain parameter (CGP). This paper is concerned with the task of estimating CGP and regularly updating it in the ADRC, thus making it possible for the controller to be set up, tuned, and commissioned with a single stroke of a key by the industry personnel. The proposed approach integrates the classic ADRC with an extremum seeking-based parameter estimation of the CGP and it greatly expands the operation range and the robustness of the ADRC-based approach, relieving the designer from the tedious task of empirical tuning. An illustrative simulation example is provided to validate the proposition.

Keywords: active disturbance rejection control (ADRC), critical gain parameter (CGP), extremum seeking (ES)

1. INTRODUCTION

From the latest trends in automatic control, one may notice a particular class of techniques that depart from strictly model-based designs of the textbooks, and strictly model-free solutions such as those found in the daily practice in industry. These are the techniques in the spirit of active disturbance rejection paradigm [1-3]. Bridging the gap between model-based and model-free control strategies, as it is classified in between these two extremes, this paradigm provides a platform to systematically develop practical and effective control designs while keeping the required model information to a bare minimum.

The mentioned model-based design is cherished in the modern control theory, which is known for its rigor. Its applicability is however often questioned due to the lack of detailed plant model in practice, or the cost of obtaining one. Uncertainties are inevitable in engineering practice and they often go far beyond the scope of the theories of robust or adaptive control [4, 5]. In many cases the control design must be, and is, carried out without much model information, where strictly model-based designs, such as classic adaptive control or feedback linearization, show their limitations.

The model-free design, on the other hand, symbolized in the time-tested PID solution, is a tool of choice for practitioners. It can tolerate a predefined set of exogenous signals, while accomplishing its mission satisfactorily without the need for control reconfiguration by the operator. However, the lack of effective counter measures against unknown disturbances, both internal and external, makes these designs, like gain-scheduling or fuzzy-logic, limited in practice. Despite their drawbacks pointed out in [1, 6], model-free approaches, usually based on conventional PID, are by far the most common control algorithms in industrial applications.

There is an everlasting demand from the industry to bridge the control theory-practice gap [7, 8] and to propose an effective alternative that would create a synergy of both model-based and model-free approaches, reinforcing their advantages and limiting their shortcomings. This need is also noticeable in academia in search of a new paradigm with new technologies [9]. Active disturbance rejection techniques were introduced as a potential solution to that problem.

Even though the active disturbance rejection control approaches, broadly considered here, go under different names and were proposed by different research groups spread all over the world, they share a common theme in how they define and solve the problem of system uncertainties.

Whether it goes by the name of active disturbance rejection control (ADRC [1, 2]), model-free control (MFC [10])¹, extended high gain observer-based control (EHGO [11]), or generalized proportional integral observer-based control (GPIO [12]), the active disturbance rejection paradigm is based on one simple premise: as long as the discrepancies between the real process and its assumed mathematical model as well as the influence of any unknown external disturbances are compensated for in real time, the detailed mathematical model of the

¹The reader should understand the MFC as a technique that is free from a “precise” mathematical model of the plant.
plant is not required. It means that an exemplary complex process can be treated from a control design point of view as a simple, disturbance-free one, since the unmodeled terms are estimated and canceled in real time.

Much work has been done so far by various researchers to further explore the power of these disturbance-centric designs, including thorough theoretical analyses (recently summed up in [13]), comparisons with other techniques [14], various improvements [15] industry-inspired laboratory experiments [16, 17], recent market launches from control chip manufacturers Texas Instruments and Freescale Semiconductor, and even actual factory validations [18].

The considered disturbance-centric control algorithms are usually designed and implemented around a following, specific form of a constantly updated nominal model:

\[ y^{(n)} = F + bu \]  

(1)

which can describe a wide range of dynamic systems. Parameter \( n \) is the relative order of the process model (given or to be determined), \( y \) is the system measurable output, \( u \) is its input, \( F \) is the system state- and/or control-dependent overall unknown dynamics, often referred as the total disturbance (i.e. lumped combination of modeling discrepancies and external disturbances), \( b \neq 0 \) is the input channel process gain, treated in the considered control methodology as a (locally) constant parameter. Since \( y \) “scales” the input signal \( u \), it directly influences the stability of the closed-loop control system, hence its proper evaluation is crucial. Due to its importance it will be referred as a critical gain parameter (CGP).

For the system model (1), under the assumptions \( \hat{F} = F \) and \( \hat{b} = b \), a following control action can be proposed:

\[ u \triangleq \frac{-\hat{F} + v}{\hat{b}} \quad \text{which is chosen significantly different from the real one.} \]

\[ y^{(n)} = v \]  

(2)

Hence, the need is to find whether it is possible to relax (or even remove) the requirement on prior information on the unknown \( b \) and make the whole considered disturbance-rejection framework even more effective, in terms of speed and precision of disturbance reconstruction and attenuation as well as to unburden the designer from the tedious task of CGP empirical tuning. Such solution, when applied to the standard ADRC, would make it closer to become a true turnkey design.

2.1. Motivation

In terms of control applications, an ideal turnkey control solution is a control system that can be straightforwardly implemented into a given process, is immediately ready to use upon implementation, and is designed to fulfill a certain task without further user intervention. Such control system is highly desirable in industry as it provides simplicity and intuitiveness to the operators as well as effectivness of task realization due to both robust and adaptive features.

Techniques like auto-tuning, model-predictive control, multi-model control, neural networks, or fuzzy-logic controllers, were all proposed over the years to try to push the conventional control designs towards true industrial turnkey solutions, however with variable success in this area.

The active disturbance rejection control solutions have been introduced as a new paradigm to overcome the disadvantages of the aforementioned conventional industrial control tools. They have already been proven to be appealing to industry practitioners, however disturbance-centric methods are not turnkey solutions yet. True turnkey operation requires a lot of information, most of which is already known in the considered paradigm. This leaves the problem of CGP estimation mostly unresolved.

These limitations are usually due to the assumed structure of \( F \), chosen tuning procedure, and/or operating conditions (e.g. sampling rate, measurement noises). The problem of acquiring \( F \) is however beyond the scope of this work.
2.2. Known solutions

There are some recorded attempts in the literature to tackle the problem of CGP tuning, other than the already mentioned trial-and-error approach.

An open-loop parameter estimation technique was presented in [19] based on direct computation of the input gain in the form: \( \hat{b} \approx \frac{y^{(\infty)}(0^+)}{u^{(0^+)}}, \) where \( y^{(\infty)}(0^+) \) is the \( n \)th-order system output, \( u^{(0^+)} \) is the control signal, both observed in some predefined initial time \( t_0 \). The disadvantages of this approach lie in strong assumptions that there is no influence of the total disturbance in the initial system operation (i.e. \( F = 0 \)) and that the higher-order derivatives of the output \( y \) can be computed (problematic in case of noisy output measurement), if not available through direct measurement. Nevertheless, in some scenarios, this approach can give some, even initial, understanding of \( b \), especially if the system behavior is mostly unknown.

In [20], the proposed approach starts with a conventional total disturbance observer-based reconstruction for some predefined time period. Then, both \( F \) and \( b \) are assumed to be unknown, time-varying parameters and are estimated separately using a projected gradient algorithm. The disadvantage of this approach lies in the complexity of its derivation and its implementation difficulty.

A closed-loop algebraic identification technique has been applied in [21] to a flexible joint manipulator in order to identify the partially unknown system CGP (in this case: natural frequency of a flexible robot) and update the designed GPIO controller.

Same estimation tool has been used in [22] to identify the lumped combination of induction motor parameters. In this approach, the parameters that were part of the input dynamics were identified separately, which required extra implementation and resulted in additional computational complexity.

2.3. Proposed solution

This paper proposes a combination of conventional disturbance-rejection control strategy (as seen in [2]) with an extremum seeking algorithm [23, 24] to estimate the unknown CGP. The extremum seeking (ES) is a non-model based real-time optimization approach for dynamic problems, where only limited knowledge of a system is available, which corresponds with the minimum-model idea of ADRC.

3. CASE STUDY

3.1. System description

In Fig. 1, a liquid tank with one inlet and one outlet is presented, based on [25]. By manipulating the valve with the governing action \( u \) the inlet flow \( f_{in} \) is controlled. The outlet flow \( f_{out} \) is caused by the hydrostatic pressure resulting from a nonzero gravity acceleration. The current liquid level, denoted as \( h \), is measured with a floating sensor. Due to the specific shape of the tank (i.e. nonparallel walls), the cross-section of the tank (\( \Lambda \)) is a function of level \( h \) and is denoted as \( \Lambda(h) \).

![Fig. 1 The considered tank level control problem [25].](image)

From the control point of view, the above system is a nonlinear SISO plant and the control task is to make the liquid level \( h \) track the user-specified level \( h_d \) by manipulating the valve position \( u \). Following practical assumptions are met.

A1) Function \( \Lambda(h) > 0 \) is unknown and unmeasurable.

A2) Input flow is a linear function dependent on the control signal: \( f_{in} = \rho u \), where \( \rho \) is unknown.

A3) Output flow is an unknown nonlinear function of \( h \) and unknown set of parameters \( p \), hence: \( f_{out} = \Psi(h, \rho, p) \).

A4) Level \( h \) is the only measurable feedback signal.

A5) Desired level \( h_d \) is piecewise constant: \( h_d = 0 \).

The process dynamics is obtained from the volume balance equation as:

\[
\dot{V} = f_{in} - f_{out} = \rho u - \Psi(h, \rho) \tag{3}
\]

and since \( dV = \Lambda(h)dh \), where \( dh \) is infinitesimally small slice of liquid at level \( h \), the above equation can be rephrased as:

\[
\Lambda(h)\dot{h} = f_{in} - f_{out} = \rho u - \Psi(h, \rho) \tag{4}
\]

3.2. Conventional ADRC

Tank system from (4) is a first order, nonlinear, and mostly uncertain plant model. Parameters \( \rho \) and \( p \) are unknown, while \( \Lambda(h) \) and \( \Psi(h, \rho) \) are unknown and additionally varying (as functions of \( h \)).

In order to apply the standard ADRC control structure a following system remodeling of (4) based on (1) can be conducted:

\[
\dot{h} = \frac{f_{in} - f_{out}}{\Lambda(h)} = -\frac{\Psi(h, \rho)}{\Lambda(h)} + \frac{\rho}{\Lambda(h)} u \tag{5}
\]

Under the assumption that the total disturbance consists uncertainties in modeling both \( \dot{F}(h, \rho) \) and \( b(h) \):

\[
F(h, u, \rho) = \dot{F}(h, \rho) + \left( \frac{\rho}{\Lambda(h)} - \dot{b} \right) u \tag{6}
\]

the system can be expressed in form of a following nominal model (cf. (1)):

\[
\dot{h} = F(h, u, \rho) + \dot{b}u \tag{7}
\]
where $\hat{b} > 0$ is the CGP being rough estimate of $b(h)$.

Since $F(h, u, p)$ is assumed to be unknown, a following total disturbance model is proposed:

$$\frac{d}{dt} F(h, u, p) = 0$$  \hspace{1cm} (8)

which treats this uncertainty $F(\cdot)$ as a piecewise constant signal. Hence, the extended state-space model of the above process with following choice of state variables:

$$x \triangleq [x_1 \ x_2] = [h \ F(\cdot)]$$

is expressed as:

$$\dot{x} = A \hat{x} + Bu + LC (x - \hat{x})$$  \hspace{1cm} (9)

with the aim $\hat{x} \to x$, where $L$ is the vector of observer gains and $\epsilon$ is the estimation error vector.

An extended state observer (or ESO), which is the core any ADRC structure, can be designed for the above virtually augmented system as:

$$\dot{\hat{x}} = A \hat{x} + Bu + LC (x - \hat{x})$$  \hspace{1cm} (10)

and comparing the results by sides a following set of observer gains is computed as: $L = [l_1 \ l_2] = [2\omega_0 \ \omega_0^2]$, where $\omega_0 > 0$ stands for the observer bandwidth (design parameter).

In order to apply the disturbance-rejection control, a following governing action is proposed:

$$u \triangleq \frac{-\hat{x}_2 + v}{\hat{b}} = \frac{-\hat{F}(\cdot) + v}{\hat{b}}$$  \hspace{1cm} (11)

which after fulfilling assumptions $\hat{F} = F$ and $\hat{b} = b$ (cf. Introduction) results in perfect disturbance cancellation. The remaining dynamics is represented with a chain of integrators: $\dot{h} = v$.

The new outer-loop control $v$ for the resultant disturbance-free system model, which is now trivial to govern, can be designed even as a simple proportional controller:

$$v \triangleq k_p (x_{1d} - x_1) = k_p (h_{1d} - h)$$  \hspace{1cm} (12)

where $k_p$ is the user-defined proportional gain and $e \triangleq h_{1d} - h$ is the level control feedback error.

Application of controller (12) to the integrator-like dynamics yields:

$$\dot{h} = k_p (h_{1d} - h)$$  \hspace{1cm} (13)

for which the error dynamics (under the assumption A5) is: $\dot{e} + k_p \epsilon = 0$.

3It is a reasonable assumption in engineering practice as long as the control sampling frequency is sufficiently high.

3.3. Proposed ADRC (with the estimation of CGP)

Extremum seeking [23, 24] is an empirical real-time optimization scheme in which no exact descriptions of the model is required. However, the objective function of the optimization problem must be available from process measurements. The ES can be used to estimate unknown parameters of a dynamical system such that the extremum of a predefined cost function is obtained.

The fundamental element of the ES mechanism is the dither signal, which in the considered case changes the estimated CGP with every algorithm iteration by sinusoidally perturbing the $b$ value. It then computes the gradient of cost function $\nabla J$ and finds the cost function direction of decrease. The result of optimization (i.e. estimated $\hat{b}$) continuously updates both the control rule and the observer of the conventional ADRC structure, as seen in Fig. 2.

The used ES scheme is presented in Fig. 3, in which $J$ is the mentioned cost function, $\alpha$ is the amplitude of sinusoidal perturbation, $\omega$ is its pulsation, and $k$ is the iteration number. The block $\frac{k + 1}{k + 1}$ can be considered as a gradient-computing element with a high pass filter, where $h \in (0; 1)$ is a cut-off frequency that should be below the perturbation pulsation $\omega$. The block $\frac{1}{1 + \gamma \omega T}$ is a discrete integrator with gain $k_1$, where $\gamma = k_1 T_P$ (and $T_P$ is the sampling period). The equations of the ES optimization algorithm seen in block diagram in Fig. 3 can be written in a discrete form as:

$$\zeta(k) = -h \zeta(k - 1) + J(k - 1)$$

$$\hat{b}(k + 1) = \hat{b}(k) - \gamma \alpha \cos(\omega k)[J(k) - (1 + h) \zeta(k)]$$

$$\hat{b}(k + 1) = \hat{b}(k + 1) + \alpha \cos(\omega (k + 1))$$

where $\zeta$ is an auxiliary virtual signal.

In the considered case study, two types of cost functions are tested:

$$J_{\text{ideal}} = 0.01 \int_0^T |h(t) - \hat{b}| dt \quad \text{and} \quad J_{\text{real}} = \int_0^T |e| dt$$

The ES scheme in an ideal situation should simply minimize cost function $J_{\text{ideal}}$ to find the CGP. Hence, such test is conducted first to validate the ES mechanism alone. The result is depicted in Fig. 4 and Fig. 5 in which the ES convergences quickly (around iteration $n = 20$) and
is kept in close neighborhood of the actual process CGP throughout the rest of the simulation.

However, based on a practical assumption that the real value of CGP is not available, an ITAE-like criterion function $J_{\text{real}}$ is chosen instead to make the study closer to what it would be like in real control scenario. The performance of the ES for such case is also seen in Fig. 4 and Fig. 5 and one can notice there that the optimization algorithm found its minimum (from $n = 600$ not in the actual value of CGP, but rather in an approximated value $b \approx 1.65$).

By analyzing Fig. 6 on the other hand it is seen that the CGP optimized by the ES, whether it was chosen early in the optimization process ($n = 50 \rightarrow b = 2.234$) or near the end when the cost function reached its minimum ($n = 2000 \rightarrow b = 1.608$), gave almost similar performance of the ADRC compared to the one obtained by ADRC tuned with the real value of CGP (perfect case where $b = b(h)$). It means that an ideal estimation of CGP is not necessary in case of a practical ADRC design as the uncertainty $\triangle b = b(h) - b$ is compensated in part by the disturbance rejection loop (as seen in (5)-(7)). The use of ES however expands the robustness of the ADRC framework as the CGP can be roughly estimated (but giving satisfactory performance), instead of blindly manually tuned, thus causing less uncertainty for the disturbance observer to handle. In the same figure, one can see that highly improper manual choice of CGP results, for this particular process, in very low performance in terms of convergence speed (for $b_{\text{man}} = 15$ and $b_{\text{man}} = 5$) or unacceptable signal jitter (for $b_{\text{man}} = 0.01$), which indicates an obvious fact that the robustness of ADRC in terms of uncertainty in choosing CGP has its limitations.

In Fig. 7, the performance of conventional ADRC is also confronted with the proposed ADRC+ES approach in terms of robustness against gradual changes of the process CGP. A clear advantage of the optimized version of ADRC is seen when looking at the computed values of the integral criterion $J_{\text{real}}$.

Parameters chosen for the Matlab/Simulink simulation are gathered in Table 1.

### 4. SUMMARY

In this work, a step was taken towards a transition of active disturbance rejection-based control design to a turnkey industrial solution. An extremum seeking estimation of the unknown CGP was presented to increase the robustness of the standard ADRC design and unburden the control designer from the tedious task of its manual tuning. This simple, yet effective, approach was introduced and verified with a simulation case study.

### REFERENCES

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![Fig. 4](image1.png) The ES-based estimation of the process CGP (based on $J_{\text{ideal}}$ and $J_{\text{real}}$).

![Fig. 5](image2.png) The result of ES-based optimization of cost functions $J_{\text{ideal}}$ and $J_{\text{real}}$.

![Fig. 6](image3.png) A comparison of similar ADRC designs but with different $b$ tuning.

![Fig. 7](image4.png) A comparison between conventional ADRC and the proposed ADRC+ES in case of changeable CGP.