

An Adaptive-Robust Strategy Design for Process Control

Dumitru Popescu^{1,2}, Catalin Dimon¹ and Pierre Borne³

¹*Department of Automatic Control and Systems Engineering, University Politehnica of Bucharest, Splaiul Independentei 313, Bucharest, Romania*

²*Academy of Romanian Scientists, Strada Ilfov 3, Bucharest, Romania*

³*Centre de Recherche en Informatique, Signal et Automatique de Lille, Ecole Centrale de Lille, Villeneuve d'Ascq, France*

Keywords: Adaptive Control, Robust Control, Adaptive-Robust Control, Design Methodology, Model Degradation, Optimal Control.

Abstract: The paper presents a new design strategy for industrial process control applications. The adaptive-robust control approach considers both adaptive control advantages and robust control benefits; the connection between the two concepts preserves the imposed performances for the closed loop nominal control system. The combined adaptive-robust solution introduces the same integral criterion for parameters identification of the process and for the control algorithm design. An optimal integral criterion and an appropriate robust measure for degradation of the system performances due to variation of the model are introduced in an iterative mechanism. The theoretical approach presented in this paper is validated on a close loop control system, the application being developed in simulation. The proposed strategy is aiming to implement adaptive-robust control in practical process applications.

1 INTRODUCTION

The 1960-1980s became the most important period for the development of control theory and in particular adaptive control. System identification and parameter estimation played a crucial role in the reformulation and redesign of adaptive control (Astrom & Wittenmark, 2008; Landau, 1995).

Adaptive control systems can automatically adjust its parameters to compensate variations in the process ensuring imposed performances even when the system's dynamics change or uncertainties are present. This adaptive system identifies in closed loop parameters in real time, adapting the controller's action to the applications where process parameters are unknown or time-varying (Popescu & Gentil, 1998; Foulloy et al., 2004; Popescu et al., 2008).

As a difference from an adaptive control strategy, in robust control rather than relying on real-time adaptation to measured variations, the controller is designed a priori to maintain performance under the assumption that certain system parameters are uncertain, but within known bounds.

The start of the theory of robust control took shape in the 1980s and is still active today. The modern theory of robust control system began in the late

1990s and soon developed a number of techniques for dealing with bounded system uncertainty.

Robustness is the ability to keep imposed performance unchanged under external disturbances and uncertainties. Robust control is a technique focused on ensuring a control system's performance despite uncertainties in the process or its environment. It aims to maintain imposed performance even when faced with disturbances, parameter or dynamic model structure variations. Robust control is crucial for applications with parameters and structure uncertainties, where stability and reliability are essential.

2 CONTROL STRATEGIES

2.1 Adaptive Control

The evolution of systems theory during the 70s-80s allowed the growth of interest and progress in adaptive control strategies. The rapid development of numerical computing resources, programming and simulation facilities contributed to the emergence and development of numerical methods for data acquisition and processing, modelling and

identification of processes and design of control algorithms. Under these favourable conditions, the possibility of transferring the performance of control systems obtained in simulation to real applications in processes appeared. As a result, for real-time control, adaptive strategies were recommended and implemented in industrial process automation.

The adaptive control strategy proposes for each sampling moment, a re-identification of the process and a re-design of the control system. It ensures the maintenance of nominal imposed performances on the physical system that drives the process, at each sampling moment.

The computational effort is significant and demanding for processes with rapid evolution and these limitations were cancelled by the robust control strategy. The adaptive control mechanism is illustrated in Figure 1.

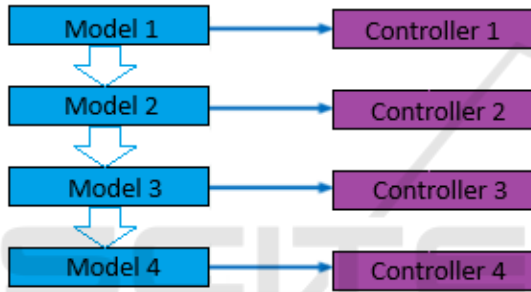


Figure 1: Adaptive control scheme.

The adaptive control mechanism is based on the recursive relationship for repeated estimation of model parameters and design of the control algorithm, after the relation:

$$(C_k, M_k) \rightarrow (C_{k+1}, M_{k+1}) \quad (1)$$

where C_k and C_{k+1} are the controllers at step k and $k+1$, M_k and M_{k+1} are the models at step k and $k+1$.

Adaptive control remains a recommended solution for processes with model parametric uncertainty (invariant structure and variable parameters) and for slowly variable processes described by low-order models (Astrom, 1983; Chalam, 1987; Anderson, et al., 1986).

Successes after the 1980s, however, were soon followed by controversies over the practicality of adaptive control concerning the computational effort for the reidentification of model parameters and the redesign of the controller in real-time closed loop system. Thus, the robust control alternative began (Ogata, 1990; Lewis et al., 2012; Wang et al., 2013; Doelman et al., 2009).

2.2 Robust Control

Robust control is a field of automatic control theory, recommended for preserving the stability and performance of systems with parametric and/or structural model uncertainty. Robust design methods ensure a maximum uncertainty region through robustness corrections, in order to attenuate the effects of disturbances. The robust controller is tolerant to the action of disturbances and to the nonlinearities in the system for a collection of models associated with different operating regimes of the process (Dullerud & Paganini, 1999).

Duncan McFarlane and Keith Glover of Cambridge University propose a design method for a robust H-infinity loop-shaping system in the frequency domain by minimizing the disturbance-output sensitivity function (McFarlane & Glover, 1992). The optimal-robust controller guarantees that the system ensures an invariance of the performance under the action of disturbances.

An important approach for the design of robust systems in input-output representation is presented in (Popescu et al., 2017). Robustness indicators in the frequency domain (robustness margin and disturbance-output sensitivity function) are introduced to evaluate the robustness of the system and a design method based on the remarkable properties of the disturbance-output sensitivity function is proposed. The nominal control system is adjusted so that the sensitivity function respects, in the frequency domain, a template imposed by successive calibration techniques.

From an application-oriented perspective, sliding mode control (SMC), represents an emerging area within robust control. Its inherent robustness to uncertainties, combined with its relative design simplicity, has led to its widespread adoption across a range of practical applications (Bojan-Dragos et al., 2024). Other areas of application concern power control for renewable sources of energy (Ghalem et al., 2018).

The robust control strategy is represented in Figure 2 and remains recommended for models with parametric and/or structural uncertainty and for nonlinear process models. Robust control preserves system stability of the system and tolerates model uncertainties caused by the action of disturbances or process nonlinearities. The robust controller preserves system performance for a class of models associated with possible process operating regimes (Popescu et al., 2017; Green & Limebeer, 2012; Popescu et al., 2008).

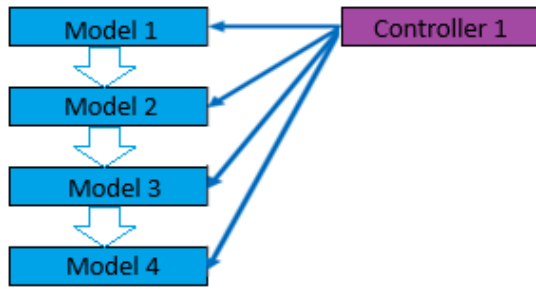


Figure 2: Robust control scheme.

The robustness reported to system performance is expressed by relation (2), which expresses the performance difference between the physical system and the nominal system:

$$\left| \frac{CP}{1+CP} - \frac{CM}{1+CM} \right| \rightarrow \text{small} \quad (2)$$

where C is the controller computed for process P , estimated by model M .

2.3 Adaptive-Robust Control

By the middle 1980s, several new redesigns and modifications were proposed and recommended, leading to a series of work known as robust adaptive control.

The efficiency of integrated control systems in automation solutions dedicated to technological processes is determined by the process identification and the system control design, two extremely important concepts that ensure the performance of the system. The behaviour of control systems in industrial applications depends directly on the quality of the mathematical model that expresses the process dynamics and the control algorithm and therefore the interdependence between the two concepts to ensure the required performances is obvious. For a high level of performance, the model must adapt when it becomes uncertain for the process, and the control algorithm must be tolerant to the action of disturbances. Thus, starting with the 1990s, a new concept was highlighted under the name of identification for robust control, a concept that later supported the adaptive-robust control strategy (Athans et al., 2005; Ioannou & Sun, 2013; Narendra & Annaswamy, 1986).

Important results on adaptive-robust control strategies are obtained after 1990s and involved the understanding of the various robust modifications and their unification under a more general framework. The adaptive-robust control strategy, proposed in this

paper, combines the advantages of adaptive control and robust control respectively, by minimizing the computational effort and by increasing the transfer of simulation results in real time applications. This strategy is shown in Figure 3.

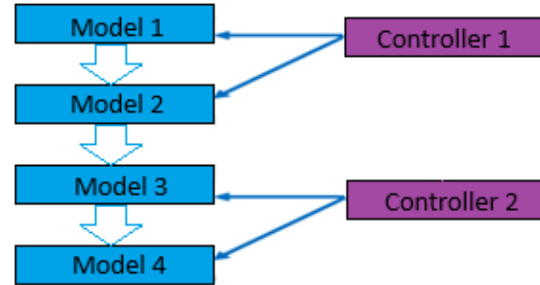


Figure 3: Adaptive-robust control scheme.

3 ADAPTIVE-ROBUST CONTROL METHODOLOGY

The main objective for this strategy is to combine resources offered by adaptive and robust control in a complementary manner to obtain high-performance results in the automation of industrial processes.

The identification mechanism must be integrated into an automatic control system and therefore a set of models attached to the process dynamics must be considered, if the nominal performances from the simulation are to be maintained for the operation of real processes. It is therefore proposed to perform an identification and calculate a real-time command, for the regulation of the process subjected to disturbances.

Let us consider the nominal system (NS) with the nominal performances (NP) validated in simulation, represented in Figure 4:

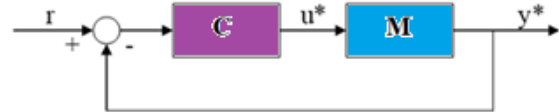


Figure 4: Nominal control system (NS).

and the physical real system (RS) with performances to be achieved (RP) on the physical process, represented in Fig. 5:



Figure 5: Real control system (RS).

It is desired that the performances obtained in the simulation are found as achieved performances, under the conditions in which the process changes its nominal operating point under the action of disturbances.

In practice, the identification problem is solved by minimizing the criterion constructed with the estimation error and separately the optimal command is calculated by minimizing another optimality criterion depending on the regulation error system, as follows:

- if a compensator C is known, the optimal identification model M can be determined using an identification criterion J_I :

$$M = \arg \min_M J_I(C, M) \quad (3)$$

- if an identification model M is known, the optimal compensator C can be determined using a control criterion J_C :

$$C = \arg \min_C J_C(C, M) \quad (4)$$

The complementary relationship between the problems of identification and control design is supported by an iterative process (Gliga et al., 2008; Levreetsky & Wise, 2024; Pham et al., 2025). The two problems above can be defined in a unified manner, which once again emphasizes the complementarity between the two optimization problems within the general problem of designing automatic control systems.

Our approach is based on the idea that identification should be carried out for the purpose of control design and not separately. For this reason, a single criterion remains important, for example J_C .

Given an optimization criterion J (for example, $J \equiv J_C$) and a corresponding norm, its optimal value is obtained by minimizing $\|J\|$ on the set of model-compensator pairs associated with the process.

In practice, the compensator built from an estimated model must lead to similar performances in simulation and on the operating process. There are thus two additional types of restrictions imposed by the criterion J :

$$\|J(C, M)\| < \delta \quad (5)$$

$$\|J(C, P) - J(C, M)\| \ll \|J(C, M)\| \quad (6)$$

where δ is the degradation error. The norms in the above inequalities have natural interpretations, such as:

- $\|J(C, M)\|$ represents the nominal performance;
- $\|J(C, P)\|$ represents the performance achieved during operation;
- $\|J(C, P) - J(C, M)\|$ measures the degradation of the nominal performance, while the compensator was built starting from the estimated model M and not from the real model P .

Constraint (5) ensures good nominal performance, while constraint (6) refers to robustness. The value of $\|J(C, M)\|$ being sufficiently small, the performance degradation will also be reduced.

We should also point out that this constraint does not necessarily have to be verified if the nominal performance $\|J(C, M)\|$ is close to the realized performance $\|J(C, P)\|$. As this is difficult to test, the robustness constraint (6) is imposed. If this is verified, then the nominal and realized performances are close.

The criterion J can be used to trigger an iterative calculation process aiming to obtain a model-compensator pair as close as possible to the optimal pair. It is sufficient to use the performance degradation measure for both the optimization and identification criterion of the nominal performance $\|J_I\|$ and for the optimization function in the evaluation of the command $\|J_C\|$ (Borne et al., 2013; Stefanoiu et al., 2014).

The generic stage of this mechanism is described below (for all $i \in \mathbb{N}$):

$$\begin{cases} M_{i+1} = \arg \min \|J(C_i, P) - J(C_i, M)\| \\ C_{i+1} = \arg \min \|J(C_i, M_{i+1})\| \end{cases} \quad (7)$$

For each iterative step, the constraints (5) and (7) must be verified, expressed in the form:

$$\|J(C_{i+1}, M_{i+1})\| < \delta \quad (8)$$

$$\|J(C_{i+1}, P) - J(C_{i+1}, M_{i+1})\| \ll \|J(C_{i+1}, M_{i+1})\| \quad (9)$$

Relations (7), (8) and (9) constitute the core of the iterative process. The recursive algorithm is shown in the diagram in Figure 6.

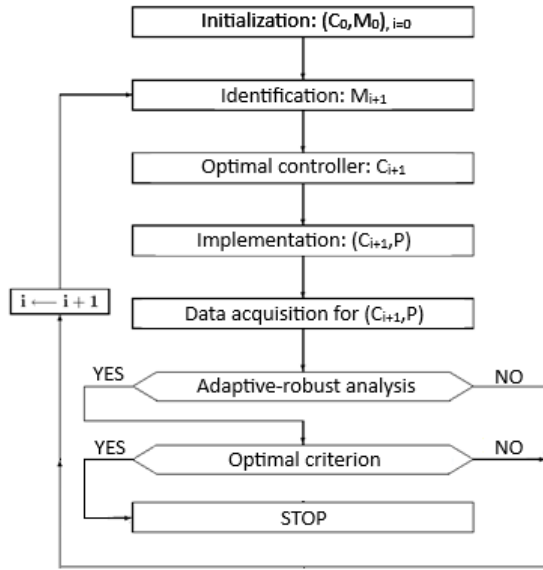


Figure 6: Recursive adaptive-robust algorithm.

The recursive algorithm will stop while the conditions (8) and (9) are verified, otherwise it goes to the identification of the model, and the algorithm starts again. The controller that satisfies condition (8) is the robust adaptive controller implemented on the real system structure (RS).

Let us consider:

$$J = \min \int e^2(t) dt \quad (10)$$

the optimal integral criterion for designing the controller, where $e(t)$ is the control error of the closed loop system.

The expression (10) becomes:

$$J = \min \int e^2(C, M) dt \quad (11)$$

which accepts a direct representation of the criterion as follows:

$$J = \min(C, M) \quad (12)$$

For a fixed model M , identified from the measure the robustness degradation, we can compute the new controller:

$$J = \min(C) \quad (13)$$

The main steps of the proposed algorithm are the following:

- A closed-loop control system (C_0, M_0) , which ensures performance at a nominal operating point of the process P_0 , is considered.

- If the perturbed process changes the operating point P_i driven by the system (C_i, M_i) to the new point P_{i+1} , a new model M_{i+1} is re-identified by minimizing the performance degradation due to the model parametric uncertainty.

- A new controller C_{i+1} is recomputed using the optimality criterion J .

- The recursive procedure ends if the performance degradation becomes insignificant.

As mentioned earlier, the following optimal integral criterion J is considered:

$$J = \int_{t=0}^{\infty} e^2(t) dt \quad (14)$$

After some mathematical transformations, detailed in (Calin et al., 1979), the direct expression of the integral criterion is obtained as follows:

$$J = \frac{T_i + K_r k \tau}{2 K_r k (1 + K_r k)} \quad (15)$$

The unique optimality criterion J is used to identify the process model by minimizing the degradation measure and respectively to recompute the controller by minimizing the same criterion. After estimating the new model, the new controller is designed to preserve the system performance using the relations (7). Thus, the limitations of the closed-loop model adaptation strategy given by the redesign of the control algorithm at each sampling moment are reduced by the effect of the robust strategy.

4 STUDY-CASE AND SIMULATIONS

A simple study case for understanding the adaptive-robust approach is presented considering a first order process model and a PI controller for the system. For higher order systems, the design methodology remains the same, just the number of mathematical calculations increases with the order of the process model and of the controller complexity.

Let us consider a process expressed using a first order transfer function:

$$P(s) = \frac{k}{\tau s + 1} \quad (16)$$

and the PI control algorithm which will be used for the system:

$$C(s) = K_r \left(1 + \frac{1}{T_i s} \right) \quad (17)$$

Let us consider the process from (16) given by the parameters $k = 2$ and $\tau = 10$. We can initialize the controller by using a poles placement method, considering as performances: zero overshoot and 40 seconds response time. The computed controller is given by the parameters $K_{r,0} = 0.5$ and $T_{i,0} = 10$. The system response is represented in Figure 7. A 10% disturbance is added to the output of the system at time $t=250$ s, which is rejected. It should be noted that the computed controller will be maintained as long as the degradation error criterion given by (8) is verified. The degradation error in this case will be $\delta = J(C_0, M_0) = 5$.

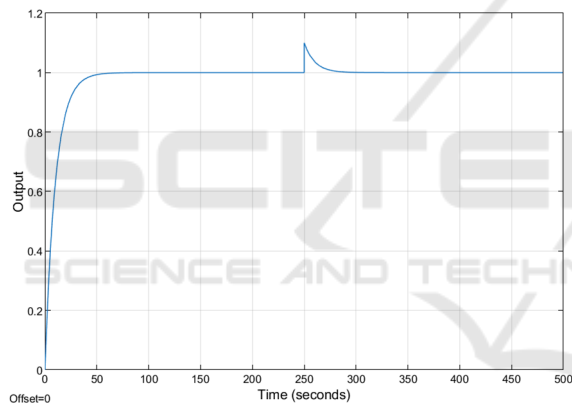


Figure 7: System response for (C_0, M_0) .

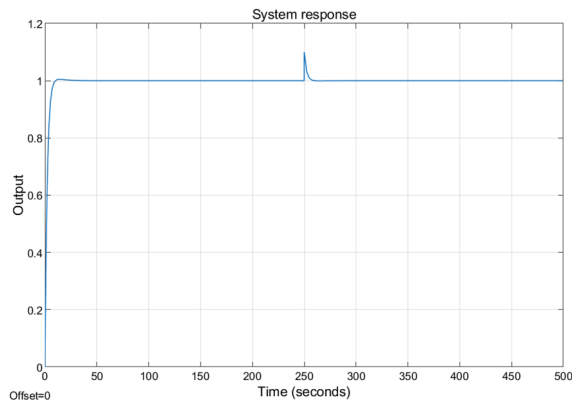


Figure 8: System response for (C_i, M_i) .

By using the Cauchy gradient method with the criterion function given by (15), the algorithm will compute a new controller only when necessary. The optimum values for the controller at iteration i : $K_{r,i}^* = 10.592$ and $T_{i,i}^* = 8.2574$. The degradation error will be given by the new value $\delta = J(C_i, M_i) = 1.0454$. The system response is shown in Figure 8.

In time the model of the process will change, such that the controller will not be able to assure the nominal performances. Such a case is represented in Figure 9, where the process is identified by a new model M_{i+1} . By applying the same principle, we obtained the controller C_{i+1} and the system response is represented in Figure 10. The degradation error is given by $\delta = J(C_{i+1}, M_{i+1}) = 0.3885$.

It can be noticed that the system performances are verified; in fact, we obtained better response time compared with the initial response (the response time is about 33 seconds).

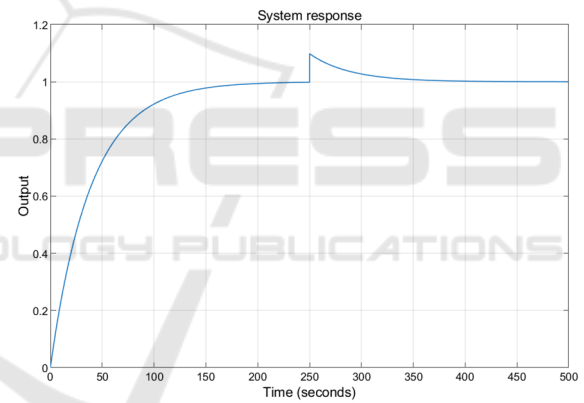


Figure 9: System response for (C_i, M_{i+1}) .

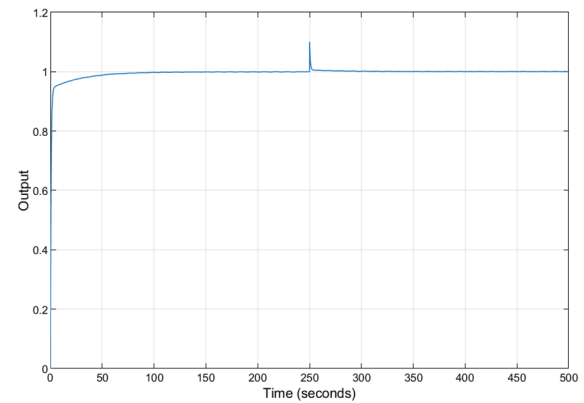


Figure 10: System response for (C_{i+1}, M_{i+1}) .

5 CONCLUSIONS

The paper proposes a new adaptive-robust control strategy for the development of industrial automation applications.

The main objective for this strategy is to combine the advantages offered by adaptive and robust control in a complementary manner to obtain high-performance results in the automation of technological processes with parametric and/or structural uncertainties.

Adaptive-robust control is recommended for processes with parametric and/or structural uncertainty, tolerant to the action of disturbances and nonlinearities in the process.

Adaptive-robust control is based on the concept of robust degradation measure and uses a recursive calculation procedure, by using a single optimality criterion that minimizes the degradation measure for the identification operation, and which calculates the optimal command.

The theoretical results validated in simulation can be transferred as efficient solutions for the automation of real technological processes and installations guaranteeing superior performances in operation.

REFERENCES

- Anderson, B.D.O., Bitmead, R.R., Johnson, C.R., Kokotovic, P.V., Kosut, R.L., Mareels, I., Praly, L., Riedle, B. (1986). *Stability of Adaptive Systems*, M.I.T. Press, Cambridge, Massachusetts.
- Astrom, K.J. (1983). Theory and applications of adaptive control - a survey, In *Automatica*, vol.19, no.5, pp. 471-486.
- Astrom, K.J., Wittenmark, B. (2008). *Adaptive Control*, Courier Corporation.
- Athans, M., Fekri S., Pascoal, A. (2005). Issues on robust adaptive feedback control. In *Preprints of the 16th IFAC World Congress*, pp. 9-39.
- Bojan-Dragos, C.A., Precup, R.E., Petriu, E., Tibre, R.A., Han, T. (2024). Sliding Mode and Super-Twisting Sliding Mode Control Structures for Vertical Three-Tank Systems. In *Studies in Informatics and Control Journal*, Vol. 33, No. 3, 2024.
- Borne, P., Popescu, D., Filip F.G., Stefanoiu, D. (2013). *Optimization in Engineering Sciences- Exact Methods*, J.Wiley Press, London.
- Calin, S., Tertisco, M., Dumitrache, I., Popeea, C., Popescu, D. (1979). *Optimizations in industrial automation*, Tehnica Press, Bucharest.
- Chalam, V. V. (1987). *Adaptive Control Systems: Techniques and Applications*, New York.
- Doelman, N., Fraanje, R., Houtzager, I., Verhaegen, M. (2009). Adaptive and real-time optimal control for adaptive optics systems. In *ECC-European Control Conference*, Proceedings.
- Dullerud, G.E., Paganini, F. (1999). *A Course in Robust Control*, Springer-Verlag, Berlin.
- Foulloy, L., Popescu, D., Dauphin-Tanguy, G. (2004). *Modelisation, Identification et Commande des Systemes*, Romanian Academy Press, Bucharest.
- Ge, S.S., Wang, C., Li, Y., Lee, T.H., Ang, M.H. (2013). Adaptive optimal control for linear discrete time-varying systems. In *IEEE Conference on Cybernetics and Intelligent Systems*, Proceedings.
- Ghalem, A., Tayeb A., Attallah, S., Abdeldjabbar, K.M. (2018). Robust and modern control of VSC-HVDC. In *U.P.B. Sci. Bull., Series C*, vol. 80(2).
- Gliga, L., Cosmin, M., Lupu, C., Popescu, D. (2008). Adaptive-Robust Control, a computational efficient real time simulation. In *EMES International Conference*, Oradea.
- Green, M., Limebeer, D.J.N. (2012). *Linear Robust Control*, Courier Corporation.
- Ioannou, V.P., Sun, J. (2013). *Robust Adaptive Control*, Courier Corporation.
- Landau, I.D. (1995). *Identification et Commande des Systemes*, Hermes Publishing, Paris.
- Levreetsky, E., Wise, K. (2024). *Robust and Adaptive Control: With Aerospace Applications (Advanced Textbooks in Control and Signal Processing)*, SpringerPress.
- Lewis, F.L., Vrabie, D., Syrmos, V.L. (2012). *Optimal Control*, John Wiley and Sons.
- McFarlane, D., Glover, K. (1992). A loop-shaping design procedure using H_{∞} / synthesis. In *IEEE Transactions on Automatic Control*, vol. 37, no. 6, pp. 759-769.
- Narendra, K.S., Annaswamy, A.M. (1986). Robust Adaptive Control in the Presence of Bounded Disturbances. In *IEEE Transactions on Automatic Control*, vol. 31, no. 4, pp. 306-315.
- Ogata, K. (1990). *Modern Control Engineering*, Practice Hall, New Jersey.
- Pham, D.A., Han, S.H., Kong, K.J. (2025). Time-Specified Adaptive Robust Control Framework for Managing Nonlinear System Uncertainties. In *Appl.Sci.*, 16(6).
- Popescu, D., Gentil, S. (1998). *Commande Numerique et Intelligence Artificielle en Automatique*, Tehnica Press, Bucharest.
- Popescu, D., Stefanoiu, D., Lupu, C., Petrescu, C., Ciubotaru, B., Dimon, C. (2008). *Industrial Automation*, Agir Press, Bucharest.
- Popescu, D., Stefanoiu D., Borne, P. (2017). *Process Control Design for Industrial Applications*, John Wiley Press, London.
- Stefanoiu, D., Borne, P., Popescu, D., Filip, F.G. (2014). *Optimization in Engineering Sciences- Metaheuristic, Stochastic Methods and Decision Support*, J.Wiley Press, London.