Adaptive Control Systems: Past, Present, and Future.

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Progress in Adaptive Control Systems: Past, Present, and Future

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***Abstract*—This paper briefly reviews state-of-the-art adaptive control systems. It includes a general introduction, followed by the fundamental motivations behind the inception of adaptive controls as well as their historical time-line. We also present several types of adaptive control strategies that have been broadly investigated. Furthermore, we elaborate cutting-edge technological developments in adaptive controls and also discuss their pros and cons. We hope that this review paper can be useful to help researchers and practitioners to identify potential research problems and solutions as well as benefits and limitations associated with each technique.**

Keywords*—*Adaptive controls, literature review.

I. INTRODUCTION

UNCERTAINTY and errors in modelling are unavoidable. In practice, the dynamics of the systems may not be fully understood and their parameters may vary over time. To cope with this challenging issue, modern control systems need to satisfy a certain degree of robustness and adaptivity. According to Oxford dictionary 'to adapt' means make suitable for a new use or purpose or become adjusted to new conditions. It has been established beyond doubt that the ability to accept new circumstances and to conform with it is an essential feature to maintain the stability and the performance of control systems [1]. Owing to this, an adaptive control system can be defined as a class of controller that can adjust its own behaviours, in response to the dynamics of the process and the disturbances [2]. Thus, the topic covers a systematic approach for on-line automatic adjustments of controller parameters in order to achieve a certain desired criteria given the unknown or varying dynamics of the plants. What really differentiates adaptive controllers to other control schemes is related to their *adaptation mechanisms*, which mostly rely on the initial knowledge as well as previous and current measurements about the process or plant being controlled. One straightforward implementation of adaptive control is in the aerospace industry, particularly for both manned and unmanned military operations, in which battle damage can be sustained.

Adaptive control works by modifying the control law employed to overcome slowly time varying changes of any parameters of a particular system. For instance, an aircraft operates over a wide range of speeds and altitudes, and their dynamic are nonlinear and conceptually can also be of time varying nature. As it flies, aircraft mass slowly decreases due to fuel consumption. Accordingly, we need such a control law that can adapt itself to new circumstances. Compared to fixed-gain controllers, the benefits of adaptive counterparts are numerous. First, considering the fact that all system models must contain a certain degree of uncertainties as they are not fully capable of capturing the dynamics of the physical systems; it is beneficial to have a system that can conform with it. In real world, besides modelling errors, there are many source of uncertainties, such as unforeseen adverse conditions of the system due to component failures, structural damage, etc [3]. Subsequently, the nature of fixed-gain controllers is inherently static, as they cannot improve their performance based on their past and current measurements, while most systems are inherently dynamic. While adaptive control can be less dependent to the accuracy of the mathematical models of the system, fixed gain controllers heavily rely on it, as they are derived under an assumption that there will be no variation in system dynamics. Addressing the limitation of fixed gain controllers which can constantly degrade the performance of the system, as the dynamics of the plant progressively changes from one operating region to another; current research trend in modern control systems moves towards the developments of flexible controllers that can easily accommodate the changes in both signal and system models (i.e., plant characteristics and disturbance models).

While fixed-gain controllers are only suitable for time-invariant systems [4], most process dynamics in nature are inherently time-varying (e.g., aircraft dynamics due to variations in atmospheric conditions, speed, and altitude.) Moreover, the performance of modern linear time-invariant (LTI) robust controls (e.g., H_2, H_∞ as is in [5], and μ-synthesis as is in [6]), and other fixed-gain controls [4] may deteriorate for large uncertainty, caused by unexpected conditions such as failure or degradation in system components. Although it is possible to schedule the gain of the controllers under some predictable variations; in most cases the nature of the uncertainty is highly unpredictable. Also, while robust controls are also designed to deal with uncertainty, its performance may not be better-off than the performance of adaptive control in the face of constant or slow-varying system parameters.

However, the good news is that adaptive controls can be easily implemented as an addition on top of other control schemes (e.g., robust and optimal controls, which are of fixed gain nature). While robust control is a powerful method to overcome parameter variations of the system model, it also depends on the range of uncertainty domain itself. For instance, sometimes, a large amount of uncertainty can be handled, while another time, only a small amount of uncertainty can be accommodated. Thus, if the system fails to accommodate a full range of possible parameter variations, one needs to consider adaptive controls [7]. Putting adaptive control on top of robust control systems can significantly enhance the performance of the system (e.g., implementing adaptive control to tune robust control). Likewise, employing the principle of robust controls for designing adaptive controls (e.g., Robust Multiple Model Adaptive Control schemes (RMMAC), as described in [8]) can lead to improved performance. Yet another advantage of adaptive control over robust control is in the sense that it does not need prior information about the bounds on these uncertain or time-varying parameters; while robust control guarantees that if the changes are within given bounds the control law need not be changed. Instead, adaptive control is precisely concerned with control law changes, i.e., to correctly learn the plant, track its parameter variations and adjust them. However, it should be highlighted that although those two control strategies are complementary to each other, one should carefully consider the trade-off between them.

Since its inception in around 1950s, adaptive controls have been extensively studied. Motivated by the need to improve the performance of the fixed-gain control systems, much effort has been spent to address these shortcomings. Some practical examples of the implementation of adaptive control systems are as follows. The authors in [9] implemented MIT rule (a popular adaptive control algorithm founded by a group of researchers from the Massachusetts Institute of Technology) for controlling ball and beam system; while in [10] the authors designed an adaptive control for a quadcopter UAV. Meanwhile, our research group in UNSW Canberra has strong focus on design and implementation of adaptive controls in robotic platforms (e.g., unmanned underwater vehicles as is in [11]).

However, we notice that despite there being many research papers in adaptive controls, there is a lack of a formal review of the literature in the subject matter. Addressing the shortcomings, we define our high-level problem statement in our review as follows. Given the unpredictable dynamics of most process systems, how one could develop a flexible control system that can quickly accommodate the variations in complex behaviours of the plants (e.g., unpredictable parameter deviations and uncertainties) across all time intervals $\forall t > 0$ to satisfy a certain index performance criteria. The remedy of this problem can be achieved by also taking take robustness issues into account (i.e., to begin with robust control systems). We proceed as follows. While Section 2 briefly elaborates the history of adaptive control, Section 3 discusses the division of adaptive controls. Meanwhile, Section 4 highlights state-of-the-art adaptive controls, i.e., the pros and cons of each technique. Furthermore, Section 5 concludes this paper and points out some future trends in this topic.

II. Time-line of Adaptive Controls

According to the International Federation of Automatic Control (IFAC) in [12], the history of adaptive control can be summarised as follows. Motivated by the need of high-performance flight control systems (e.g., X-15 experimental aircraft, as also mentioned in [1]), there was a significant growth of interest in adaptive controls in 1950s. In 1951, researchers successfully developed a self-optimising controller for the combustion engine, and a flight test was successfully conducted. Between 1957-1961, the applications of dynamic programming in adaptive controls were investigated. In 1958, model reference adaptive control (MRAS) was implemented to solve flight control problems. Furthermore, in 1965, the Lyapunov theory was introduced to address stability issue in MRAS. Meanwhile, in the 1970s-1980s there were significant developments in the area of self-tuning regulators. Furthermore, gain scheduling was introduced to address the solution of flight control systems. From 1980 onwards, there have been significant developments in process control systems, and as a result adaptive controls also started to be commercially implemented [1]. Meanwhile, in early the 1990s, the robustness of adaptive controllers were addressed.

III. Classifications of Adaptive Controls

In this Section, we will discuss the classification of adaptive controls based on the structure of the control systems, the signal processing method as well as the algorithm itself. We begin with the well-known model reference adaptive control (MRAS) solved via MIT and the Lyapunov rules, direct and indirect adaptive controls, deterministic and stochastic systems as well as feedback and feed-forward adaptive controls.

1) Model Reference Adaptive Control (MRAS): Direct and Indirect Methods: MRAS is an important part of adaptive control systems. The system employs a desired model to express the desired performance of the closed loop control system. To achieve this, the parameter of the controller (adaptation gain) is adjusted according to the error signal which is defined as the difference between the system output and the model output, see Fig. 1.

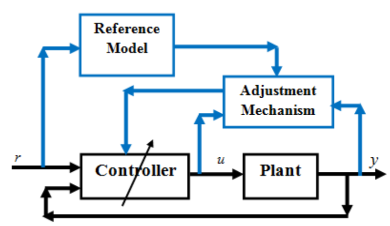

Fig. 1. Model Reference Adaptive Systems (MRAS), which can be regarded as a subset of direct adaptive system. In this case, the desired performance is given by the reference model connected to the system input reference signal u. The control loop will be adjusted by the output signal of the model through the adaptation mechanism. In addition to normal feedback structure, adaptive controls employ extra loop, namely, "*adaptation loop*" (represented in blue) to compensate any variations in the dynamics of the process and to compensate the disturbances.

Given a controllable plant $P(s)$ with an input output pair $\{u(t),\ y(t)\}$ represented by the following state space equations.

$$\dot{x}_k(t) = Ax_k(t) + Bu_k(t),\ y_k(t) = Cx_k(t) \tag{1}$$

where A indicates $n \times n$ system matrix, B denotes an input matrix, and C depicts an output matrix. Given the state space model as in (1), the transfer function of the plant can be depicted by $P(s) = C(sI - A)^{-1}B = k_p \frac{N(s)}{D(s)}$. Likewise, the reference model, which is directly connected to the reference signal $r(t)$ can be modeled as follows: $W_m = k_m \frac{N_m(s)}{D_m(s)}$, where $N_m(s)$ is a Hurwitz polynomial of degree m, $D_m(s)$ is also a *Hurwitz* polynomial of a degree n, and k_m is the gain of the system.

One well-known solution to this method can be achieved by means of the sensitivity concept via *the gradient descent* method, known as the MIT rule. In short, the MIT gradient descent method can be formulated as follows [1]. Given k_c is the variable gain controller specifically designed to minimise a certain loss function $J(k_c) = \frac{1}{2}e(t)^2$, where $e(t) = y_p(t) - y_m(t)$ then the following condition holds: $\dot{k}_c = -\gamma \frac{\partial J}{\partial k_c}$, where γ is a positive constant representing its descent rate. Thus, we finally arrive at $\dot{k}_c = -\gamma e(t) \frac{\partial e}{\partial k_c}$. Despite its intuitive nature, however, it should be pointed out the stability of the system is not guaranteed, as it really depends on the value of γ. To overcome the limitation of the MIT rule, one may consider the Lyapunov method. It is shown, see [1], that the stability of the Lyapunov method is guaranteed, given bounded input in terms of input signal, error, and controlled variables denoted by $u_c,\ e(t),\ y(t)$, respectively.

While indirect method of adaptive controls rely on the parameter estimation of the plant based on its input and output data to systematically adapt the controllers' parameters so that the plant can be constantly forced to mimic the behaviours of the model (i.e., $\lim_{t\to\infty} |e(t)| = \lim_{t\to\infty} |y_p(t) - y_m(t)| = 0$); in direct method, there is no use of plant identification. Nevertheless, the system employs the error signal as a result of the implementation of the following equation:

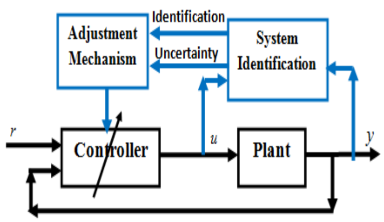

Fig. 2. Model Identification Adaptive Control (MIAC) which is as a subset of indirect adaptive control systems. This idea is also in parallel to concept of *self-tuning regulator (STR)*, where the system relies on the estimation process of the unknown parameters of the plant (i.e., system identification technique) to optimise the performance of the controller.

In more detail, the major difference between direct and indirect methods can be summarised as follows. First, a reference model is employed in the direct method, while the indirect method implements the identified model acquired from online process (e.g., online system identification). Second, to update the parameters of the controller, indirect adaptive controls employ the identification error, while in direct control, the error signal in the control loop is used to update the control parameters. This way, one can directly estimate the parameters of the controller in direct adaptive controls. However, it should be pointed out that the algorithm was derived under several assumptions. In addition, direct adaptive control is also restrictive to certain classes of systems [1]. These may limit the practical usefulness of direct adaptive controls.

2) Deterministic and Stochastic Adaptive Controls: Based on their signal processing systems, adaptive controls can be broken down into two parts (i.e., deterministic and stochastic). While deterministic adaptive controls neglect the effects of noise on the future propagation of their system states; stochastic adaptive controls, which can be regarded as a subset of a stochastic control theory, employ stochastic models in describing the disturbance of the system. The objective of the system is to minimise the response to random initial conditions as well as disturbances, and measurement errors. Some straightforward implementation of the stochastic adaptive control are due to *minimum-variance controller* [13] and *moving average controller* as is in [14], leading to some variants such as stochastic indirect self-tuning regulator, minimum variance self tuning regulator, as well as generalised direct self-tuning regulator. However, it should be noted that the drawback of this control scheme is due to its reliance on the sampling period [1].

Another example of current state-of-the-art stochastic adaptive control can be found in [15], where the authors discussed the effects of input quantization on the performance of the system, where the unknown parameters modeled using Gauss-Markov process. The authors developed dual controller based on the analysis of cautious control law. The excitation of parameter estimations that improves the closed loop performance is generated by means of quantisation errors of the logarithmic quantiser. Besides, the authors also proposed an alternative approach by adopting the cautious control law and the logarithmic quantisation to guarantee the accuracy of future estimation. The exciting effects of the quantisation in the feedback loop is demonstrated in the proposed control scheme.

3) Feedback and Feedforward Adaptive Controls: Feedback control systems have been proven to effectively work, even in the presence of little information regarding the dynamics of the plants. While most control systems employ feedback controls to stabilise the plant, there are some cases where feedforward controls can also work effectively, i.e., under condition that it is possible to measure the disturbance acting in the system. However, since the information will be passed to the plant directly, without measuring the response of the plant (i.e., being an open loop), we need to have accurate mathematical models, describing the dynamics of the process. Thus, this will signify the importance of identification and adaptation mechanisms. Nonetheless, it should be pointed out that feedback control systems can be made less sensitive to uncertainty in modelling and measurements.

One example of the implementation of adaptive feedforward control can be found in [16], where the author developed an adaptive feedforward controller to calculate the required force for a wafer stage in a lithographic tool to fabric integrated circuits (ICs). The system determines the required force to move the stage. The author employed rapid online least square identification to estimate the mass parameters. The author observed that there are two factors that limit the accuracy of the system. First, the acceleration of the system in response to the calculate force from the controller, which is really dependent on the position of the stage. The author attempts to address this issue by means of online estimation, previously discussed. Second, the system requires a higher-order feedforward model considering the dynamic resonance of the system. His research clearly demonstrates the effectiveness of its feedforward adaptive control, as it significantly decreases the dependency of the position of the wafer stage, resulting in improved settling time leading to improvements in throughput.

IV. State-of-the-Art Adaptive Controls

In this Section, we will briefly discuss some current state-of-the-art adaptive controls. We further elaborate the benefits and limitations associated with each algorithm.

A. Multi-Model Adaptive Control (MMAC)

Conceptually, MMAC can be regarded as a hierarchical control system consisting of a set of finite local controllers connected to a high-level supervisor via a switch, or also known as "supervisory switching" system [17]. The underlying principles of MMAC is to obtain a finite set of controller $\{C_1, C_2, \dots C_n\}$ so that any plants $\{P_1, P_2, \dots P_n\}$ represented, whose parameters are given by by $\{\lambda_1, \lambda_2, \lambda_3, \dots \lambda_n\} \in \Lambda$, which typically a bounded connected set, can be efficiently stabilised by at least one controller within the set. The term efficient refers to suboptimal condition, i.e., the ability of the controller to closely approach the limit of the optimality condition, but not necessarily be fully optimal [3]. To accomplish this task, the system is led by a supervisor, at high level, to closely monitor the performance of a set of controllers by performing identification via hypothesis testing [3]. Once the performance of the current controller is considered unsatisfactory, the supervisor will switch the task into another controller. This way, one can expect to determine the most suitable controller after a number of switching.

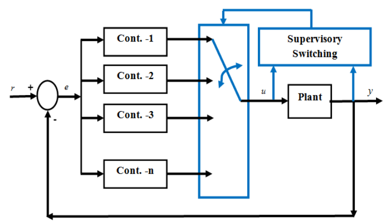

Fig. 3. Supervisory control for multi-model adaptive control.

Motivated by the need to address instability, there are some advantages of switching-based adaptive controls [17]. First, the system has rapid adaptation to sudden parameter changes, which is highly desirable. However, there are also some possible drawbacks relating to this method. First, there is no rule on how many plants should be chosen. Second, there is a chance that the supervisor may pick up the wrong controller, i.e., there is no guarantee that after switching process, the chosen controller will remain the most suitable candidate for the plant. Thus, safe switching is desperately required to ensure that a destabilizing controller is disconnected from the plant, leading to the study of multiple model adaptive control with safe switching [18].

Some current state-of-the-art MMAC can be found in [19], [20], and [21], where the authors developed robust MMAC for candidate controller sets and the supervisor using mixed μ-synthesis method. Each candidate is assigned a posterior probability function representing its closeness to the true plant, which is later will be used to weight the output of the controllers. Accordingly, the candidate that has highest probability will be switched to the loop. Their research indicates that the system is able to demonstrate rapid adaptation, to outperform the performance of non-adaptive μ-synthesis compensator, although one needs to carefully compensate uncertainty in its stochastic disturbance model.

Furthermore, Kuipers and Ioannou in [17] introduced a deterministic robust adaptive control, namely, adaptive mixing control based on some well-known concepts derived from linear time-invariant (LTI) system (e.g., mixed μ-synthesis). The authors aim to introduce an MMAC scheme which is able to achieve not only global boundedness of all system signals, but also regulation of all plant signals in the absence of uncertainties (e.g., error in modelling, disturbance and noise). The authors demonstrate that their propose algorithm can drive all the states to zero, indicating a stable system, while the parameter estimations converge to their true values. However, one possible disadvantage of the proposed control scheme is due to the absence of discontinuous switching logic, that has been replaced by a smooth interpolator, so that the system may not be able to rapidly compensate a sudden change in the plant as in switching-based adaptive control.

B. Safe Adaptive Control

Stability is an important issue in adaptive control, considering the fact that many cutting-edge algorithms cannot rule out the chance of inserting a destabilising controller in the systems, leading to a catastrophic mistake when implemented. Thus, the research challenge here, as is in [3], is to guarantee the stability of the closed loop control system of feedback interconection $[P, C_1]$ given limited amount of information obtained from noisy measurements by verifying, without insertion of the actual controllers, that the introduction of the new controller C_2 can fully stabilise the plant. As is in [8], this theory can fully guarantee the stability of the closed loop control system given the existence of stabilising controller.

One application of safe adaptive control in multi-model adaptive control (MMAC) can be found in [3], where the authors introduced the concept of safe switching. To measure the benefits of the proposed control scheme, the authors employed frequency-dependent technique and Vinnicombe metric [22] to guarantee that the change in controller is sufficiently small, so that unstable closed loop control system can be avoided. The system also requires that the initial controller is a stabilising one. However, the system requires the identification of the model of the plant, leading to relative safety guarantee, instead of absolute one, as given by its quantitative probabilistic guarantee. Considering hard error bounds on the identification of the transfer function, the authors nonetheless claim that it would be still possible to achieve an absolute guarantee on the safety of the switching process.

C. Gain Scheduling

Gain-scheduling is a well-known approach in non-linear control that have been widely implemented, especially in the area of flight control systems and process control since around 1960s. Owing to the principle of 'divide and conquer,' as stated in [23], this method heavily relies on the linearisation technique. The system aims to split the nonlinear design task into a set of linear sub-tasks. In general, there are two major parts in this process [23]. First, stability analysis connecting the relationship between the stability of the non-linear system with one from the associated linear system counterparts. Second, the approximation depicting the relationship between the solution of the non-linear system, in regards to the solution for the associated linear systems.

Mathematically, the gain scheduling control can be formulated as follows. Given the nonlinear state space equation

$\dot{x} = f(x,r)$ with non linear output equation $\dot{y} = g(x,r)$, and let $(\tilde{x}(t), \tilde{y}(t), \tilde{r}(t))$ be the specific trajectory of the non-linear system as, i.e., an equilibrium operating point, where $\tilde{x}$ is a constant; the non-linear system can be approximated using series expansion theory elaborated as follows [23].

$$\begin{aligned} \delta\dot{\hat{x}} &= \nabla_x f(\tilde{x},\tilde{r})\delta\hat{x} + \nabla_r f(\tilde{x},\tilde{r})\delta_r, \\ \delta\hat{y} &= \nabla_x g(\tilde{x},\tilde{r})\delta\hat{x} + \nabla_r g(\tilde{x},\tilde{r})\delta_r, \end{aligned} \tag{2}$$

where $\delta_r = r - \tilde{r}$, $y = \delta y + \tilde{y}$, and $\delta x = x - \tilde{x}$. It is apparent that the non-linear system is stable relative to the trajectory $(\tilde{x}(t), \tilde{y}(t), \tilde{r}(t))$given the linear time-varying system as depicted in (2) is stable with respect to the the approximation error.

An example of a typical gain scheduling system can be found in [24], where the authors developed a gain scheduling strategy by means of fuzzy system (i.e., time-varying fuzzy sliding mode control) for parallel parking of a ground robot in the face of nonholonomic and input saturation constraint. The control objective of the system is to mimic human driving experience in performing parallel parking. This can be achieved by scheduling the control parameters and tracking the local path. Compared to conventional gain scheduling system, the proposed algorithm has several advantages listed as follows. First, it requires small data base while enlarging space of interest. Second, it also allows zero velocity crossing, and demonstrates the ability to overcome mechanical constraints. The authors highlight the effectiveness of the system through a series of computer simulations and practical experiments.

D. Auto-Tuning or Self-Tuning

In control theory, the terms 'auto-tuning' and 'self-tuning' are interchangeable as they refer to the ability of the control systems to perform an automatic tuning function or self-optimisation in the absence of human intervention. There have been many auto-tuning methods developed for industrial control systems such as 'Ziegler-Nichlos-based self-oscillating' or based on a certain database and rules known as 'expert systems' (e.g., fuzzy logic or genetic algorithms) to evaluate the performance of the control systems (e.g., damping factor, natural frequency osculation, and the dc gain of the transfer function [1]. Given a set of tuning (built-in) rules, one can subsequently set the parameters of the controllers, in response to the recorded experimental data. This method can also involve both deterministic (e.g., pole placement, model-reference) and stochastic control laws as well as direct and indirect approaches, as described in the earlier Section of this review.

E. Model-free Adaptive Controls

The nature of model-free adaptive control could potentially address some concerns arising from model-based controls in the absence of identification of the mathematical model of the plant. To replace the existing controller, the system utilises real-time information data to simultaneously predict the performance of each candidate, before making any decision, i.e., the system predicts the performance of each controller as if the had been allocated in the main loop.

For instance, Battistelli et al. in [25] introduced a new supervisory control, by extending *unfalsified control* in [26], [27] to accommodate time-varying systems. The system employs a set of controllers and a supervisory unit, whose task is to allocate the best controller in order to minimise a certain cost-function. The authors introduced the concept of *fading memory* paradigm, so that one can evaluate the cost functions used for controller switching over a certain time-window. In regards to this concept, the authors employ the concept of a dynamic window, that is, a window with a variable length over the time. In more detail, the author proposed the use of a *resetting logic* so that the length of the time window can be adjusted on-line, in line with the adaptation rules. The past records of memory can be discarded, if they do not contain relevant information to stability. This way, the stability of the plant can be preserved, especially for those whose parameters slowly change. The authors employed the concept of *hysteresis logic* to switch into a new controller, when the system detects a substantial difference between performance levels.

F. Adaptive Neuro-Control and Fuzzy Logic

Leveraging on the suitability of neural networks (NN) in approximating non-linear functions as well as their flexibility in adopting different training algorithms, many researchers around the globe have developed adaptive neurone-control techniques. For instance, Patino and Liu in [28] implemented NN to address the classical problem in MRAS, especially for a class of first-order continuous time nonlinear dynamical system. The authors introduced a controller structure that can employ a radial basis function network or a feedforward neural network to deal with the nonlinearities in the system model. Owing to the advantage of the Lyapunov theory, the authors developed a stable controller adjustment mechanism by means of σ-modification law. Their research indicates that the system can successfully assure the convergence of the control error around zero. It should be pointed out that the activation signal can be generated from the difference between the reference model output and the plan output of the parameter adaptation mechanism. The authors highlight the efficacy of their proposed system through a simulation study using two examples of non-linear plants.

Furthermore, our research group in UNSW Canberra has successfully designed adaptive control systems for an autonomous underwater vehicle (AUV) based on the concept of fuzzy logic system. For instance, the authors in [11] employed a system identification method to model the non-linear dynamics of an underwater vehicle as a black box, which has an input-output relationship based on an on-line adaptive fuzzy technique. Back-propagation method is employed to update the parameter of the fuzzy inference system. Moreover, the system fully employs a fuzzy logic control system to coordinate all of its motions in 6 degrees of freedom. This way, one can eliminate the requirement to have complex mathematical equations in modelling the dynamics of the system, as one used in model-based adaptive control systems.

G. Iterative Learning Control (ILC)

Motivated by the ability of human to learn, there have been a surge of interests in ILC to answer the fundamental research question on how machines can perform better every time they perform their tasks. ILC is well-known for its ability to improve transient response of uncertain dynamic systems which are of repetitive nature in their operation (e.g., robotic manipulator, or chemical reactor) [29]. The term 'repetitive' can also be translated into 'periodical,' (e.g., periodically disturbed, or periodically driven system).

The mathematical description of ILC can be depicted as follows. Given a system represented in (1), the control task is to achieve a tracking trajectory y_k to follow the desired output y_d within a fixed time interval $t \in [0, T]$. One potential solution of this servo control problem is to define an "Arimoto-type" equation as follows [30]:

$$u_{k+1} = u_k + \Gamma \dot{e}_k, \tag{3}$$

in which, $e_k(t) = y_d(t) - y_k(t)$ and Γ is the diagonal learning matrix, so that the following steady-state condition is satisfied [30]:

$$lim_{k \to \infty}\{y_k(t) - y_d(t)\} = 0. \tag{4}$$

where $t = kT$ denotes the sampling time, for $t \in [0,\ T]$, provided,

$$\|I - CB\Gamma\|_i < 1, \tag{5}$$

Considering (5), it should be noted that one major advantage of this algorithm is due to the fact that Γ can be computed in the absence of system matrix A, showing the effectiveness of the system against uncertainty in modelling, although it still requires some knowledge regarding the structure of the system [29].

Accordingly, a more general expression can be developed (e.g., PID-like update law as is in [31]):

$$u_{k+1} = u_k + \Phi e_k + \Gamma \dot{e}_k + \Psi \int e_k dt \tag{6}$$

in which, $\Phi,\ \Gamma,\ \Psi$ are also the learning gain matrices.

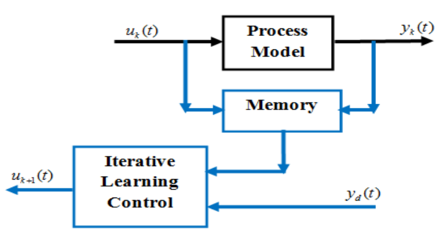

Fig. 4. Block diagram of the conceptual process in iterative learning control (ILC). As can be seen, the future value of control signal depends on the history of the input and output measurements, $u_k(t)$ and $y_k(t)$ as well as the desired trajectory as indicated by $y_d(t)$.

Thus, it should be highlighted that ILC controller make the use of past information to enhance the performance of a repetitive or periodic system, which can also be illustrated in Fig 4, that is, the outcome of the future iterations depend on the history of control inputs as well as the transient error. As depicted in [29], ILC can also be considered as a combination of both feedback and feed forward controls, as ILC attempts to determine the best feedforward gain in time domain as well as the best feedback controller in iteration domain. As depicted in [29], ILC is also found to be very effective in controlling non-minimum phase system (i.e., one with a right hand plane zero), due to the presence of its noncausal filter (i.e., a filter whose outputs are reliant on its future input).

H. Dual Adaptive Control

Dual adaptive control can be defined as one that incorporates the existing uncertainty into its control strategy, so that the system can achieve the control objectives while assisting the plant to improve its estimation. While the adaptive part determines the controller parameters on-line, the dual parts assists it by achieving optimal excitation on top of the control actions. Thus, the benefits of this control schemes are multifold. First, the system has already taken into account the accuracy of the estimation. Second, the estimation process can be expedited by its optimal excitation. This will lead to a smooth transitional behavior achieved by means of shorter adaptation time [32].

The underlying idea is to set dual goals for the controllers (i.e., the first goal is to control the process, while the objective is to get more information by injecting a probing signal). Thus, by acquiring more information one can expect to better control performance in the future steps. However, there is a conflicting objective here, since to acquire more information, one will need to disturb the process.

As depicted in [33], we will highlight the complexity of dual adaptive control as follows. First, given the N-stage criterion loss function as follows:

$$J_N = E\{1/N \sum_{t=1}^{N} ((y(t) - y_r(t))^2)\}, \tag{7}$$

where $y(t)$ denotes the controlled variable and $y_r(t)$ indicates a reference signal and E indicates the expected operator. The loss function should be minimised with respect to the following control signals: $u(0), u(1), ..., u(N-1)$.

Given the remaining part of the control horizon, we can introduce a notion of hyperstate ζ, including parameter estimate accuracy, and the history of inputs and outputs of the systems.

$$V(\zeta(t), t) = \min_{u(t-1)\dots u(N-1)} E\{1/N \sum_{t=1}^{N} ((y(t) - y_r(t))^2)|y_{t-1}\}, \tag{8}$$

Considering the dynamic programming, the optimal dual controller satisfies the following Balman equation as follows:

$$V(\zeta(t), t) = \min_{u(t-1)} E(y(t) - y_r(t))^2 + V(\zeta(t+1), t+1)|y_{t-1}, \tag{9}$$

It becomes apparent now that the challenge related to this equation is associated with its nested minimisation and mathematical expectation, making numerical solution is the only possible way to solve it, even for the simplest case [33].

This type of controller is well-suited for short horizon optimisation and especially when the initial estimate is poor, so that one can steadily improve it, before reaching the end of control horison. In addition, it is also appropriate for rapid variations in system parameters, accompanied with a different sign of gain (i.e., for the case of systems with even nonlinearity, with near extremum operation point, such as the grinding process in the pulp industry [34], [33].

I. Adaptive Pole Placement

Pole placement control has long been known for its ability to modify the position of the closed loop poles of the plant without canceling them. This control scheme is applicable in both minimum and non-minimum phase of linear-time invariant system [35]. Considering the benefits of adaptive controls, some researchers have attempted to design adaptive pole-placement control (APPC) which are mostly developed under non-direct approach of adaptive controls. Owing to the principle of variable structure control (VSC), comprising of a switching control law to limit the dynamics of the system to follow a sliding surface, the authors in [35] design and perform the stability analysis of a Variable Structure Adaptive Pole Placement Controller (VS-APPC). In short, the algorithm aims to shift the pole location of the original plant $\dot{y} = ay+bu$, where a and b are unknown constant, given control law $u = -ky+r$, where $k = \frac{a+a_m}{b}$, and r is the reference input, so that the following closed loop model given by $\dot{y} = -a_m y+b_r$, where $-a_m$ indicates the desired pole location can be achieved. This way, one can keep the zero, unlike model reference control (MRC) that cancles the zeros of the plant and replace it with a new one. Their research demonstrates that the system leads to reasonably fast transient response.

V. Conclusion and Future Trends

We have discussed several types and potential applications of the most widely used adaptive control systems from various perspectives (e.g., direct and indirect, deterministic and stochastic as well as feedback and feedforward systems). Since the field is an active research area, there is a a lot more to be done, and we feel that what we presented in this paper is only the tip of the iceberg. It is understood that this research field remains fertile as many concepts are still somewhat immature.

In general, the advancements of microprocessors and high-speed computing technology shall enable further development and practical implementation of adaptive techniques on high-bandwidth system instead of on low-bandwidth and benign dynamics [36]. Driven by high-performance requirements, while some control algorithms allow complex and computationally intensive controls, others impose severe computational constraints. Thus, it should be highlighted that computational complexity plays an important role in setting the appropriateness of choosing a certain control algorithm give a specific process or system.

We also envisage that future research will be moving closer towards the developments current algorithms towards linear parameter varying (LPV) systems, in response to the developments of cutting-edge system identification, robust control theory as well as non-linear control counterparts. It should be highlighted that the robustness analysis of gain-scheduled and other non-linear control systems remains immature. Furthermore, it should be noted that gain-scheduled control systems often violate several conditions, such as the behavior in the face of slow variation in system parameters. Considering the cross-coupling issue, adaptive control for multi-input, multi-output (MIMO) systems also deserves further attention owing to the traditional approach of single-input, single-output (SISO) system that can fail to work, given strong cross-coupling within the internal state variables. These issues are worth considering for further study. In what follows, we will briefly elaborate some possible future work in this area, in more detail.

A. Multi-Model Adaptive Control and Safe-Switching

Considering the progress in MMAC, there are some worth considering research gaps. The first issue is to enable parametric and non parametric uncertainty in the plant due to unmodelled dynamics which can be properly addressed by employing robust control for each controller. Second potential issue is due to switching process as to avoid connection with destabilsing controller. Some algorithms could allow a controller to be switched to one that was actually destabilising. The supervisor would observe the difficulty and switch it out, but not before the occurrence of some very large signals, which was deleterious. Thus, it is essential to introduce a form of safe control that can switch less frequently and only switches after verifying that the proposed new controller will not be destabilising. Furthermore, investigating stability analysis of this type of control system remains a fertile research area. Also, there is an urgency to extend some applicable classes of plants and its variations that can be handled by a certain adaptive control technique [3].

Fast switching for gain scheduled control systems is worth studying. There are some theoretical gaps in the formulations of gain scheduled algorithms. In gain scheduling, due to some variations in operating point the gain may vary. A finite number of controllers are required such that there is always one controller within the set that can satisfactorily control the plant at any chosen operating point. It is also necessary that the algorithm should switch the correct controller, typically by monitoring the operating point. The research questions relating to the area of rapid determination of the stabilizing controllers in the event that a destabilising controller has been accidentally chosen is worth investigating. Also, the theoretical validations of some gain-scheduled controllers are not well-established [3].

B. Robust-Adaptive and Adaptive-Robust Controls

As highlighted in the previous section, the robustness and adaptivity issues often go hand-in-hand. Considering the uncertain nature of a certain physical system, there is a need to robustify the adaptive schemes, at the same time, there is another demand to make robust control more adaptive in order to achieve a better performance. Thus, these modifications lead to fertile future work in this area. By taking into account constraints imposed by the sensitivity function, this will allow the robustness of the systems to be improved along with the performance of adaptive schemes.

While adaptive robust control put its emphasis on developing robust linear control design, robust adaptive control points out robust adaptation mechanisms [37]. In fact, the robustness of adaptive controls is different from LTI system as the reference signal also plays a crucial role in determining the convergence of the system by influencing the identification loop. Hence, there is an urgent demand to quantify the robustness of the adaptive systems. Also, current control theory does not allow for direct comparison of the robustness of different adaptive systems, making it difficult to study which algorithm is better in terms of its robustness [36].

C. Fuzzy or Neural Networks for ILC

We also envisage that the roles of non model-based control systems (e.g., fuzzy logic, neural networks or genetic algorithms) will become progressively more important as they can offer alternative solutions to minimise the effect of uncertainty, in the absence of complex mathematical burden. For instance, fuzzy logic or neural networks can be used to address the emerging problem of gain scheduling approach in response to the restriction to near equilibrium as a result of equilibrium linearisation of the plant). In this avenue, one may consider linear or quasi-linear parameter-varying formulations as well as off-equilibrium linearisation [23]. Yet another fertile research area in gain scheduling control is due to relaxation issue in determining slow variation condition (i.e., to ensure that the system will not rapidly jump between operating regions) [23]. The issue of obtaining necessary and sufficient condition for the stability of non-linear systems still requires further improvement.

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