

# Active Disturbance Rejection Control: A Paradigm Shift in Feedback Control System Design

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**Abstract:** The question addressed in this paper is: just what do we need to know about a process in order to control it? With active disturbance rejection, perhaps we don't need to know as much as we were told. In fact, it is shown that the unknown dynamics and disturbance can be actively estimated and compensated in real time and this makes the feedback control more robust and less dependent on the detailed mathematical model of the physical process. In this paper we first examine the basic premises in the existing paradigms, from which it is argued that a paradigm shift is necessary. Using a motion control metaphor, the basis of such a shift, the Active Disturbance Rejection Control, is introduced. Stability analysis and applications are presented. Finally, the characteristics and significance of the new paradigm are discussed.

## I. INTRODUCTION

In this paper we argue for the necessity of a paradigm shift in feedback control system design. As feedback control permeates all fields of engineering, such a paradigm shift obviously could have significant engineering implications. To make the paper readable to a potentially wide range of readers, who otherwise might not be thoroughly versed in the field, we first examine some common notions and assumptions in this section.

Historically, feedback control was the very technology that propelled the industrial revolution. Watt's flyball governor used in the steam engine was a feedback control device that marks the beginning of mankind's mastering of nature's raw power. Today, from manufacturing to space exploration, it is hard to imagine an engineering system that doesn't involve a feedback control mechanism of some kind.

The concept, theory and applications of feedback control have drawn great interests from both theoreticians and practitioners alike. There is currently a vast literature on the theory of feedback control, accumulated over more than six decades of investigations. Its development more or less parallels that of a branch of applied mathematics. Initially, in the 40s and 50s of the last century, control theory provided mathematical explanations of the ingenious feedback control mechanisms used, for example, in the military applications in the World War II. Gradually, helped by the government funding during the cold war, it grew into a distinct academic discipline, posing its own questions, such as the optimal control formulation, and establishing its own mode of investigation, mostly axiomatic and deductive.

The object of feedback control is a physical process where a causal relationship is presumed between its input and output. In a feedback control system, the input variable is to be manipulated by a controller, so that the output changes in a desirable way. It is important to note that in

practice the control law, i.e., the equations that describes how the controller works, is usually determined empirically [1,2]. Control theory, however, presumably establishes the science behind such practice. It presupposes that the dynamics of the physical process be captured mathematically, and it is on this mathematical model that rests the *paradigm* of modern control.

With mathematical rigor, this paradigm provides a conduit to invaluable insights on how and why feedback control works. For example, the mathematical analysis of the flyball governor lead to a better understanding of the oscillation or even instability problems sometimes seen in the operation of steam engines. Moreover, the paradigm furnishes a framework whereby the control law is obtained deductively from the mathematical axioms and assumptions. The development of linear optimal control theory is a case in point. Assuming that 1) the plant dynamics is captured by a mathematical model that is linear and time-invariant; 2) the design objective is captured in a cost function; linear optimal control theory, from the Kalman Filter to the  $H_\infty$ , represents a sequence of major achievements of modern control theory.

The reliance of the modern control paradigm on detailed mathematical models of physical systems and deductive reasoning did not go unquestioned. For example, Han wondered if modern control theory is about controlling mathematical models, instead of the actual physical plants [3]. Ho suggested empirical control science, employing the hypothetico-deductive methodology, as an alternative, complimentary to the dominant axiomatic approach [4]. That is, he proposed that deductive reasoning be replaced with inductive reasoning, and that new control laws be discovered through experimentation. There have also been strong movements in the development of model-free control design methods, including those based on artificial intelligence, artificial neural networks, and fuzzy logic.

Parallel to the development of the ever more mathematical control theories, practitioners have shown their unyielding preference for simplicity over complexity. Over 90% of industrial control is of the simple, some may even say primitive, proportional-integral-derivative (PID) type [2], which was first proposed by Minorsky in 1922 [5]. The controller is mostly designed empirically, and it does not require a mathematical model of the physical process. It is in this background of well established modern control theory and, to some degree, primitive engineering practice that the perennial theory-practice debate continues.

In this paper, through the reflection on the nature of existing paradigms in section II, concerning both theory and

practice, we hope to establish the necessity of a paradigm shift. The active disturbance rejection concept, introduced in section III, could very well serve as the basis of the new paradigm, which is characterized in section IV. Also included in section III is the demonstration of the broad range applications of the active disturbance concept. Finally, the paper is concluded with a few remarks in Section V.

## II. THE EXISTING PARADIGMS

In this section we attempt to reflect on the paradigm out of which modern control theory grew. In comparison we also describe the nature of engineering practice. The discrepancy of the two perhaps explains the rudimentary cause of the theory-practice gap and provides the motivation for a paradigm shift.

### 2.1 The Modern Control Paradigm

Using motion control as a *theme problem* in this paper, consider an electromechanical system governed by the Newtonian law of motion

$$\ddot{y} = f(y, \dot{y}, w, t) + bu \quad (1)$$

where  $y(t)$ , or simply  $y$ , is the position output,  $b$  is a constant,  $u$  (short for  $u(t)$ ) is the input force generated typically by an electric motor,  $w$  (i.e.,  $w(t)$ ) is an extraneous unknown input force (known as the external disturbance), and  $f(y, \dot{y}, w, t)$  represents the combined effect of internal dynamics and external disturbance on acceleration.

In the model-based design, assuming that the desired closed-loop dynamics is

$$\ddot{y} = g(y, \dot{y}) \quad (2)$$

the feedback control design is carried out as follows:

Step1: Find an approximate, usually linear, time-invariant and disturbance-free, analytical expression of  $f(\dot{y}, y, w, t)$ ,

$$\bar{f}(y, \dot{y}) \approx f(y, \dot{y}, w, t) \quad (3)$$

through the modeling process;

Step2: Design the control law

$$u = \frac{-\bar{f}(y, \dot{y}) + g(y, \dot{y})}{b} \quad (4)$$

to satisfy the design goal, approximately if not exactly.

Note that both the well-known pole-placement method for linear time-invariant systems and the feedback linearization method for nonlinear systems can be characterized in (4). The key assumption is that the analytical expression  $\bar{f}(y, \dot{y})$  is sufficiently close to its corresponding part  $f(y, \dot{y}, w, t)$  in physical reality. Specifically, in the case of the industrial motion control system described in (1),  $f(y, \dot{y}, w, t)$  is generally nonlinear and time-varying. It is sometimes not even well-defined mathematically, such as in the cases of hysteresis in motor dynamics and backlash in gearboxes. To assume (3) holds in general seems to be overly optimistic indeed. In fact, when this model-based approach is put to practice, it was

often found that engineers spent most of time on modeling rather than on control design. This is perhaps the main reason that led some to question whether control theory is all about the models and little about controls.

Generalizing from the above illustration, the paradigm established, implicitly, in modern control theory can be characterized as follows: 1) the physical process be described accurately in a mathematical model; 2) the design objectives be described in yet another mathematical model, either in the forms of differential equation, as in (2), or as a cost function to be minimized; 3) the control law be synthesized that meets the objectives; and 4) a rigorous stability proof be provided. We denote this as the *modern control paradigm* (MCP). To be sure, the model dependence issue has been recognized by many researchers, and various techniques, such as Robust Control and Adaptive Control, have been suggested to make the control system more tolerant of the unknowns in physical systems [6]. Another school of thought is the use of disturbance observers to estimate and cancel the discrepancies between the physical system and its model. See, for example, a survey of these observers in [7]. The question still remains: to what extent must a control design be dependent on an accurate model as in (3)?

### 2.2 The Error-Based Empirical Design Paradigm

Many in academia hold the view that the main issue practitioners face is that of application, i.e., understanding and applying control theory in their trade. Upon close examination, one can clearly see that practitioners operate in a completely different mindset when it comes to designing and operating a feedback control system. It is centered around and driven by the tracking error, as shown below. We denote this paradigm as Error-based Design Paradigm (EDP).

Let  $r$  be the desired trajectory for the output to follow. A practical control design problem is to synthesize a control law so that the tracking error  $e=r-y$ , or simply denoted as the error, is small. With  $f(y, \dot{y}, w, t)$  in (1) unknown, the *empirical approach* relies on human intuition and insight about the plant in devising a control law. The general idea is that, since the objective of control is to keep the error small, control actions should be based on its behavior. By characterizing the error numerically in terms of its present value, the accumulation of its past values, and the trend of change for the immediate future, the control action can be divided as the response to each term. And this gives rise to the most popular controller used in industry: the PID controller, defined as  $u = k_p e + k_i \int e + k_d \dot{e}$ , where desired performance is sought by manually adjusting (tuning) the controller parameters  $k_p$ ,  $k_i$ , and  $k_d$ . This controller is simple to implement and intuitive to understand. Its popularity and longevity in practice is indisputable evidence to the vitality of the EDP.

Since its debut eighty years ago, many improvements have been made to (4) over the years, such a gain-scheduling and the use of nonlinear gains, to make it more powerful in handling difficult tasks. But there is also a sense that human biology itself is a source of good control

mechanisms and this rich body of expertise should be exploited. This leads to the second kind of method in EDP, one that is based on the symbolic description of the error behavior. The control action is deduced in the same fashion of human reasoning, using a rule-based system built from human intuition. To account for the ambiguity of linguistic descriptions, a membership grade is assigned to each member of the set of symbolic values. And this led to the well-known field of fuzzy logic control (FLC).

In summary, the MCP and EDP both seem inadequate in addressing the fundamental issue of feedback control. The former may be overly presumptive in what we know about the dynamics of the physical system to be controlled, while the latter seems far from efficient and systematic. The solution, it seems, must be sought outside of the existing paradigms.

### 2.3 The Necessity of a Paradigm Shift

Control theory, as a part of general systems theory (GST), is applicable to all engineering disciplines. Bunge refers to GST as “distinctly technological metaphysics” [8]. It poses a serious challenge to both popular philosophies of science: empiricism and rationalism. It even poses difficulties to the definition of science [8]. The theory-practice gap is merely a manifestation of the tension between empiricism and rationalism. The MCP has reached a juncture where it can no longer give satisfactory answers to the questions raised by its failure to significantly penetrate engineering practice. As far as the progress of science is concerned, according to Kuhn, it will eventually be replaced by another paradigm that provides better answers [9].

The physical systems to be controlled, such as an industrial manufacturing process, are always in the state of flux. The operating condition is locked in the perpetual change: the temperature, the characteristics of the material being handled, the wear and tear of machinery, human factors, etc. But the goal of building such a process is to produce manufactured goods with highly consistent quality amid uncertainties in process dynamics. It is a quest for certainty amidst chaos. It was pointed out, correctly in [10], that engineering practice is an inexact science. And this must be reflected in the paradigm of feedback control.

The precision of mathematics brings rigor to the science of feedback control but it is the physical reality a control system must contend with. As Albert Einstein elegantly put it, “As far as the laws of mathematics refer to reality, they are not certain, and as far as they are certain, they do not refer to reality.” The idea is that the laws of mathematics are certain in their formal, analytic status. In this they do not contain any subject matter, and hence do not refer to reality. They are “stuff-free”. If, however, we interpret the axioms, then they refer to reality, but they are no longer pure mathematical statements and are therefore not certain [11]. Nicholas Rescher suggests that, concerning our knowledge of reality, there is an inverse relationship between precision and security. That is, the more precise our description is, the less secure we are about its correspondence to reality [12]. He also points out that, in practice, effective actions do not require perfect information.

Questioning the necessity of the mathematical model, imposed by the MCP, Han suggests that the robust control problem is a *paradox* that might not be resolvable within the paradigm, in light of Gödel’s incompleteness theorem [13]. The stability and performance of a control system, designed based on an accurate mathematical model, cannot be easily made more or less independent of that model, which is the goal in robust control. The fundamental question is:

***Just what is it that we need to know about a process in order to control it?*** (Q1)

The short answers are 1) we don’t usually know enough about the physical system to have a detailed mathematical model and 2) it is doubtful that we even need it for the purpose of control. If we generalize the notion of disturbance to represent any discrepancies between the physical system and what we know about it, the words disturbance and uncertainty are *synonymous*. The essence of feedback control is, in this sense, essentially disturbance rejection. Therefore, how disturbance is dealt with is the central issue, and this is what determines the effectiveness and practicality of any paradigm. In the MCP, disturbance rejection can be seen as attained through modeling. That is, ironically, *some* of the unknown becomes known during the modeling process, and it is based on the dynamics that is known that feedback control is designed. Consequently, it should not be surprising that the MCP is largely confined to the control problems where the process dynamics is well known, while engineers, dealing mostly with uncertain dynamics, resort to empirical methods.

## III. ACTIVE DISTURBANCE REJECTION CONTROL

Active disturbance rejection control (ADRC) is Han’s way out of the robust control paradox [14-16]. The term was first used in [17] where his unique ideas were first systematically introduced into the English literature. Originally proposed using nonlinear gains, ADRC becomes more practical to implement and tune by using parameterized linear gains, as proposed in [18]. Although the ADRC method is applicable, in general, to  $n^{\text{th}}$  order, nonlinear, time-varying, multi-input and multi-output systems (MIMO), for the sake of simplicity, its basic concept is illustrated here using the second-order motion control problem in (1).

### 3.1 The Active Disturbance Rejection Concept

At this juncture, a more specific answer to (Q1) is that the order of the differential equation should be known from the laws of physics, and the parameter  $b$  should also be known approximately in practice from the physics of the motor and the amount of the load it drives. Adopting a disturbance rejection framework, the motion process in (1) can be seen as a nominal, double integral, plant

$$\ddot{y} = u \tag{5}$$

scaled by  $b$  and perturbed by  $f(y, \dot{y}, w, t)$ . That is,  $f(y, \dot{y}, w, t)$  is the *generalized* disturbance, as defined above, and the focus of the control design. Contrary to all existing conventions, Han proposed that  $f(y, \dot{y}, w, t)$  as an analytical expression perhaps is not required or even

necessary for the purpose of feedback control design. Instead, what is needed is its value estimated in real time. Specifically, let  $\hat{f}$  be the estimate of  $f(y, \dot{y}, w, t)$  at time  $t$ , then

$$u = (-\hat{f} + u_0)/b \quad (6)$$

reduces (1) to a simple double-integral plant

$$\ddot{y} \approx u_0 \quad (7)$$

which can be easily controlled.

This demonstrates *the central idea of active disturbance rejection*: the control of a complex nonlinear, time-varying, and uncertain process in (1) is reduced to the simple problem in (7) by a direct and active estimation and rejection (cancellation) of the *generalized disturbance*,  $f(y, \dot{y}, w, t)$ . The key difference between this and all of the previous approaches is that no explicit analytical expression of  $f(y, \dot{y}, w, t)$  is assumed here. The only thing required, as stated above, is the knowledge of the order of the system and the approximate value of  $b$  in (1). The  $bu$  term in (1) can even be viewed as a linear approximation, since the nonlinearity of the actuator can be seen as an external disturbance included in  $w$ . That is, the ADRC method applies to a processes of the form

$$\ddot{y} = p(y, \dot{y}, w, u, t) \quad (8)$$

of which (1) is an approximation, i.e.,  $p(y, \dot{y}, w, u, t) \approx f(y, \dot{y}, w, t) + bu$ . Obviously, the success of ADRC is tied closely to the timely and accurate estimate of the disturbance. A simple estimation such as  $\hat{f} = \hat{\dot{y}} - u$  may very well be sufficient for all practical purposes, where  $\hat{\dot{y}}$  denotes an estimation of  $\dot{y}$ .

### 3.2 The Extended State Observer and the Control Law

There are also many observers proposed in the literature, including the unknown input observer, the disturbance observer, the perturbation observer, and the extended state observer (ESO). See, for example, a survey in [7]. Most require a nominal mathematical model. A brief description of the ESO of (1) is described below. The readers are referred to [14,19,20] for details, particularly for the digital implementation and generalization of the ESO in [20].

The ESO was originally proposed by J. Han [14-16]. It is made practical by the tuning method proposed in [18], which simplified its implementation and made the design transparent to engineers. The main idea is to use an augmented state space model of (1) that includes  $f$ , short for  $f(y, \dot{y}, w, t)$ , as an additional state. In particular, let  $x_1 = y$ ,  $x_2 = \dot{y}$ , and  $x_3 = f$ , the augmented state space form of (1) is

$$\begin{aligned} \dot{x} &= Ax + Bu + Eh \\ y &= Cx \end{aligned} \quad (9)$$

with 
$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ b \\ 0 \end{bmatrix}, C = [1 \ 0 \ 0], E = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Note that  $x_3 = f$  is the augmented state and  $h = \dot{f}$  is a part of the jerk, i.e., the differentiation of the acceleration, of motion and is physically bounded. The state observer

$$\begin{aligned} \dot{z} &= Az + Bu + L(y - \hat{y}) \\ \hat{y} &= Cz \end{aligned} \quad (10)$$

with the observer gain  $L = [\beta_1 \ \beta_2 \ \beta_3]^T$  selected appropriately, provides an estimate of the state of (9),  $z_i \approx x_i$ ,  $i=1, 2, 3$ . Most importantly, the third state of the observer,  $z_3$ , approximates  $f$ . The ESO in its original form employs nonlinear observer gains. Here, with the use of linear gains, this observer is denoted as the linear extended state observer (LESO). Moreover, to simplify the tuning process, the observer gains are parameterized as

$$L = [3\omega_o, \ 3\omega_o^2, \ \omega_o^3]^T \quad (11)$$

where the observer bandwidth,  $\omega_o$ , is the only tuning parameter.

With a well-tuned observer, the observer state  $z_3$  will closely track  $x_3 = f(y, \dot{y}, w, t)$ . The control law

$$u = (-z_3 + u_0)/b \quad (12)$$

then reduces (1) to (7), i.e.,

$$\ddot{y} = (f - z_3) + u_0 \approx u_0 \quad (13)$$

An example of such  $u_0$  is the common linear proportional- and derivative control law

$$u_0 = k_p(r - z_1) - k_d z_2 \quad (14)$$

where  $r$  is the set point. The controller tuning is further simplified with  $k_d = 2\omega_c$  and  $k_p = \omega_c^2$ , where  $\omega_c$  is the closed-loop bandwidth [18]. Together with the LESO in (10), (14) is denoted as the parameterized linear ADRC, or LADRC.

### 3.3 Stability Analysis

With  $f(y, \dot{y}, w, t)$  completely unknown, can we guarantee the LADRC system presented above to be stable in any sense? Let  $e$  be the tracking error in the observer,  $e = x - z$ ,

$$\dot{e} = A_e e + d, \quad (15)$$

with

$$A_e = A - LC = \begin{bmatrix} -\beta_1 & 1 & 0 \\ -\beta_2 & 0 & 1 \\ -\beta_3 & 0 & 0 \end{bmatrix}, \text{ and } d = Eh$$

**Lemma 1:** Assuming the observer gain in (10) is chosen so that  $A_e$  is Hurwitz, the observer error,  $e$ , for the LESO is bounded for any bounded  $h$ .

Proof: With  $A_e$  Hurwitz, let  $V = e^T P e$  be a Lyapunov function, where  $P$  is the unique solution of the Lyapunov equation  $A_e^T P + P A_e = -Q$  and  $Q$  is a positive definite matrix. Then,

$\dot{V} = -e^T Q e + 2d^T P e =$   
 $-(e^T Q^{\frac{1}{2}} - d^T P Q^{-\frac{1}{2}})(e^T Q^{\frac{1}{2}} - d^T P Q^{-\frac{1}{2}})^T + (d^T P Q^{-\frac{1}{2}})(d^T P Q^{-\frac{1}{2}})^T$   
 which implies that  $\dot{V} < 0$  if

$$\|e^T Q^{\frac{1}{2}} - d^T P Q^{-\frac{1}{2}}\|_2 > \|d^T P Q^{-\frac{1}{2}}\|_2$$

or equivalently

$$\|e^T Q^{\frac{1}{2}}\|_2 > 2 \|d^T P Q^{-\frac{1}{2}}\|_2 \quad (16)$$

For  $Q=I$ , i.e., an identity matrix,  $\dot{V} < 0$  if

$$\|e\|_2 > 2 \|P d\|_2 \quad (17)$$

which implies that  $\|e\|_2$  decreases for any  $e$  that satisfies (17). Hence  $e$  is bounded. Q.E.D.

Note that the Lemma 1 can be readily generalized to the dynamic system described by

$$\dot{\eta} = M\eta + g(\eta) \quad (18)$$

with  $\eta \in \mathfrak{R}^n$  and  $M \in \mathfrak{R}^{n \times n}$ . The corresponding lemma is:

**Lemma 2** The state  $\eta$  in (18) is bounded if  $M$  is Hurwitz and  $g(\eta)$  is bounded.

Combining Lemma 1 and 2, the boundedness of LADRC can be shown as follows:

**Theorem 1:** The LADRC design of (10), (12), and (14) yields a BIBO stable closed-loop system if the observer (10) itself and the state feedback control law (14) for the double integrator are stable, respectively.

Proof: With the boundedness of the observer error,  $e$ , established in Lemma 1, the remaining task is to show that  $\bar{x} = [y, \dot{y}]^T$  is bounded. Combining (1), (12) and (14), it can be shown that

$$\dot{\bar{x}} = \begin{bmatrix} 0 & 1 \\ -k_p & -k_d \end{bmatrix} \bar{x} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ k_p & k_p & k_d & 1 \end{bmatrix} \begin{bmatrix} r \\ e \end{bmatrix} \quad (19)$$

Since  $r$  and  $e$  are bounded, by Lemma 2,  $\bar{x}$  is bounded if the characteristic polynomial for the state feedback design (14), i.e.,  $s^2 + k_d s + k_p$ , is Hurwitz. Q.E.D.

### 3.4 Applications

ADRC as a practical design method has been successfully applied in many engineering applications. The particular form of ADRC for the second order system in (1) is, not surprisingly, widely applicable to motion control problems [24-28]. The original ADRC with nonlinear gains was applied to a motion control problem with success, shown in [24]. The comparison studies in [25, 26] show that the parameterized LADRC not only gives much better performance, but it is also the easiest to tune. High precision position control applications can be found in [27,28]. Other applications to second-order nonlinear and time-varying processes include web tension regulations [29] and voltage regulation in a DC-DC converter [30].

To show how ADRC is applied to systems much more complex than those of (1), two nonlinear, time-varying MIMO control applications are briefly illustrated below.

The difficulties in controlling modern high-performance aircraft arise from highly nonlinear aerodynamic characteristics, undesired couplings between axes, and control input saturation and delay [21]. In addition, the model of the aircraft is highly complex and difficult to obtain. The ADRC allows it to be represented as

$$\begin{aligned} \dot{X}_1 &= F_1(X_1, X_2) \\ \dot{X}_2 &= F_2(X_1, X_2, X_3, X_4) + B(X_1, X_3, X_4)U \\ \dot{X}_3 &= F_3(X_1, X_4) \\ \dot{X}_4 &= F_4(X_1, X_2, X_3, X_4, U) \end{aligned} \quad (20)$$

where the vectors  $X_1, X_2, X_3$ , and  $X_4$  are the angular position, angular velocity, position, and velocity, respectively. The input  $U$  contains the angles of control surfaces. The variables to be regulated are  $X_1$  and  $X_2$ . The system dynamics, as represented by  $F_i(\cdot)$ ,  $i=1, \dots, 4$ , and  $B(\cdot)$  are nonlinear. The generalized disturbance takes the form of

$$H = \overset{\Delta}{F}_2(X_1, X_2, X_3, X_4) + (B(X_1, X_3, X_4) - B_0(V))U \quad (21)$$

where the nonsingular matrix  $B_0(V)$ , which is a function of the velocity vector  $V$ , is an approximation of  $B(X_1, X_3, X_4)$ . Then the control equation can be rewritten as

$$\begin{cases} \dot{X}_1 = F_1(X_1, X_2) \\ \dot{X}_2 = H + B_0(V)U \end{cases} \quad (22)$$

Now the control problem can be solved by using the ADRC concept. The control of  $X_2$  is accomplished by using a MIMO ESO to estimate and cancel  $H$  in (22) and reduce the process to a cascade integral plant. Then  $X_1$  can be controlled using a back-stepping method, assuming  $F_1(X_1)$  is known and invertible. More details can be found in [21], together with successful simulation results.

Another example is the jet engine control problem [22]. It is challenging because of the nature of the plant, modeled using over one hundred coupled equations, and look up tables. This is a scenario where the model-based design breaks down because the problem becomes intractable. The existing method for the high performance jet engine control is still MIMO PI with gain-scheduling. The jet engine control design is typically tested using a full computer simulation package, such as the Modular Aero-Propulsion System Simulation package, developed by the NASA Glenn Research Center. Again, the key step in solving the problem using ADRC is to reduce the plant to the form of

$$\dot{Y} = H + BU \quad (23)$$

where  $Y$  and  $U$  are output and input vectors, respectively, and  $H$  is the generalized disturbance. Employing the parameterization technique, only five tuning parameters are needed, as opposed to eighteen gains and six scheduling parameters in the previous solution. The response of the ADRC-based design compares favorably to that of the benchmark controller. See [22] for details.

#### IV. TOWARDS A NEW PARADIGM

If there is something called control science, it surely belongs to the realm of *inexact sciences* [10]. Feedback mechanisms would not be needed if there were no uncertainties. ADRC is a window through which we see new possibilities and promises beyond the MCP. Working towards a new paradigm doesn't mean starting from scratch, for there are two important aspects in control theory: analysis and design. The rigor, precision and insight provided by the mathematical tools developed in the framework of the MCP are invaluable. At the same time, it is the relentless hold on the dogmas of MCP that inhibits the scientific spirit in search of new solutions. What we need is a paradigm that *promotes innovation, not stifles it*. Engineering is the embodiment of both experience and reason. The theory-practice divergence in feedback control is the result of favoring one at the expense of the other by both theoreticians and practitioners. It is therefore evident that the new paradigm should be both *experimental* and *systematic*, as explained below.

Collectively as a profession, we haven't scratched the surface of the wonders of feedback control. One peek at nature would bring the message home: the way a bird flies in high speed through a dense forest and gives chase to a prey, and the marvelous biological control systems inside the human body. Compared to nature, the man-made feedback mechanisms are far inferior. For example, it is a cause for a big celebration, and lavish advertisements in industry, when a robot is made to walk in a manner somewhat resembling that of a human. Nature is rich with hidden treasures and we just need to find them, much like scientists discovered the laws of nature. And this calls for a truly scientific spirit: experimentation-hypothesis-validation, as suggested by Ho [4]. The original ADRC method was a result of such scientific investigations [14-16].

One may argue that practitioners have already been there and done that. Indeed, many ingenious control systems have been designed that allowed us to send the probes to Mars and to help a paralyzed person walk again. But many such engineering accomplishments made little impact on our knowledge of control theory because they were not systematically investigated and generalized. It is evident that many engineering rules of thumb have not been systematically studied and incorporated into our knowledge base. As a result, we are at the mercy of skills that can only be passed on through apprenticeship. For this reason, our inquiry must be systematic and our theory "stuff-free", i.e., the proposed new theory should not be tied down to a material process, such as a boiler temperature control system. For example, the original ADRC with nonlinear gains shows great promise as a new control technique, but the tuning required to customize it for a particular system is not entirely systematic. Further simplification and parameterization allows the controller tuning to be completely systematized, and ADRC becomes a simple and efficient engineering tool [18]. Now engineers can set up an ADRC system in minutes, instead of months, for a particular application.

The two existing paradigms, the MCP and the EDP, are opposite answers to the central question of (Q1). In the

MCP we assume detailed knowledge of the process dynamics, and the design proceeds deductively from that premise. In the EDP, on the other hand, the process is essentially treated as a black box and the design is highly empirical, relying on experience and intuition. The reality is of course somewhere in between the two extremes. Proper understanding and formulation of the middle is the key for the new paradigm. ADRC is an answer to (Q1) that *strikes a balance between the mathematical precision and practical uncertainty*. Using the motion control problem in (1) as an example, ADRC requires the knowledge that the system is second-order, and the value of  $b$ , which is approximately known based on the size of the motor and the range of the load. But, at the same time, ADRC allows the combined impact of internal dynamics and external disturbance, represented by  $f(y, \dot{y}, w, t)$ , to be totally unknown. Such characteristics are unchanged as ADRC is extended to higher order and/or MIMO systems [18,20-22].

In a term familiar to engineers,  $b$  is essentially the high frequency gain of the process and, if it is not obtained from the first principals, it can be easily determined numerically from the input-output data [23]. The bottom line is that ADRC requires very little knowledge of the dynamics, and yet, it is systematic and general. This is because, through active disturbance estimation and cancellation in real time, the physically process is first forced to behave like a predetermined, simple, cascade integral plant, which is then used as a design model for the control law derivation. The effect of uncertain dynamics is virtually eliminated for the purpose of feedback control by the active disturbance rejection.

Using (1) again as an illustration, the ESO provides a real time estimate of the disturbance,  $\hat{f}$ , which allows the plant to be first reduced to (7), i.e., the design model  $\dot{y} \approx u_0$ . In other words, *ALL* motion control problems represented by (1) are reduced to the mathematical model in (7), which is linear, time-invariant, simple, and known. This reduction in the complexity of the problem is almost mind-boggling. Furthermore, the conventional boundaries setting apart different control theories are completely dissolved here. It makes little difference whether  $f(y, \dot{y}, w, t)$  itself is linear or nonlinear, time-varying or time-invariant, and known or unknown.

The novelty of an ADRC-based paradigm is even more evident in the context of adaptive control. In adaptive control, it is assumed that the analytical expression of  $f(y, \dot{y}, w, t)$  is available with time-varying parameters. Controller adaptation is then carried out by estimating these parameters and updating the controller parameters accordingly. ADRC can be seen in this context as a fixed parameter controller that adapts to the changes in  $f(y, \dot{y}, w, t)$ , not by estimating its parameters, but by canceling it in the control law altogether. It brings vastly fluctuating physical processes in the form of (1) to the tranquility of (7). This is what sets apart the new paradigm from the old.

## V. CONCLUDING REMARKS

Engineering is an inexact science, in which we deal with uncertainties in reality by way of approximations. It is an embodiment of experience and reason. Control theory, as a general systems theory that permeates all engineering disciplines, must reckon with the nature of engineering. In feedback control we seek certainties amid fluctuations, and the practice dictates that our methods be “approximation-proof”. This creates an inherent tension between engineering practice and modern control theory, where mathematical rigor and precision are prized over utility. In the spirit of Thomas Kuhn, we propose a paradigm shift in this paper as a way out of this dilemma. Through reflection on the current paradigms in both theory and practice, the necessity of the paradigm shift is demonstrated. We further offer the Active Disturbance Rejection Control as the basis of such a shift, providing the framework, the objectives and constraints for future control theory development. We further argue that the new paradigm needs to be both experimental and systematic, striving for a balance between experience and reason. A class of motion control problems is used throughout the paper to give realism to the discussion and to show practical insights into engineering practice. Preliminary stability analysis and initial engineering applications of ADRC are also presented. Much work, both experimental and analytical, is still ahead.

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