





IOSUD – "DUNĂREA DE JOS" UNIVERSITY OFGALAȚI Doctoral School of Fundamental and Engineering Sciences



PhD THESIS

PhD Thesis Summary

CONTRIBUTIONS REGARDING THE AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES

PhD candidate,

Larisa CONDRACHI (DIACONU) Eng.

Scientific supervisor,

Professor Marian BARBU, PhD Eng.

Series: I8: Systems Engineering No. 9 GALAŢI 2022











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Series: I8: Systems Engineering No. 9 GALAŢI 2022











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THESIS TABLE OF CONTENTS

INTRODU	CTIONIX
LIST OF F	IGURESXVII
LIST OF T	ABLES XXI
ABREVIA	ΓΙΟΝΧΧΙΙΙ
Chapter 1:	ANAEROBIC DIGESTION PROCESSES1
1.1	Types of anaerobic digestion1
1.2	Description of phenomena occuring in an anaerobic digester2
1.3	The existing instrumentation in the case of anaerobic digestion processes4
1.4	State of the art in mathematical modeling of anaerobic digestion processes
1.5	State of the art in the automatic control of the anaerobic digestion processes7
Chapter 2:	MATHEMATICAL MODELING OF ANAEROBIC DIGESTION PROCESES
2.1	The ADM1 mathematical model11
2.1.1	Implementation of the ADM1 mathematical model in Simulink 14
2.2	The AM2 simplified mathematical model21
2.2.1	Implementation of the AM2 mathematical model in Simulink
2.3	Compatibility of the ADM1 and AM2 mathematical models25
Capitolul 3	3: AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES USING THE MODEL FREE CONTROL METHOD
3.1 processes	Defining of the automatic control problem in the case of anaerobic digestion
3.2 processes	Usage of Model Free Control in automatic control of the anaerobic digestion
3.2.1	General considerations regarding the Model Free Control method
3.2.2	Tuning the controller when using the MFC for PDA
3.2.3 digeste	Tuning of the controller parameters to change in load regime of the anaerobic er
3.2.4	Conclusions
Capitolul 4	4: DATA-DRIVEN BASED AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES
4.1 Feedback	Automatic control of anaerobic digestions processes using the Virtual Reference Tuning method
4.1.1	VRFT algorithm, synthesized with data from the virtual plant
4.1.2	Controller synthesis using the usual VRFT algorithm43

Condrachi	Larisa (DIACONU)	Thesis table of contents
4.1.3	Simplified VRFT algorithm synthesized with data from the	e virtual plant 48
4.1.4	Contoller synthesis using simplified VRFT algorithm	
4.1.5	PDA control results using the VRFT approach	
4.2 method	Automatic control of anaerobic digestion processes using t	he Internal Model Control
4.2.1	Principle of approaching the IMC method based on data-	driven 57
4.2.2	Chosing the rederence model within IMC method	
4.2.3	Design of the control structure within IMC method	
4.2.4	Checking the robust stability under the IMC method	
4.2.5	Validation by simulation of the control law obtained by da	ta-driven IMC method. 68
4.3 Reference	Automatic control of the anaerobic digestion processes usin Iterative Tuning	ng the Fictitious 73
4.3.1	The principle of the usal variant of the FRIT method	
4.3.2	Usage of FRIT method to obtain an PI controller in the ca	ase of PDA76
4.3.3	Usage of FRIT method to obtain a PID controller in case	of PDA 80
4.3.4	Usage of Fictitious Reference Non-Interative Tuning (FR	NIT) in case of PDA 83
4.4	Conclusions	
Capitolul	5: IMPLEMENTATION OF A PLATFORM BASED ON THE TESTING THE CONTROL SOLUTIONS	HILD PRINCIPLE FOR
5.1	Structure an implementation of the testing platform	
5.2 running th	Description of the software applications developed and des e model in real time	scription of the procedure 94
5.3	Experimental results obtained with the testing platform	
5.3.1	Estimation of the influent concentration using a neural es	timator101
5.3.2 open	Neural estimator for the concentration of the influent built	with date collected in
5.3.3 close	Neural estimator for the concentration of the influent built loop	with data collected in104
5.3.4	Testing a control solution applied on the HILS platform	
5.4	Conclusions	
Capitolul	6: CONCLUSIONS	109
6.1	Original contributions	
6.2	Disemination of the obtained results	110
6.3	Future research directions	111
BIBLIOGE		

SUMMARY TABLE OF CONTENTS

INTRODU	CTIONVII
Chapter 1:	ANAEROBIC DIGESTION PROCESSES1
1.1	Types of anaerobic digestion1
1.2	Description of phenomena occurring in an anaerobic digester1
1.3	The existing instrumentation in the case of anaerobic digestion processes2
1.4	State of the art in mathematical modeling of anaerobic digestion processes2
1.5	State of the art in the automatic control of the anaerobic digestion processes
Chapter 2	MATHEMATICAL MODELING OF ANAEROBIC DIGESTION PROCESSES4
2.1	The ADM1 mathematical model4
2.1.1	Implementation of the ADM1 mathematical model in Simulink
2.2	The AM2 simplified mathematical model5
2.2.1	Implementation of the AM2 mathematical model in Simulink
2.3	Compatibility of the ADM1 and AM2 mathematical models6
Chapter 3	AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES USING THE MODEL FREE CONTROL METHOD
3.1 processes	Defining of the automatic control problem in the case of anaerobic digestion
3.2 processes	Usage of Model Free Control in automatic control of the anaerobic digestion
3.2.1	General considerations regarding the Model Free Control method8
3.2.2	Tuning the controller when using the MFC for PDA10
3.2.3 anaero	Tuning of the controller parameters to the change in the load regime of the obic digester
3.2.4	Conclusions
Chapter 4	DATA-DRIVEN BASED AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES
4.1 Feedback	Automatic control of anaerobic digestion processes using the Virtual Reference Tuning method
4.1.1	VRFT algorithm synthesized with data from the virtual plant
4.1.2	Controller synthesis using the usual VRFT algorithm15
4.1.3	Simplified VRFT algorithm synthesized with data from the virtual plant
4.1.4	Controller synthesis using simplified VRFT algorithm
4.1.5	PDA control results using the VRFT approach
4.2 method	Automatic control of anaerobic digestion processes using the Internal Model Control

4.2.1 Principle of approaching the IMC method based on data-driven 20 4.2.2 Choosing the reference model within the IMC method 22 4.2.3 Design of the control structure within the IMC method 23 4.2.4 Checking the robust stability under the IMC method 24 4.2.5 Validation by simulation of the control law obtained by data-driven IMC method. 25 4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obt
4.2.2 Choosing the reference model within the IMC method 22 4.2.3 Design of the control structure within the IMC method 23 4.2.4 Checking the robust stability under the IMC method 24 4.2.5 Validation by simulation of the control law obtained by data-driven IMC method. 25 4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method. 26 4.2.8 Usage of FRIT method to obtain a PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3.1 Estimation for the concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the inf
4.2.3 Design of the control structure within the IMC method 23 4.2.4 Checking the robust stability under the IMC method 24 4.2.5 Validation by simulation of the control law obtained by data-driven IMC method. 25 4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.2 Neural estimator for the concentration of the influent built with data collected in open loop 36 5.3.3.1
4.2.4 Checking the robust stability under the IMC method 24 4.2.5 Validation by simulation of the control law obtained by data-driven IMC method. 25 4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.3 Neural estimator
4.2.5 Validation by simulation of the control law obtained by data-driven IMC method. 25 4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in open loop. 36 5.3.4 Testing a control solution applied on the HILS platform 37
4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method 26 4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PI controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3.1 Estimation of the influent concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the influent built with data collected in open loop 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions
4.2.7 The principle of the usual variant of the FRIT method 26 4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.3 Neural estimator for the concentration of the influent built with data collected in open loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 39
4.2.8 Usage of FRIT method to obtain a PI controller in the case of PDA 27 4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.3 Neural estimator for the concentration of the influent built with data collected in open loop. 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 39
4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA 28 4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 36 5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 39
4.2.10 Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA 29 4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 39
4.3 Conclusions 30 Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 6.1 Original contributions 39
Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR 31 5.1 Structure and implementation of the testing platform 31 5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39
5.1Structure and implementation of the testing platform315.2Description of the software applications developed and description of the procedureunning the model in real time325.3Experimental results obtained with the testing platform345.3.1Estimation of the influent concentration using a neural estimator355.3.2Neural estimator for the concentration of the influent built with date collected in open loop365.3.3Neural estimator for the concentration of the influent build with data collected in closed loop365.3.4Testing a control solution applied on the HILS platform375.4Conclusions38Chapter 6: CONCLUSIONS3939
5.2 Description of the software applications developed and description of the procedure unning the model in real time 32 5.3 Experimental results obtained with the testing platform 34 5.3.1 Estimation of the influent concentration using a neural estimator 35 5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop 36 5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 6.1 Original contributions 39
5.3Experimental results obtained with the testing platform.345.3.1Estimation of the influent concentration using a neural estimator355.3.2Neural estimator for the concentration of the influent built with date collected in open loop.365.3.3Neural estimator for the concentration of the influent build with data collected in closed loop.365.3.4Testing a control solution applied on the HILS platform.375.4Conclusions.38Chapter 6: CONCLUSIONS.396.1Original contributions.39
5.3.1Estimation of the influent concentration using a neural estimator355.3.2Neural estimator for the concentration of the influent built with date collected in open loop365.3.3Neural estimator for the concentration of the influent build with data collected in closed loop365.3.4Testing a control solution applied on the HILS platform375.4Conclusions38Chapter 6: CONCLUSIONS396.1Original contributions39
5.3.2Neural estimator for the concentration of the influent built with date collected in open loop
5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop 36 5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 6.1 Original contributions 39
5.3.4 Testing a control solution applied on the HILS platform 37 5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 6.1 Original contributions 39
5.4 Conclusions 38 Chapter 6: CONCLUSIONS 39 6.1 Original contributions 39
Chapter 6: CONCLUSIONS
6.1 Original contributions
6.2 Dissemination of the obtained results
6.3 Future research directions 40
BIBLIOGRAPHY

INTRODUCTION

The continuous and sustained development of the society actively contributes to the damage of the environment. In the case of water, this is done by two mechanisms: by generating excessive water consumption and by discharging polluting water. Without measures being taken to limit the effect of human activities on water quality, society cannot continue its current development.

Excessive water consumption is a worrying problem because it leads to huge amounts of polluted water. This water is called wastewater and we need to collect it and subject it to treatment processes before it is reintroduced into the natural circuit by discharge into rivers, lakes, seas, etc. In recent years, important steps have been taken in this regard, the solution adopted being the development of sewer systems and wastewater treatment systems. Obviously, these solutions must take into account the nature of the pollutants that affect the water, the type of community for which these solutions are developed, but also the cost involved in the implementation and operation of wastewater treatment systems.

There are multiple technologies for wastewater treatment, but they can be grouped into two main categories: aerobic and anaerobic. According to the specialized literature, in the case of large and medium urban communities, the technologies of aerobic treatment with activated sludge are preferred [1]. This technology involves the consumption of organic pollutants from wastewater, in the presence of oxygen, by populations of microorganisms called activated sludge. Although this is an efficient solution, it has three main disadvantages: a high electricity consumption due to aeration, a low efficiency in the case of high concentrations of the influent and a large amount of excess activated sludge resulting from aerobic treatment units.

In view of the environmental restrictions adopted at global level, and in particular at European Union level, there is a need for wastewater treatment technologies to become more efficient, both in terms of wastewater treatment efficiency and in terms of the energy consumption involved. The use of process control techniques is a reliable method for increasing the efficiency of wastewater treatment technologies in relation to the two aspects mentioned before. The importance of this aspect is also proven by the huge number of papers on this topic in the main stream of publications published in the last 10 years.

OBJECTIVE AND STRUCTURE OF THE PhD THESIS

The PhD thesis entitled "CONTRIBUTIONS REGARDING THE AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES" aims at analyzing and applying modern techniques of automatic control in the case of anaerobic digestion processes with their testing in an environment as close as possible to the industrial reality. In order to achieve this, it was taken into account a complex mathematical model for the design and validation of automatic control structures, a mathematical model which is considered in the specialized literature as standard, when describing the process of anaerobic digestion. Moreover, a testing platform has been designed and realized using the Hardware In The Loop Simulation principle, a platform which allows testing control structures and transmitting data to a cloud-computing component, for higher-level processing.

Chapter 1 contains a presentation of the process approached and the state of the art regarding the research in the field. Thus, the main types of anaerobic digesters, the description

of the phenomena taking place in an anaerobic digester, as well as the instrumentation are presented. By the end of the chapter, it is presented the state of the art in the field of mathematical modeling and control of anaerobic digestion processes.

Chapter 2, entitled Mathematical modeling of anaerobic digestion processes, the main mathematical models in the specialized literature for the anaerobic digestion process are presented. Thus, the following are presented: the complex Anaerobic Digestion Model No. 1 (ADM1), considered as a standard in terms of depth of description of the phenomena that occur within an anaerobic digester, and the simplified model AM2, which makes a global description of biomass production, organic substrate consumption and biogas production in the case of anaerobic digestion. By the end of the chapter, it is presented the compatibility of the described models ADM1, and AM2 respectively.

Chapter 3, The automatic control of anaerobic digestion processes using the Model Free Control method, proposes the use of the complex mathematical model ADM1 as a virtual plant and it investigates the possibility of using the Model Free Control methods in the case of anaerobic digestion processes. Thus, within the chapter we start from the study of the static and dynamic properties of the anaerobic digestion process and the formulation of the control problem. Given the complexity of the model used as a virtual plant, an appropriate method would be the Model Free Control. Thus, the general approach, proposed by the group led by Professor Fliess, is presented firstly, an approach that leads to obtaining an intelligent controller called iP, iPI etc., and the main methods of tuning these controllers being also analyzed. Starting from the observation that in real applications the load regime (concentration of influent) of the anaerobic digester is variable in time, a method of tuning the parameters of the controller is proposed to ensure the stability of the system in a wide range of operating regimes, the proposed method being validated by numerical simulation.

Chapter 4, entitled Data-driven based automatic control of anaerobic digestion processes, investigates the applicability of three data-driven methods, being proposed adaptations of these methods in relation to the peculiarities of the studied process, validation being made by numerical simulation considering again the complex mathematical model ADM1 as a virtual plant. A first method considered is Virtual Reference Feedback Tuning (VRFT), in this case two solutions are used to determine the parameters of the controller: the algorithm corresponding to the usual VRFT method and a simplified algorithm. The design of the controller in the case of both solutions is analyzed in the context of anaerobic digestion processes. The second method considered is Internal Model Control. An important aspect of this approach is the choice of the reference model. It must be chosen taking into account the following aspects: essential information about the desired dynamics for the closed-loop process, the level of dynamic errors resulting in a closed loop for the adopted reference model and the maximum amplitude of the disturbance that would cause a major deterioration in the quality of control. All the aspects addressed are customized for the case of anaerobic digestion processes. In the case of this method, given the uncertainties affecting this type of process, the issue of checking robust stability is also considered. Thus, the numerical simulation analysis of the performances of the synthesized control law followed three aspects: reference tracking, disturbance rejection, and the effect of measurement noise on the output variable. The last method studied was Fictitious Reference Iterative Tuning (FRIT). In this case, the use of the FRIT method to obtain PI and PID-type controllers in the case of anaerobic digestion processes was analyzed, being considered both the iterative and non-iterative tuning of the controller parameters. By the end of the chapter, the main conclusions on the use of datadriven control methods in the case of anaerobic digestion processes are presented.

Chapter 5 presents the design and implementation of a Hardware In The Loop Simulation (HILS) platform for testing and validating control solutions. The peculiarity of this platform is the

ability to run in real time and the fact that it can be used for any type of process. It also includes a cloud computing component that offers the possibility of storing and processing the signals of interest acquired, thus allowing the processing of data from the process at a higher hierarchical level.

Chapter 6 of the thesis exposes the conclusions extracted from the undertaken research, the original contributions of the doctoral research theme, but also the scientific works in which the scientific contributions of the thesis were disseminated.

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Chapter 1: ANAEROBIC DIGESTION PROCESSES

With the sustainable development of society, the level of water pollution has also increased. Currently, industrial, domestic and agricultural activities contribute to the production of a large volume of wastewater, but also to a high energy consumption.

Under these circumstances, in order to reduce the volume of wastewater, the solution adopted was wastewater treatment using the anaerobic digestion process. The major advantages of this process are the possibility of treating an influent with a high concentration of organic pollutants and the production of biogas. Biogas is a renewable energy resource which can be exploited to reduce energy consumption.

The anaerobic digestion process is one of the longest-used processes for wastewater treatment and sludge stabilization [2]. Research on the applicability of the anaerobic digestion process covered areas ranging from municipal sewage sludge to liquid organic fraction, especially industrial, then municipal from solid waste and agricultural residues [3].

Anaerobic digestion is a biochemical process by which microorganisms decompose organic material in the absence of oxygen, resulting in carbon dioxide (CO_2) and methane (CH_4) [4].

A key factor in achieving a valuable production of methane is the influent. Its composition requires special attention because the conditions of biodegradability differ depending on its origin. The most common types of organic material used to obtain biogas are [5]: Manure and sludge; Agricultural residues and by-products; Organic wastes from the food and agri-food industry (of plant and animal origin); Organic fractions of municipal and food waste; Wastewater and sewage sludge; Dedicated energy crops.

1.1 Types of anaerobic digestion

With regard to the activity considered, wastewater treatment systems, which include the process of anaerobic digestion, are of two types:

- Independent domestic or industrial digesters;
- **4** Digesters that are included in municipal wastewater treatment plants.

1.2 Description of phenomena occurring in an anaerobic digester

Knowledge of these phenomena is useful both in the design and operation of anaerobic digesters, and in understanding the occurrence of disturbances and their attenuation. Conceptually, the process of anaerobic digestion includes several stages, which describe the main biochemical and physico-chemical processes that take place in an anaerobic digester. The stages of the anaerobic digestion process are [6]: disintegration, hydrolysis, acidogenesis, acetogenesis and methanogenesis.

Disintegration is the first stage of the anaerobic digestion process. At this stage, complex composite particles are disintegrated into carbohydrates, proteins, lipids and soluble inerts.

Hydrolysis is the second stage and it has the role of hydrolyzing the carbohydrates, proteins, lipids and soluble inerts by means of hydrolytic bacteria. Following this stage, carbohydrates are converted into monosaccharides, lipids into fatty acid chains (LCFA) and proteins into amino acids.

Acidogenesis is the stage by which acidogenic bacteria convert monosaccharides, amino acids and fatty acids into: dissolved hydrogen, carbon dioxide and volatile fatty acids (VFA), consisting mainly of propionic acids, butyric, valeric and acetic acids.

Acetogenesis is the stage by which acetogenic bacteria act on volatile fatty acids and fatty acid chains to produce acetate and hydrogen.

Methanogenesis marks the final stage of the process of anaerobic digestion. At this stage, acetoclastic and hydrogenophilic bacteria convert acetic acid and hydrogen into methane.

1.3 The existing instrumentation in the case of anaerobic digestion processes

Regarding the monitoring and control of anaerobic digestion processes, an essential aspect is the existence of instrumentation, obviously with an emphasis on the existence of online instrumentation [7], [8]. Therefore, a large number of variables are of interest when monitoring the anaerobic digestion process, and by default there are several types of instrumentation capable of generating relevant information. A classification of the types of instrumentation available in the literature is:

- **On-line instrumentation** is capable of acquiring and sending data, in real time to a computer or other acquisition system;
- Off-line instrumentation is capable of measuring and storing data;
- **In-line instrumentation** involves sensors or tools that are placed directly in a process flow that naturally provides online data.

1.4 State of the art in mathematical modeling of anaerobic digestion processes

Knowledge of the anaerobic digestion process is an important step for monitoring and controlling the performance of anaerobic fermentation. Consequently, mathematical models can be a useful tool for deepening and understanding complex systems to facilitate the design and operation of a process. In 1983, a model was presented, capable of making a more complex description of the physical, chemical and biological phenomena that take place in the process of anaerobic digestion. The mathematical model is called Anaerobic Digestion Model No.1 (ADM1) [9] and, without a doubt, it is considered the most evolved model even at the moment. However, the complexity of this model, with 35 state variables, makes it difficult to use it in control problems.

Consequently, there has been a continuous effort to obtain simplified models that allow the application of methods to obtain software solutions for estimating state variables and parameters of interest or for implementing control solutions. Thus, the mathematical model proposed in [10], can be mentioned in which a model with 6 state variables is proposed. A detailed description of the most important mathematical models describing the process of anaerobic digestion is presented in Chapter 2.

1.5 State of the art in the automatic control of the anaerobic digestion processes

There is a variety of control structures that have been reported in the literature with the aim of bringing substantial improvements to the anaerobic digestion process. The implementation of the first application of classical control over the anaerobic digestion process was carried out in 1974. The authors applied an on/off control to a rector-type reactor with continuous stirring flow. Due to the limiting factors that classical control presents, the researchers' attention was focused on the development of new types of advanced control, in order to improve the accuracy of anaerobic digestion process control.

Therefore a first category of advanced control is represented by rule-based expert systems and fuzzy expert systems. For instance, in the paper [12] an expert real-time monitoring system was tested. Another type of control, developed in [13], provides for the successful application of a control based on fuzzy logic techniques and knowledge techniques implemented on rules on a hybrid UASB+AF reactor.

Instead, linearization control focuses on existing mathematical models [3]. An example of linearization control with the addition of a simulated substance (acetate) applied to the anaerobic digestion process was applied in [14]. Satisfactory results were also reported in [15], for the control of an AFB reactor using the exact linearization control technique. To be close to practical situations, a new robust adaptive control structure using a linearizing control law combined with an interval observer capable of estimating a lower and upper bound of non-measurable states and a parameter estimator for the unknown kinetics of the process, was proposed in [16]. Other works using linearizing control in the case of anaerobic digestion processes are illustrated in: [17], [18].

Other types of control applied to the anaerobic digestion process have also been identified in the scientific literature. Therefore, to address optimization and dynamics issues in [7], [19], an algorithm for the extremum seeking control of anaerobic digesters was investigated. Other approaches in the literature are based on adaptive multivariable control [20], predictive control [21] or robust control [22], [23].

The analysis of the state of the art on the automatic control of anaerobic digestion processes has shown that two types of applications have been developed in the literature: classical or artificial intelligence-based structures that have been validated on the physical process or by numerical simulation on a complex mathematical model of the type ADM1, and advanced control structures, which have been validated on simplified mathematical models. However, given the "distance" existing between the simple mathematical models and the complex mathematical model ADM1, the approach assumed by this doctoral thesis to find advanced methods of control that can be used for the problem of automatic control of the anaerobic digestion process is justified.

Chapter 2: MATHEMATICAL MODELING OF ANAEROBIC DIGESTION PROCESSES

Within this chapter, the main mathematical models existing in the literature for the process of anaerobic digestion are presented.

As mentioned in the presentation of the state of the art in the field, two types of mathematical models have been developed in the literature: a complex model, especially dedicated to the issue of knowledge and analysis of the process, and a simplified model, used in the design of advanced control structures. The following is a description of the complex mathematical model ADM1 and the mathematical model AM2.

2.1 The ADM1 mathematical model

The mathematical model ADM1 proposed by the International Water Association [6] is considered the most detailed model, which provides an overview of the processes taking place in an anaerobic digester. Initially, the original ADM1 model [9] contained 24 equations of state, but it subsequently underwent modifications by the authors Blumensaat and Keller to make it more robust. Following the changes, the model contains 35 state equations describing process dynamics, 19 biochemical process rates, 6 acid-base kinetic processes and 3 gas-liquid transfers [24].

The 19 biochemical process rates occur in the liquid medium. These are: disintegration; hydrolysis of carbohydrates; protein hydrolysis; lipid hydrolysis; absorption of monosaccharides; absorption of amino acids; absorption of long-chain fatty acids; absorption of valerate; absorption of butyrate; absorption of propionate; absorption of acetate; hydrogen absorption; decomposition of X_{su} ; decomposition of X_{aa} ; decomposition of X_{fa} ; decomposition of X_{c_4} ; decomposition of X_{pro} ; decomposition of X_{ac} ; decomposition of X_{h_2} [25].

Within ADM1, the acidogenesis stage is described by the reaction rates. They are of three types [25]: proportional, such as in the case of protein or lipid hydrolysis; Monod-type parameters; double Monod-type parameters. The reactions that take place in the liquid medium inside the anaerobic digester are described by means of 24 equations of state, of which 12 equations describe the substrate components and the rest describe the biomass components:

$$\frac{dS_i}{dt} = \frac{Q_{ad}}{V_{ad,liq}} \cdot \left(S_{i,in} - S_i\right) + \sum_{j=1}^{19} v_{i,j} \cdot \rho_j; \ i = \overline{1,12};$$
(2.1)

$$\frac{dX_i}{dt} = \frac{Q_{ad}}{V_{ad,liq}} \cdot \left(X_{i,in} - X_i\right) + \sum_{j=1}^{19} v_{i,j} \cdot \rho_j; \quad i = \overline{13,24};$$
(2.2)

where: $\sum_{j=1}^{19} v_{i,j} \cdot \rho_j$ represents the sum of the kinetic rates, $i = 1 \dots 12$ represents the index of the substrate components, $i = 13 \dots 24$ is the index of biomass components, $j = 1 \dots 19$ represents the 19 biochemical reactions considered, v are considered as stoichiometry coefficients, which give the weight with which a reaction occurs in the case of a term, Q_{ad} is the

flow rate of the influent in the digester, $V_{ad,liq}$ is the volume of liquid in the digester, $S_{i,in}$ is the concentration of the component S_i in the influent [25].

The determination of the gas flow rate is carried out using the relation below:

$$Q_{gas} = k_p \cdot \left(P_{gas} - P_{atm} \right) \tag{2.3}$$

where k_p is the output flow coefficient, P_{atm} is atmospheric pressure, and P_{gas} is the pressure of the gas.

The gas pressure is given by the formula:

$$P_{gas} = S_{gas,h2} \cdot \frac{R \cdot T_{ad}}{16} + S_{gas,ch4} \cdot \frac{R \cdot T_{ad}}{64} + S_{gas,co2} \cdot R \cdot T_{ad} + p_{gas,h2}$$
(2.4)

where *R* is the universal constant of the ideal gas, T_{ad} is the temperature in the anaerobic digester (considered a constant equal to 35°C) and $p_{gas,h2}$ is the pressure of water vapor [25].

2.1.1 Implementation of the ADM1 mathematical model in Simulink

The implementation and simulation of the ADM1 mathematical model was done in the MATLAB environment, the Simulink toolbox. For the implementation of the ADM1 model, four types of influents were analyzed: activated sludge, vinasse, milk whey and domestic water.

2.2 The AM2 simplified mathematical model

The AM2 model was developed as part of a European Economic Community project [10]. This model had two objectives: numerical simulation of the dynamics of anaerobic digestion process and design of a system useful in monitoring and control issues. Consequently, the model involves two stages: at the first stage of acidogenesis the acidogenic bacteria X_1 degrades the substrate organic S_1 and produces volatile fatty acids S_2 and CO_2 . Fatty acids form the substrate S_2 , which in its turn feeds the bacterial population X_2 . Population of metanogene bacteria X_2 uses, in the second stage, that of methanogenesis, the volatile fatty acids as a substrate for the growth and production of CO_2 and methane [26].

Finally, the model is defined by 4 differential equations: two for the mass balances of bacterial populations X_1 , respectively X_2 and two for organic substrate S_1 si VFA (S_2) [26].

$$\frac{dX_1}{dt} = [\mu_1(S_1) - \alpha D]X_1$$
(2.5)

$$\frac{dX_2}{dt} = [\mu_2(S_2) - \alpha D]X_2$$
(2.6)

$$\frac{dS_1}{dt} = D(S_{1in} - S_1) - k_1 \mu_1(S_1) X_1 \tag{2.7}$$

$$\frac{dS_2}{dt} = D(S_{2in} - S_2) + k_2 \mu_1(S_1) X_1 - k_3 \mu_2(S_2) X_2$$
(2.8)

where S_{1in} (*gCOD/L*) and S_{2in} (*mmol/L*) are the influent concentrations of S_1 respectively S_2 and D is the dilution rate.

Moreover, the following algebraic equation for the methane gas flow is provided.

$$q_{CH_4} = k_6 \mu_2(S_2) X_2 \tag{2.9}$$

2.2.1 Implementation of the AM2 mathematical model in Simulink

For the modeling and simulation of the AM2 mathematical model, the MATLAB environment, the Simulink toolbox, was used.

2.3 Compatibility of the ADM1 and AM2 mathematical models

For a better understanding of the compatibility of the two mathematical models, an association of the state variables of the ADM1 model with the state variables of the AM2 model was used.

The bacterial populations (X_{su} , X_{aa} , X_{fa} , X_{ac} , X_{h2} , X_{c4} , X_{pro}) corresponding to ADM1 model, are associated in AM2 model in two populations: a population responsible for the acidogenesis stage (X_1) and a population responsible for the methanogenesis stage (X_2).

The acidogenesis stage X_1 , is the sum of degradations of monosaccharides, amino acids and long-chain fatty acids [27].

$$X_1 = X_{su} + X_{aa} + X_{fa} (2.10)$$

The population of metanogene bacteria is represented by the sum of degradations of acetate, hydrogen, valerate, butyrate and propionate [27].

$$X_2 = X_{ac} + X_{h2} + X_{c4} + X_{pro}$$
(2.11)

The concentration of organic substrate (S_1) shows the correspondence in soluble substrates ADM1, which are monosaccharides, amino acids, long-chain fatty acids, composite particles, carbohydrates, proteins and lipids [27]. Basically S_1 is characterized by *COD* [26].

$$S_1 = S_{su} + S_{aa} + S_{fa} + X_C + X_{ch} + X_{pr} + X_{li}$$
(2.12)

The correspondence of the concentration of organic acids (S_2) it is given by soluble compounds: valerate, acetate, butyrate and propionate, practically S_2 behaves like a pure acetate [26].

$$S_2 = S_{va} + S_{ac} + S_{bu} + S_{pro}$$
(2.13)

The COD - ul is composed of the sum of S_1 and S_2 , where S_1 represents the concentration of the components of the organic substrate and S_2 represents the concentration of volatile fatty acids.

$$COD = S_1 + S_2 \tag{2.14}$$

The TSS - ul is the total concentration of the solids in suspension

$$TSS = X_1 + X_2$$
 (2.15)

Chapter 3: AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES USING THE MODEL FREE CONTROL METHOD

Within this chapter, the use of the Model Free Control method in the case of anaerobic digestion processes is presented. Thus, it starts from the study of the static and dynamic properties of the anaerobic digestion process and the formulation of the control problem. Given the complexity of the mathematical model used, the ADM1 model, it is proposed to use it as a *virtual plant*, and an appropriate method of controlling it would be the Free Control Model.

3.1 Defining of the automatic control problem in the case of anaerobic digestion processes

The anaerobic digester used in the case study presented has the liquid volume V_l = $3400m^3$ and gas volume $V_q = 300m^3$. As stated in previous chapters, there are currently two approaches regarding the anaerobic digestion processes: 1) the use of simplified models, (for example, models of type AM2); 2) the development of a detailed, highly complex mathematical model such as ADM1. Usually, in the problem of anaerobic digestion control, simplified models are used, which allow the use of observers and control methodologies based on analytical models. The complex mathematical model ADM1 is unsuitable for the synthesis of control algorithms, but it allows detailing the phenomenology in the process and highlighting the influences of some endogenous factors on the dynamics of the process. Under these conditions, the numerically simulated ADM1 can be used as a virtual plant for qualitatively investigating the static and dynamic properties of the anaerobic digestion process and for preliminary validation, by numerically simulating the performance of the control algorithms. This approach is used in this chapter in the context of investigating the applicability of the Model Free Control (MFC) method in the case of anaerobic digestion processes. This is due to the fact that the MFC approach does not require the use of an analytical model, as the case may be in most of the algorithms cited in the literature.

Dynamic properties of the PDA in relation to the command variable Q_{ad} and with the disturbance S_{1in} are illustrated in Figure 3.1. Four operating modes were considered here, defined by the average values [200; 300] $[m^3/d]$ of the flow rate Q_{ad} and the average values [27; 37] [mg/l] of the disturbance S_{1in} . In these operating regimes, step variations in the influent flow rate of amplitude equal to 20 $[m^3/d]$ where applied.

In view of the above, the objective of the control problem is to adjust the variable Chemical Oxygen Demand (*COD*) to an imposed reference, defined by the relation $COD = S_1 + S_2$, where S_1 is the sum of the concentrations of the components of the organic substrate, and S_2 is the concentrations of volatile fatty acids. The control variable of the adjustment loop is the dilution D (or the flow rate of the influent in the anaerobic digester, $Q_{ad} = V_l \cdot D$), and disturbance variables are variations in concentrations in the influent, S_{1in} and S_{2in} .



Fig. 3.1 The step response of the PDA in different operating regimes, defined by average values of Q_{ad} și S_{1in}

3.2 Usage of Model Free Control in automatic control of the anaerobic digestion processes

3.2.1 General considerations regarding the Model Free Control method

The most general dorm of the PDA is:

$$F(t, y, \dot{y}, \dots, y^{(n)}, u, \dot{u}, \dots, u^{(m)}, u_{pk}, \dot{u}_{pk}, \dots, u^{(m_k)}_{pk}) = 0$$
(3.1)

where *y* is the command (y = COD), *u* is the command ($u = Q_{ad}$) and u_{pk} , k = 1,2, are the disturbance variables ($u_{p1} = S_{1in}, u_{p2} = S_{2in}$). In the MFC approach, instead of the unknown model (3.1) the "ultralocal" model is used [28], [29]:

$$y^{(v)} = F + \alpha u \tag{3.2}$$

where: the order of the derivative v has a low value, 1 or 2, F is a variable that is estimated at every discrete moment of command calculation, and α is chosen by the designer so that $\alpha \cdot u$ and $y^{(v)}$ "be the same size" [29], [30], [31].

The ideal MFC command is of the form:

$$u = [-F + \dot{y}_r + R(e)]/\alpha$$
(3.3)

where R(e) is the command component given by a classic :

$$R(e) = K_P e + \frac{1}{T_i} \int e dt + T_d \dot{e}$$
(3.4)

where $e = y_r - y$, and y_r is the reference of the loop. Depending on ow the non-zero values of the parameters are chosen K_P , T_i , T_d , are obtained the controllers called *iP*, respectively *iPI*, *iPI*, *iP*², etc. From relations (3.2), (3.3) and (3.4) the following is obtained:

$$(1+T_d)\dot{e} + K_p e + \frac{1}{T_i} \int e dt = 0$$
(3.5)

Based on this equation, the variable under the conditions of the ideal and the unknown command given by the equation (3.3), is based on the unrealistic assessment in [29], that the tuning of the parameters K_P , T_i si T_d " therefore becomes simple". In reality, the command actually used is:

$$u = [-\hat{F} + \dot{y}_r + R(e)]/\alpha$$
(3.6)

where \hat{F} si \dot{y}_r are the current estimates of the variables *F* and \dot{y}_r .

To determinate the estimate \hat{F} two approaches are encountered in literature. The first of these, used in [29] and [30] starts form the "ultralocal" model for discrete time:

$$\dot{y}[k] = F[k] + \alpha u[k-1]$$
(3.7)

resulting in:

$$\hat{F}[k] = \hat{y}[k] + \alpha u[k-1]$$
(3.8)

in which $\hat{y}[k]$ is the estimation of the output derivative. From (3.6) and (3.8), results the command law:

$$u[k] = u[k-1] + \frac{1}{\alpha} \left[\dot{y}_r[k] - \dot{y}[k] + R(e[k]) \right]$$
(3.9)

If the derivatives in the equations (3.9) are calculated by the simple relations:

$$\dot{y}_r[k] = \frac{1}{T_s} (y_r[k] - y_r[k-1])$$
(3.10)

$$\dot{\hat{y}}[k] = \frac{1}{T_s} (y[k] - y[k-1])$$
(3.11)

where T_s is the sampling period, then various command laws are obtained by making the explanation of R(e[k]). If $R(e[k]) = K_p e[k]$ an *iP* controller is obtained with the command law:

$$u[k] = u[k-1] + \frac{1}{\alpha T_s} [e[k] - e[k-1]] + \frac{K_p}{\alpha} e(k)$$
(3.12)

Comparing this relation with the command equation of a classic *PI* controller with the parameters K_P and K_I , it results that the equation (3.9) of the *iP* controller is a *PI* command law with the parameters:

$$K_P = \frac{1}{\alpha T_s}; K_I = \frac{K_P}{\alpha T_s}$$
(3.13)

In the same way, the link between the parameters of the iPI controller with those of the classic PI^2 controller is established. In the following, only the controllers of the type iP and iPI are used.

The second approach to determining the estimate \hat{F} , used in [29] and [32], is based on the equation (3.6). From this equation, \hat{F} , is obtained, to which a mobile window filtering is applied. In the simplest case, for *iP* controller, when $R(e) = K_p \cdot e$, it results that:

$$\widehat{F}(t) = \frac{1}{\tau} \int_{t-\tau}^{t} \left[\dot{y}_{y}(\varsigma) - \alpha u(\varsigma) + K_{p} e(\varsigma) \right] d\varsigma$$
(3.14)

where $\tau > 0$ is chosen when tuning the controller.

An important problem that arises when implementing controllers in the MFC approach is noise reduction, given the need to determine the variable $\dot{\hat{y}}$. In the works [28] and [33] it is

recommended to use a procedure for obtaining this variable, based on a *Finite Impulse Response* (FIR) filter, which is synthesized from the Taylor series development of the variable y(t).

3.2.2 Tuning the controller when using the MFC for PDA

In the absence of a theoretical support based on the analytical model of the process, the "trial and error" method is frequently used when tuning the parameters of the controller. To highlight the effects on the dynamics of the control loop produced by each parameter, in the schematic drawing of the anaerobic digestion process control system, given in Figure 3.2, the two components of the command were highlighted u[k]: the component $u_p[k]$, which derives from the equation of the "ultralocal" model, and the component $u_R[k]$, which is inserted by the command law R(e). The parameter K_P depends only on α , while the rest of the parameters of the command law depend, in addition, on the parameters included in the R(e[k]) as well.



Fig. 3.2 Schematic drawing of the PDA control system using the MFC

In the process of tuning the parameters, it is first considered the situation when $u_p[k] \neq 0$ and $u_R[k] = 0$. Then a step variation is applied to the reference $y_r(t)$, the control loop response being given in Figure 3.3.



Fig. 3.3 The step responses of the system for command u_p for different values of the parameter α

Therefore, the tuning of the *iP* controller by the method "trial and error" has led to parameters $\alpha = 0.025$ and $K_p = 0.35$, which determines K_p and K_I depending on T_s . The performance of the PDA control system with the *iP*, in conditions of the absence of noise affecting the output of the process, are illustrated in Figure 3.4



Fig. 3.4 Response to step and ramp signals of the system with *iP* controller

The computation of the estimation of the derivative \hat{y} , given the existence of the output noise is an important issue in PDA control, as well as in any other biotechnological process. In this regard, two solutions were used. The first of these consists in the use of the relation (3.14). The FIR filter equation is obtained by discretizing the time and calculating the integral by a numerical method, for instance, the trapeze method.

The second solution is to use a derivative with the transfer function $s/(T_0s + 1)$, followed by a higher filter of the *Infinite Impulse Response* type. Chebyshev *II* type filters and Bessel filters of order 8 were used. The behavior of the control system with the *iPI* controller, when the system is disturbed, is illustrated in Figure 3.5.



Fig. 3.5 The response of the system affected by noise: the reference (black);); COD when S_{1in} has a random component (red); COD when the output is contaminated by noise (dotted blue)

)

3.2.3 Tuning of the controller parameters to the change in the load regime of the anaerobic digester

The PDA control system operates under the *COD* stabilization regime at an imposed reference point, when the main disturbance S_{1in} remains constant. In real applications S_{1in} has a variable value and contains an important random component. Figure 3.6 illustrates the operation of the control system when the reference point has a ramp variation followed by a stabilization regime, provided that the load regime has a random component and the *iPI* controller has constant parameters corresponding to the static gain obtained for $\alpha = 0.025$.



Fig. 3.6 Reference (red) and controlled variable (blue)

There are two unstable operating areas:

a) when the reference value is very low, and the controller greatly reduces the input rate.

b) when the load is large, and the reference value can only be ensured by substantially reducing the input flow rate.

If the characteristics shown in Figure 3.1 are examined, there is a significant increase in the nonlinear character of the static characteristics at low values of the Q_{ad} . Under these conditions, in order to ensure the stability of the system, it is necessary to reduce the static gain of the controller by increasing the parameter α . Therefore, this solution must be activated periodically, at a time scale corresponding to the adaptive regime of the controller. Activating it at any point of time would mean radically and inopportunely changing the law of control. The structure drawing of the α parameter adaptation solution is given in Figure 3.7.

The equation
$$\alpha = F(Q_{ad})$$
 is linear:
 $\alpha = 0.2375 - 0.000385Q_{ad}$ (3.15)

The equation (3.15) provides low values α for high flow rate of Q_{ad} and values of 0.2 at low and very low flows. The parameter α change is made periodically at the time scale corresponding to the change in the average load value. For this purpose, the sampler-hold assembly (zero order hold) is used, which works with a sampling period $T_a = 10[d]$, much longer than the sampling period T_s . The results obtained under the presence of S_{1in} disturbance and a high frequency noise affecting the controlled variable are illustrated in Figure 3.8. This illustrates the stable operation of the system in a very wide range of load regime.







Fig. 3.8 Reference (red) and controlled variable (blue) (a); α parameter (b)

3.2.4 Conclusions

Since the experimental identification of PDA to obtain its mathematical model is less attractive due to the long duration of the dynamic regime and the need to repeat this procedure because of process variation, the MFC approach can be a viable solution for controlling this process. In the absence of an analytical model of the process, the MFC proposes a methodology in which the "trial and error" method has an important weight in determining the parameters of the controller law. In this context, qualitative knowledge of the static and dynamic properties of PDA based on the ADM1 model, used as a *virtual plant*, is very useful.

The results obtained confirm this, in particular those relating to the use of a parameter adaptation system to ensure system stability in a wide range of operating regimes, which corresponds to the testing of the control solution under realistic conditions close to the operating conditions of anaerobic digesters in practice.

Chapter 4: DATA-DRIVEN BASED AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES

Within this chapter, the applicability of data-driven methods in the case of anaerobic digestion processes is investigated, adaptations of three methods being proposed in relation to the peculiarities of the studied process, and the validation being made by numerical simulation considering again the complex mathematical model ADM1 as *a virtual plant*. A first method considered is Virtual Reference Feedback Tuning (VRFT), in this case two solutions are used to determine the parameters of the controller: the algorithm corresponding to the usual variant of the VRFT method and a simplified algorithm. The second method considered is Internal Model Control. An important aspect of this approach is the choice of the reference model. The last method studied was Fictitious Reference Iterative Tuning (FRIT). In this case, it was analyzed the use of the FRIT method to obtain in the case of anaerobic digestion processes some PI and PID controllers, being considered both the iterative and non-iterative tuning of the controller parameters. By the end of the chapter, the main conclusions on the use of data-driven control methods in the case of anaerobic digestion processes are presented.

4.1 Automatic control of anaerobic digestion processes using the Virtual Reference Feedback Tuning method

4.1.1 VRFT algorithm synthesized with data from the virtual plant

Using the ADM1 model, the data $\{\Delta u(t) = \Delta Q_{ad}(t), \Delta y(t) = \Delta COD(t)\}$ is determined by numerical simulation, in which $\Delta Q_{ad}(t)$ is a random sequence, the spectral model of which is considered known. Using the record $\{\Delta u(t), \Delta y(t)\}_{t=\overline{1,N}}$ the control algorithm shall be deducted in accordance with the schematic drawing in Figure 4.1, where RM is a reference model, DC represents a dynamic compensator and Δd represents the disturbance. The signal $\Delta y(t)$ obtained by simulating the ADM1 model is transferred through the inverse model RM^{-1} and the virtual reference \hat{r} , virtual error $\hat{\varepsilon}$ and its integral $\hat{\varepsilon}_1$ are obtained.



Fig. 4.1 Structure of the proposed control loop for the VRFT method

According to [34] RM is chosen in the form of:

$$H_{RM}(z^{-1}) = \frac{z^{-(n_r+1)}(1-\alpha)^{n_r}}{(1-\alpha z^{-1})^{n_r}}, \alpha = exp(-T_s\widetilde{\omega})$$
(4.1)

where $n_r, \tilde{\omega}$ are parameters chosen by the designer, which determine the bandwidth of the system in closed loop and T_s is the sampling period. The inverse model is:

$$H^{-1}{}_{RM}(z^{-1}) = \frac{(1 - \alpha z^{-1})^{n_r}}{z^{-n_r}(1 - \alpha)^{n_r}}$$
(4.2)

For determining the parameters of the controller, two solutions can be applied:

- the algorithm corresponding to the usual variant of the VRFT method [34], in which *RM* effectively plays the role of a closed-loop system reference model.
- a simplified algorithm, in which *RM* has a different role than that of a reference model [35].

In the following these solutions are adapted to the particular situation of acquiring the data{ $\Delta u(t)$, $\Delta y(t)$ }_{$t=\overline{1,N}$}, these data being collected from the considered *virtual plant*, based on the ADM1 model.

In the usual VRFT method, presented in [34], the controller synthesis starts from the hypothesis that the data sequence is obtained from the actual process, which involves the presence of noise in $\Delta y(t)$. The challenge lies in adopting the optimal value of the vector of the controller parameters in relation to the performance criterion:

$$I_{VR} = \frac{1}{N} \sum_{t=1}^{N} (\Delta u_L(t) - C(z, a) \hat{\varepsilon}_L(t))^2$$
(4.3)

Knowing the data set $\{\hat{\varepsilon}_L(t), \Delta u_L(t)\}_{t=\overline{1,N}}$, the *a* parameter vector is deduced by an identification procedure (for instance, the least squares method), which achieves the minimization of the criterion (4.3).

In the VRFT method that uses actual data from the process, to determine the *a* parameter vector, it is required the use of the instrumental variable method to avoid obtaining a misplaced vector.

4.1.2 Controller synthesis using the usual VRFT algorithm

Regarding the controller synthesis, two operating regimes for the PDA were considered: when $\bar{S}_{1in} = 34[g/m^3]$ and when \bar{S}_{2in} is practically negligible ($\bar{S}_{2in} = 0.355[g/m^3]$). For the first operating regime it was imposed that $\bar{u} = \bar{Q}_{ad} = 147[m^3/d]$ to which it corresponded $\bar{y} = \overline{COD} = 4.47[g/m^3]$, and for the second operating regime it was imposed that $\bar{u} = \bar{Q}_{ad} = 332[m^3/d]$, to which it corresponded $\bar{y} = \overline{COD} = 40[m^3/d]$. Basically, the command signal $\Delta u(t)$ influences the filter transfer function by the spectral power density $\Phi_{\Delta u}(\omega)$. In the simplest approach, a high-frequency signal of the type of a random sequence of steps has been adopted for the command, $\Delta u(t)$, where the interval in which the input signal is kept constant is very small (T = 0.5[d]). It is obvious that this input signal, illustrated in Figure 4.2, has a spectral density of practically constant power in the frequency band corresponding to the reference model.



Fig. 4.2 The signal $\Delta u(t)$ used for controller

Under these conditions, the filter transfer function is:

$$L(z) \cong (1 - M(z))M(z)$$
 (4.4)

The transfer function *DC* is chosen in the form of:

$$H_{DC}(z^{-1}) = \sum_{i=0}^{m} a_i z^{-i}$$
(4.5)

therefore, the initial model *DC* can be written in the form of:

$$\Delta \hat{u} = a^T \varphi(t); t = \overline{m, N}$$
(4.6)

in which:

$$a = [a_0 a_1 \dots a_m]^T; \varphi(t) = [\hat{\varepsilon}_1(t)\hat{\varepsilon}_1(t-1)\dots\hat{\varepsilon}_1(t-m)]^T$$
(4.7)

where t is the discrete time.

To check the performance of the closed-loop system, the dataset $\{\Delta u(t), \Delta y(t)\}_{t=\overline{1,N}}$, was used, as an additional operation to identify the process. Figure 4.3 shows the Bode characteristics of the reference model (red line) and the closed-loop system (blue line) and Figure 4.4 illustrates the response of the closed-loop system $\Delta y(t)$ to a sequence of step variations of the $\Delta y_{ref}(t)$ în reference in the second operating regime.



Fig. 4.3 Bode characteristics of RM (blue) and closed loop system (red)



Fig. 4.4 The system response to a sequence of step variations of the reference

4.1.3 Simplified VRFT algorithm synthesized with data from the virtual plant

The objective imposed for synthesizing the controller using the usual VRFT approach is to minimize a criterion that reflects the difference between the closed-loop system model and the adopted reference model. In the case of simplified VRFT, the design requirement is quite different [35]: we want to compensate for the dynamics of the process and obtain, through the interaction with the designer, a compromise between the duration of the dynamic regime and the stability margin indicators.

The control diagram in Figure 4.1 is preserved, but in this case the *RM* block does not act as a reference model, although its choice is the same as in the case of the usual VRFT approach. This block helps in obtaining the $\hat{\varepsilon}_1(t)$ signal, starting from the output of the $\Delta y(t)$. Considering $n_r = 2$ in the model of the *RM* block, the transfer function of the link between $\Delta y(t)$ and $\hat{\varepsilon}_1(t)$ is:

$$H_{in}(z^{-1}) = \left(\frac{(1 - \alpha z^{-1})^{n_r}}{z^{-n_r}(1 - \alpha)^{n_r}}\right) \cdot \frac{1}{1 - z^{-1}}$$
(4.8)

with $\alpha = exp(-T_s \tilde{\omega})$. The parameter $\tilde{\omega}$ influencing the bandwidth of the *RM*, is chosen according to the duration of the dynamic regime of the process, and this duration depends on the current operating regime of the process. Figure 4.5 shows the Bode characteristics related to the transfer function (4.8) and the block *RM* for 3 values of this parameter: $\tilde{\omega} \in \{1,2,3\}$. For all these values, the *RM* bandwidth is found to be included in a frequency band in which the subsystem $H_{in}(z^{-1})$ has a constant dependent gain of $\tilde{\omega}$. It follows that this subsystem transfers a signal at the input of the *DC* namely $\hat{\varepsilon}_1(t)$ with a form that is practically identical to the $\Delta y(t)$, output, but with different amplitude $\hat{\varepsilon}_1(t) \cong H_{in}(1) \cdot \Delta y(t)$.

Under these conditions, by identifying the *DC* with the input $\hat{\varepsilon}_1(t)$ and the output $\Delta y(t)$,), a subsystem is obtained which, up to the static gain coefficient represents an approximation of the inverse model of the process and the open loop transfer function is close to that of the integrator, up to the proximity of the Shannon frequency. Effective calculation of this transfer function requires the following data $\{\Delta u(t), \Delta y(t)\}_{t=\overline{1,N}}$ to identify the process. Unlike the usual VRFT method, where process identification is only necessary to validate the performance of the

closed-loop system, the simplified VRFT method requires the calculation of the transfer function $\hat{P}(z)$ of the process by identification, in order to obtain the static gain coefficient of the controller.



Fig. 4.5 Bode characteristics of the given subsystem in equation (4.10) and of the *RM* block

The transfer function of the open loop:

$$H_{ol}(z) = \frac{1}{1 - z^{-1}} \rho \sum_{i=0}^{m} a_i z^{-1} \cdot \hat{P}(z)$$
(4.9)

where the coefficient ρ , initially considered as a unit value, it is used to adjust the static gain coefficient of the controller.

4.1.4 Controller synthesis using simplified VRFT algorithm

To illustrate the results obtained in the synthesis of the controller, a second operating regime was considered, at which the input flow is $\bar{u} = 332[m^3/d]$, and output $\bar{y} = 40[g/m^3]$. Since the new dynamic regime is faster than that of the first operating regime, the $\tilde{\omega} = 3[rad/d]$ is adopted in the module of the *RM* block.



Fig. 4.6 Evolution of the signals $\Delta u(t)$, $\Delta y(t)$ and $\hat{\varepsilon}_1(t)$

In Figure 4.6 illustrates the evolution of the output $\Delta y(t)$, as well as the input and output signals of the *DC*, $\hat{\varepsilon}_1(t) \neq \Delta u(t)$.



Fig. 4.7 Details on the form of the signals $\Delta y(t)$ where $\hat{\varepsilon}_1(t)$

Figure 4.7 illustrates that the signals $\hat{\varepsilon}_1(t)$ and $\Delta u(t)$ have practically the same shape, so that by identification of the *DC*, a good approximation of the inverse model of the process is obtained at a scale modified by the static amplification coefficient $H_{in}(1)$.

Validation of the performance of the closed-loop system with the synthesized controller was performed in a loop where the process is the *virtual plant* simulated with the nonlinear model ADM1. Figure 4.8 shows the response of the loop to a sequence of step variations of the reference value.



Fig. 4.8 System response to a sequence of step variations of the reference value

4.1.5 PDA control results using the VRFT approach

The results presented in this section refer to the performance of the *COD* control system using a control synthesized by the usual VRFT algorithm. These performances were established within the control loop that considers the virtual plant, simulated with the ADM1 complex mathematical model. The system operates with an imposed reference point, which may be modified in accordance with environmental protection requirements linked to the methane gas

production target. The main disturbance affecting the system is the random variation in the concentration of the $S_{1in}(t)$ influent.

From the results presented, a very good behavior of the control solution based on the VRFT method is observed, even in the conditions of the presence of the disturbance on the concentration of influent and the measurement noise.

4.2 Automatic control of anaerobic digestion processes using the Internal Model Control method

Internal Model Control (IMC) was introduced in [36] and is currently one of the most widespread control structures used in process engineering [37], [38], [39]. IMC has gained significance in the field of control due to its simple mechanism and intuitive design. Consequently, the adoption of the IMC structure on the control of anaerobic digestion processes is a solution of real interest. The implementation of IMC is a real challenge when it comes to calculating the inverse matrix of the transfer function of the anaerobic digestion process, since this is a complex process of large size.

In the next lines, the details of the aspects for applying the data-driven IMC method in the case of the anaerobic digestion process are presented.

4.2.1 Principle of approaching the IMC method based on data-driven

A representation of the IMC structure is shown in Figure 4.9, together with the corresponding notations.



Fig. 4.9 PDA control using the IMC structure: M(z) - reference model, $\overline{P}(z)$ – linear model of the process included in the IMC controller, Q(z) – controller

The nonlinear PDA model of ADM type is not explicitly used in the controller design, but only through the input-output data it provides. The objective pursued is to achieve a referenceoutput $(r \rightarrow y)$ in accordance with the required reference model, M(z), and to achieve a reduces effect to of the disturbance d on the output y. It is denoted by $\overline{P}(z)$ the transfer function of the linearized model at the current operating point, obtained by an ideal linearization. Obviously, P(z)is unknown. The control structure contains the controller itself, with the ideal transfer function Q(z), as well as the internal linear model of the process, $\overline{P}(z)$.

If a reference model M(z) is adopted in such a way that the transfer function:

$$Q(z) = M(z)P^{-1}(z)$$
 (4.10)

be invertible (representing a system at causal limit), then:

$$y(t) = M(z) \cdot r(t) + (1 - M(z)) \cdot d(t)$$
(4.11)

where *t* is the discrete time, and a notation of the form $y(t) = H(z) \cdot u(t)$ signifies the transfer $u \rightarrow y$ through the system H(z).

Let $\overline{Q}(z)$ be an imposed controller to compensate for the process dynamics at a performance level. By analogy with the relation (4.10), valid in the hypothesis of idealized models, P(z), is inferred, be it $\overline{P}(z)$, entering the IMC command structure:

$$\overline{P}(z) = M(z)\overline{Q}^{-1}(z) \tag{4.12}$$

If a linear controller structure is adopted in the parameters θ , that is a FIR system with the transfer function $\overline{Q}(z, \theta)$, then the determination of the vector of the parameters is made by minimizing the criterion:

$$J(\theta) = \sum_{t=1}^{N} \left(u(t) - \overline{Q}(z,\theta) \cdot \overline{r}(t) \right)^2$$
(4.13)

using the least squares method.

In conclusion, the data-driven design of the controller $\overline{Q}(z)$ uses the data u(t), y(t), collected when operating the PDA, in open loop at a given operating point, as well as the "reference" $\overline{r}(t)$ after selecting the reference model. Therefore, the optimal parameters θ^* obținuți prin minimizarea criteriului (4.13) obtained by minimizing the criterion (4.13) are not affected by the noise $y(t) - \overline{y}(t)$.

A key issue, which arises in the data-driven design of the IMC structure, is to ensure robust stability. This requirement is imposed in view of the uncertainties surrounding the adoption of the $\overline{P}(z)$ model, within the command structure. It is considered that, when choosing the model, the upper limit of the multiplicative uncertainties, expressed in the frequency range is $\overline{l}_m(\omega)$, meaning:

$$\left|\frac{P(e^{j\omega}) - \overline{P}(e^{j\omega})}{\overline{P}(e^{j\omega})}\right| \le \overline{l}_m(\omega) \tag{4.14}$$

If in a closed-loop system, the $\overline{P}(z)$ adopted model deviates from the actual model P(z) până la limita dată de (4.17), to the limit given by (4.17), then the system is stable robust. The condition that the closed-loop system is robustly stable, given in [39] also in [40], [41], is:

$$\left|M(e^{j\omega})\right| < \left|\frac{1}{\overline{P}(e^{j\omega})\overline{Q}(e^{j\omega})\overline{l}_{m}(\omega)}\right|; \forall \omega$$
(4.15)

4.2.2 Choosing the reference model within the IMC method

The choice of the reference model M(z) is made only on the basis of the input-output data available for the synthesis of the controller and imposes the desired performance of the closed loop. The choice of the M(z) is an essential problem in the design of the control structure, since it determines the concrete expressions of the transfer functions $\overline{Q}(z)$ and $\overline{P}(z)$, as well as ensuring robust stability.

The reference model must be between two limits:

1. An invertible broadband model, the highest frequency of which is limited by the Shannon frequency required for data sampling.

2. An invertible low frequency model, at the limit, can be a static amplification theoretically equal to the inverse of the static amplification of the process $\bar{Q}(z) = 1/P(1)$. In this case, it is expected that the dynamic performance of the closed-loop system will be very modest.

It was considered a process operating regime around the static operating point $COD = 1.5[g/m^3]$ and $Q_{ad} = 0.4[m^3/d]$.

The transfer function of the reference model used below is [34]:

$$H_{RM}(z^{-1}) = \frac{z^{-(n_r+1)}(1-\alpha)^{n_r}}{(1-\alpha z^{-1})^{n_r}}, \alpha = exp(-T_s\widetilde{\omega})$$
(4.16)

in which n_r is the order of the model, $\tilde{\omega}$ - the parameter that determines the width of the frequency band, and T_s is the sampling period. When increasing the parameter $\tilde{\omega}$, the duration of the dynamic regime of the reference model is reduced.

The inverse model is:

$$H_{RM}^{-1}(z^{-1}) = \frac{(1 - \alpha z^{-1})^{n_r}}{z^{-n_r}(1 - \alpha)^{n_r}}$$
(4.17)

The design of the IMC controller is made on the basis of the input-output data of the process, obtained when it works in open loop. Figure 4.10 gives the variations in relation to the average values of the output variables of the process and model identified with the method of the least squares, in the situation when it was considered that the order of the linear model was of order 4.



Fig. 4.10 Variations from the average values of the output variables of the process (blue) and the identified model (red)

In the reference model (4.16), $n_r = 2$, is adopted, which ensures a dynamic without overshoot. The choice of the $\tilde{\omega}$ parameter, determining the settling time, it is made based on prior knowledge on the dynamics of the process. The "candidate" values are adopted: $\tilde{\omega}_k$, $k = \overline{i, L}$, to be tested in the following procedure:

1. The responses to the step signal of the M(z) model, are quantitatively analyzed, in relation to the dynamics reflected by the data in the process, but also in relation to the information from the engineering practice, regarding the response time of the closed-loop process.

2. The fictious reference, $\bar{r}(t)$, is determined through the transfer of the signal y(t) by $M^{-1}(z)$;

3. Based on the data $\{y(t), \bar{r}(t)\}_{t=\overline{1,N}}$ the linear model is identified.

$$\overline{Q}(z,\theta) = \sum_{i=0}^{m} \theta_i z^{-i}$$
(4.18)

4. The graphical representation of the frequency characteristics of $\overline{Q}(z,\theta)$, is drawn, for all "candidate" values of $\widetilde{\omega}$ parameter for the reference model.

4.2.3 Design of the control structure within the IMC method

In order to improve the transparency of the correlation of the controller parameters with the parameters of the reference model, the digital-analogue conversion of the transfer functions involved in the analysis of the control structure was carried out.

Transfer function of the reference model M(s) for $\tilde{\omega} = 2.5$ is:

$$M(s) \simeq \frac{1}{(0.4s+1)^2} \tag{4.19}$$

After identifying the $\overline{Q}(z,\theta)$ model for m = 4 reducing the order of the equivalent analogue model, it is obtained that:

$$\overline{Q}(s) = \frac{0.1046(0.3978s+1)}{(0.005s+1)} \tag{4.20}$$

Figure 4.11 shows the Bode characteristics of the analogue controller (4.20) (brown), compared to that of the controller $\overline{Q}(z, \theta)$ identified (red).



Fig. 4.11 Bode characteristics for: $\overline{Q}(z, \theta)$ identified (red), low-order analogue (brown), low-order digital (blue) and limited frequency band digital (green)

It is known that the IMC structure performs a control law corresponding to a classical controller with the transfer function:

$$C(s) = \frac{\overline{Q}(s)}{1 - \overline{P}(z)\overline{Q}(s)}$$
(4.21)

4.2.4 Checking the robust stability under the IMC method

Checking the condition (4.15) requires the evaluation of the upper limit of multiplicative uncertainty $\bar{l}_m(\omega)$. As the only information available on the process carried out is the input-output data $\{u(t), y(t)\}_{t=\overline{1,N}}$, obtaining the transfer function $\bar{l}_m(\omega)$, based on these data and the transfer functions in the structure of the command law, is made by the *Empirical Transfer Function Estimate* (ETFE) method, introduced by Ljung [42] and also used in [40] and [41].

The operations required for the effective checking of robust stability are included in the following algorithm, proposed in the works [40] and [41]:

Initial data:

$$\{u(t), y(t)\}_{t=\overline{1,N}}, \ \alpha \ge 0, \ \overline{Q}(e^{j\omega}, \theta^*), \ \overline{P}(e^{j\omega}, \theta^*), \quad \omega_k = 2\pi k/N, \ k = 0, 1, 2, \dots, N-1$$

- 1. It is calculated $y_{diff}(t) = y(t) \overline{P}(e^{j\omega}, \theta^*) \cdot u(t);$
- 2. It is calculated $y_{model}(t) = \overline{P}(e^{j\omega}, \theta^*) \cdot u(t);$
- 3. It is calculated $\hat{H}_{diffN}(e^{j\omega})$ defined by $y_{diff}(t)$ as output, and u(t) as input, using ETFE;
- 4. It is calculated $\hat{P}_N(e^{j\omega})$ defined by $y_{model}(t)$ as output, and u(t) as input, using ETFE;

5. It is calculated
$$\bar{l}_m(\omega) = \frac{|\hat{H}_{diffN}(e^{j\omega})|}{|\hat{P}_N(e^{j\omega})|}$$

6. For each ω_k , $k = \overline{0, N-1}$ the condition $\left|\overline{P}(e^{j\omega}, \theta^*)\overline{Q}(e^{j\omega}, \theta^*)\overline{l}_m(\omega)\right| \le 1 - \alpha$ is checked.

Adopting $\alpha = 0.2$, the robust stability condition (4.15) is verified on the basis of the representation in Figure 4.12 of the functions $\frac{1-\alpha}{\bar{l}_m(\omega)}$ and $|\overline{P}(e^{j\omega},\theta)^*\overline{Q}(e^{j\omega},\theta^*)|$.



Fig. 4.12 Checking the robust stability of the system

4.2.5 Validation by simulation of the control law obtained by data-driven IMC method

The analysis by numerical simulation of the performances of the synthesized control law has pursued 3 aspects:

1. tracking the reference $COD^{ref}(t)$;

2. disturbance rejection $COD_{in}(t)$;

3. the effect of the measurement noise on the controlled variable.

The tracking performance of the reference is illustrated in Figure 4.13a and b.



Fig. 4.13 Tracking the reference: reference *COD* (red), controlled variable (*COD* - blue) (a); zoom (b)

- 1. The delay of the controlled variable in relation to the reference, when it has a variation close to a ramp, is less than one day and the maximum error during the dynamic regime is $\varepsilon_{COD,max}$.
- 2. The disturbance rejection was examined in relation to the variation in Figure 4.14a of COD in influent $(COD_{in}(t))$.

The evolution of the controlled variable, COD(t) – in blue, in relation to the reference $Q_{ref}(t)$ – in red, is given in Figure 4.14b.



Fig. 4.14 Evolution of $COD_{in}(t)$ (a) and evolution of the reference (red) and controlled variable (blue) (b) 25

3. The effect of a measurement noise with the standard deviation $\sigma_n = 0.0233$ on the controlled variable was tested. Under these conditions, the standard deviation of the controlled variable was $\sigma_{COD} = 0.0233$, and the evolution of this variable is given in Figure 4.15.



Fig. 4.15 Effect of measuring noise on controlled variable

4.2.6 Automatic control of the anaerobic digestion processes using the Fictitious Reference Iterative Tuning method

The Fictitious Reference Iterative Tuning (FRIT) method has frequently appeared in the literature following the publication in 2004 and 2005 of the papers [43] and [44], and it is a procedure used as an alternative to the VRFT method. Within the FRIT method, a quadratic performance criterion is minimized in which the error defined as the difference between the output variable of the process and the output variable of the reference model occurs, when at its input, a "fictitious" reference is applied. The calculation of the latter requires the transfer of the input variable of the process through the inverted controller. The optimization of the criterion is done iteratively, by a method of searching in the space of the controller parameters.

Unlike previous data-driven design methods, in the FRIT method a set of input-output data is used from the process when it is in closed loop according to the works [43], [44], [45], [46].

4.2.7 The principle of the usual variant of the FRIT method

The synthesis of the control law for anaerobic digestion processes is made considering the following initial conditions:

- 1. transfer function of the reference model, M(s), imposing the static and dynamic characteristics in closed-loop system;
- 2. controller structure with an invertible transfer function, $C(s, \rho)$, in which ρ is the vector of the parameters;
- 3. the initial value of this vector, ρ^0 , for which the closed-loop system is stable;
- 4. data set $\{u(t), y(t)\}_{t=\overline{1,N}}$ gathered in closed-loop, around the operating point provided by the reference of the control loop.

The problem of tuning the controller starts from the requirement to minimize the control error. The optimal parameter, ρ^* , is:

$$\rho^* = \arg\min\sum_{t=1}^{N} \|e(t,\rho)\|^2$$
(4.22)

where:

$$e(t,\rho) = y(t,\rho) - M(s) \cdot r(t)$$
(4.23)

in which $M(s) \cdot r(t)$ it was noted the response of the M(s) model to the reference r(t). Given the fact that the process model is not known, therefore $y(t, \rho)$ cannot be calculated, the FRIT method proposes to replace the error $e(t, \rho)$ by an estimate $\tilde{e}(t, \rho)$, hereinafter referred to as "fictitious error", which can be inferred based on the input-output dataset. The performance criterion to be minimized by an iterative numerical procedure is:

$$J(\rho) = \sum_{t=1}^{N} \|\tilde{e}(t,\rho)\|^2$$
(4.24)

The minimization of the criterion (4.24) is done by classical numerical methods. When using the Gauss-Newton method, the algorithm for adjusting the parameters:

$$\rho^{i+1} = \rho^{i} - \gamma R_{i}^{-1} \frac{\partial J(\rho)}{\partial \rho} \Big|_{\rho^{i}}$$
(4.25)

involves the calculation of the gradient of the criterion, as well as R, which represents the approximation of the Hessian matrix.

4.2.8 Usage of FRIT method to obtain an PI controller in the case of PDA

Let the input-output signals $\{u(t, \rho^0), y(t, \rho^0)\}_{t=\overline{1,N}}$, be considered, obtained by open-loop simulation of the ADM1 model around an imposed operating point.

In the issue of PDA control, it was considered a reference model of the form:

$$M(s) = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n + \omega_n^2} \tag{4.26}$$

in which $\omega_n = 2.5 \left[\frac{rad}{d}\right]$ and $\varsigma = 1$.

The objective of tuning an PI controller with the transfer function was imposed:

$$C(s,\rho) = \frac{s+\rho_2}{\rho_1 s}$$
(4.27)

where:

$$\rho = \begin{bmatrix} \rho_1 & \rho_2 \end{bmatrix} \tag{4.28}$$

and the initial parameters are: $\rho_1 = 80$; $\rho_2 = 3$.

The final parameters of the controller obtained by tuning are: $\rho_1^* = 10.47$; $\rho_2^* = 1.351$.

A more conclusive validation of the controller is done using the ADM1 model in the control loop. A few step variations of the reference around the process operating point were considered

and, in addition, a step variation of the disturbance was applied $(COD_{inf l})$. The response of the system is illustrated in Figure 4.16.



Fig. 4.16 Evolution of the reference (red), disturbance (black) and *COD*(blue) from the control loop with PI controller tuned by the FRIT method

4.2.9 Usage of FRIT method to obtain a PID controller in case of PDA

The controller with the transfer function was considered:

$$C(s,\rho) = \frac{(s+\rho_2)(s+\rho_3)}{\rho_1 s(s+\rho_4)}$$
(4.29)

In the case of using the data in the closed loop, the vector of the initial parameters was considered: $\rho^0 = [13 \quad 3.7 \quad 16 \quad 100]^T$. When adjusting the parameters of the controller, the step $\gamma = 0.02$, was used, resulting in the evolution of *J* in Figure 4.17 After 140 adjustment steps, the parameters were obtained: $\rho^* = [17.36 \quad 1.646 \quad 87.45 \quad 20.12]^T$.





Figure 4.18 shows the validation results of the controllers obtained after 80 and 140 steps of parameter adjustment.



Fig. 4.18 Evolution of the reference (blue - dashed line), disturbance (black) and the controlled variable after 80 and 140 steps of adjustment of the parameters (green and red, respectively)

4.2.10Usage of Fictitious Reference Non-Iterative Tuning (FRNIT) variant in the case of PDA

In the paper [47] it is mentioned the use of the fictitious reference in a non-recursive procedure for determining the parameters of the controller, the variant being called Fictitious Reference Non-Iterative Tuning (FRNIT). The procedure will be presented and illustrated below. In this case it is preferable to work with models with discrete time.

Let be there:

$$M(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})}$$
(4.30)

the transfer function of the reference model, and the controller of which parameters are to be estimated, are considered in the form of:

$$C(z^{-1}) = \frac{P(z^{-1})}{Q(z^{-1})} = \frac{\rho_0 + \rho_1 z^{-1} + \rho_2 z^{-2}}{(1 - z^{-1})(1/p - (1/p - 1)z^{-1})}$$
(4.31)

in which p < 1 is a pole that provides a filtering in a band near the Shannon frequency and that ensures the feasibility of calculating the transfer function $C^{-1}(z^{-1})$.

The fictitious reference is calculated similarly to the FRIT procedure. Using input-output data collected in open loop, collected from anaerobic digestion process simulation with ADM1, the application of the FRNIT variant led to a controller with the Bode characteristic in Figure 4.24, like the one obtained after 80 steps of adjusting the parameters of the PID controller with the FRIT algorithm, used with data collected in closed loop.



Fig. 4.19 Bode characteristic of the controller obtained with the FRNIT algorithm

4.3 Conclusions

The VRFT method was developed with the idea of using experimental data taken from physical plants. In the case of PDA, the collection of these experimental data can be difficult, especially given the nonlinear nature of the process. This nonlinear character requires a gain scheduling approach, with an adjustment of the parameters according to the selected operating point. In this case, the data sets must be collected in order to obtain local controllers, which involve long-lasting and expensive operations. In the approach presented, the data are obtained from a *virtual plant* carried out by simulating a complex mathematical model of anaerobic digestion, such as ADM1. Unlike the data collected from the physical plant, the two variants of VRFT algorithms presented work with noiseless data. The assumption underlying the algorithms presented is that when using the ADM1 model and its improved versions, these effects do not lead to errors that go beyond engineering practice.

Both variants of VRFT algorithms have specific advantages that recommend them for use. The remarkable aspect of applying the two VRFT methods to PDA control is the fact that the integrator-*DC* assembly in the controller structure has a nonparametric Bode characteristic of type PI, from which the transfer function of an equivalent classic PI controller is immediately obtained. Therefore, these methods allow the rapid calculation of local controllers within a PDA control gain scheduling structure.

The IMC approach is an extremely attractive solution for data-driven design of the control law for the anaerobic digestion process. However, the adoption of these methods requires the consideration of the peculiarities of these processes. As stated, due to the non-linearities of the process, the command law must be based on the gain scheduling strategy, and the design of the local controllers is based on the procedures that, according to the results presented, ensure a good reserve of robust stability. An essential step of the procedure for data-based design of the control law in the IMC structure is the choice of the reference model, which is involved in the calculation of transfer functions $\bar{Q}(z)$ and $\bar{P}(z)$.

In the case of the FRIT method, the tuning of the PI controller for the anaerobic digestion process is carried out on the basis of a convergent and monotonous iterative process, including the use of data collected in the open loop. Obviously, it is preferable for the data to be obtained in closed loop. With regard to the PID controller tuned by the FRIT method, the iterative process of tuning with open loop data is divergent. In the usual variant of the FRIT, with closed-loop data, the iterative tuning can lead to an PI control law, and by refining the process of minimizing the criterion, a controller is obtained of which Bode characteristic is closer to that of an PI controller than that of a PID.

The fictitious reference can also be used in a non-iterative process of determining parameters. The results obtained with FRNIT to obtain the parameters of the controller of an anaerobic digestion process coincide with those obtained by FRIT: the PID controller obtained is closer to an PI controller than the PID.

The use of FRNIT in the case of PDA, as in the case of other bioprocesses, has an advantage over VRFT. It is known that measuring the controlled physical variables in bioprocesses is difficult and accompanied by a high level of noise. Transferring the controlled variable y(t) through the inverted reference model amplifies this noise. In the case of FRNIT, the command u(t) is transferred through the inverted model of the controller, a simpler operation, because the noise level affecting the command given by the controller is reduced.

Validation of data-driven methods for the automatic control of anaerobic digestion processes using a virtual plant that is implemented using the complex model ADM1, together with the consideration of disturbances affecting the influence and measurement noise, justifies the choice of these control methods in the case of the analyzed process.

Chapter 5: IMPLEMENTATION OF A PLATFORM BASED ON THE HILS PRINCIPLE FOR TESTING THE CONTROL SOLUTIONS

This chapter presents the design and implementation of a platform based on the Principle of Hardware in The Loop Simulation (HILS) for testing and validating control solutions. The peculiarity of this platform is the ability to run in real time and the fact that it can be used for any type of process. It also includes a cloud computing component that offers the possibility of storing and processing the acquired interest signals, thus allowing the processing of data from the process at a higher hierarchical level.

5.1 Structure and implementation of the testing platform

The following is a detail of the components used for the development of the platform, as well as a presentation of the process of implementing a testing platform based on the Principle of Hardware in the Loop Simulation, for testing real-time control solutions.

Although, as presented above, there are several mathematical models on the market that allow the simulation of the anaerobic digestion process, including complex models such as ADM1, which can be treated as *virtual plants*, however, in order to take a step forward in the direction of testing control solutions in an environment as close to the real one as possible, within this chapter it is proposed to implement a platform based on the HILS principle to simulate and test control solutions for anaerobic digestion processes.



Fig. 5.1 Structure of the real-time testing platform based on HILS

The main components of the testing platform, shown in Figure 5.1, are:

- ✓ The process of anaerobic digestion given by a mathematical model and implemented in Simulink. Thus, the process constitutes the simulated part through a computer running under Windows 10,
- ✓ An Inteco acquisition board that is installed on the computer,
- ✓ A programmable logic controller (PLC) of the type Micro 850,
- ✓ An interactive screen of the type Panel View 800,
- $\checkmark~$ A cloud computing component to store and process data.

Figure 5.2 shows the programmable logic controller used in conjunction with additional components.



Fig. 5.2 PLC Micro 850 used for the development of the platform

The Cloud Computing component is designed to store and process data transmitted by the PLC. Data transmission in the cloud is achieved through the MQTT protocol. In our case, the PLC is the component that publishes the data, through an MQTT library (see Figure 5.3).



Fig. 5.3 Cloud Data Transmission Structure

The broker, in its turn, has the role of directing the messages to another client with the role of listener, who stores them and then processes them. Both the broker and the listener, run in a virtual machine based on Linux as an operating system and which is located in the cloud. The mentioned virtual machine has the ability to run 24 hours a day and can be accessed remotely via SSH or using desktop applications (example Putty). On this, a Producer-Consumer application runs in the Python programming language. The purpose of the application is to retrieve the data through the MQTT protocol and store it in a database using SQLite. Subsequently, the stored data can be interrogated and exported in the form of files at the user's choice.

5.2 Description of the software applications developed and description of the procedure running the model in real time

The configuration of the PLC and the implementation of applications on both PLC and Panel View was carried out in the Connected Components Workbench software.

Therefore, for the PLC, 9 programs have been developed that ensure the transfer of data between the three component parts of the developed platform. The developed programs act as tasks with well-defined requirements, under the control of the PLC's operating system.

For Panel View, 5 menus have been made that are intended for users and that contain information regarding the process to be tested. Navigating between the windows is done through the buttons arranged at the bottom of the main menu.

MAIN (see Figure 5.4) is the home page containing information on the testing structure.

CFG is a default button that allows one to configure the Panel View. It allows for changes regardless of whether an application is running.



Fig. 5.4 Screen capture MAIN

 $\ensuremath{\textit{PLC}}$ allows the visualization of input/output signals, as well as the possibility of modifying a variable.

CONTROL (see Figure 5.5) allows the activation/deactivation of the type of control implemented, as well as the graphical representation of the command. If the controller application is deactivated, the command to the process can be manually set by the user





DIGESTOR allows viewing the values of interest.

CLOUD presents the solution for data transmission in the cloud. This menu provides 4 buttons: 2 of which allow the user to connect/disconnect the PLC and 2 to determine the moment when the data acquisition is desired.

The Producer-Consumer application, developed in *Python* aims to retrieve data from the PLC through an MQTT broker and store it in a database.

Figure 5.6 shows the conceptual sequence diagram of the Cloud data storage process. As it can be seen, there are three main entities: *PLC*, the *MQTT* broker and *Customer*.

An important aspect to be mentioned is that we are dealing with the Producer-Consumer type problem. This is found both between the PLC and the MQTT broker and inside the Client. The role of the PLC is to publish the data to the MQTT broker, and the Customer in his turn subscribes to the topic *mico800/topic1* and listens to the messages received on the topic to which he subscribed. When a message is received, it is inserted into a FIFO buffer.

At the *Customer* level there is a *SQLWriter Thread*, that monitors the buffer and when messages appear, it enters the values in the database.



Fig. 5.6 Conceptual sequence diagram of the data storage process

5.3 Experimental results obtained with the testing platform

For the validation of the testing platform, both the cloud computing component and the testing component of the control solutions were considered. Thus, the AM2 mathematical model of the anaerobic digestion process (model described in subchapter 2.2) was implemented as the software model of the testing platform. This choice was determined by the need for the platform in its entirety to operate in real time. Therefore, *the virtual plant* within the testing platform is represented by the implementation in Simulink of the nonlinear mathematical AM2 model.

5.3.1 Estimation of the influent concentration using a neural estimator

In the formulation of the problem of automatic control of anaerobic digestion processes, there can be pursued two purposes:

- Obtaining an effluent of the highest quality, in which case the impact on the environment is exclusively pursued;
- Obtaining as much biogas as possible, in which case the economic benefit is exclusively pursued.

Thus, they can be considered as two terms expressing two different requirements, a compromise solution being the adoption of a criterion of the type [48]:

$$\max_{D} J = \max_{D} (q_{CH_4} + \gamma \cdot COD_{ef})$$
(5.1)

where COD_{ef} expresses the quality of the effluent, and γ is a negatively valued parameter. Thus, the problem is formulated as one of maximizing the production of biogas, limiting, by a given weighting, the term γ , but the negative effect that effluent produces is on the environment.

In order to study the behavior of this criterion, the evolution of the criterion J was considered in relation to the effluent quality for different values of the influent quality, the disturbance variable. Figure 5.8 shows the evolution of the optimization criterion J in relation to the reference value applied to the designed control system, COD_{sp} , for different values of influent quality, COD_{in} .



Fig. 5.7 Evolution of the criterion *J* in relation with COD_{sp} for different values of COD_{in} optimal regime characteristics (blue $COD_{in} = 0.965$; red $COD_{in} = 1.4475$; magenta $COD_{in} = 1.93$; green $COD_{in} = 2.4125$; yellow $COD_{in} = 2.895$; black $COD_{in} = 3.3775$; cyan $COD_{in} = 3.86$)

From the figure we can see that the maximum value of the criterion *J* depend on COD_{in} . The optimal regime characteristics of the process are given by the function $COD_{sp} = f(COD_{in})$, where for COD_{sp} we get the maximum value of the criterion *J* when the quality of the influent is COD_{in} . Thus, based on the AM2 model (described in chapter 2) and given the quality of the influent, COD_{in} , we can determine at any time the optimal reference point value for the control loop $Q_{ad} - COD$.

Thus, given that the optimal point of operation depends on the concentration of the influent, it becomes of interest to estimate the concentration of the influent at the input of the anaerobic digester. One solution is to implement a neural estimator for estimating the COD_{in} . Taking into account the cloud computing component developed within the platform, we will further test both

the collection and transmission of data from the programmable logic controller, as well as the implementation of a neural estimator within the cloud component.

In this case, two approaches were analyzed: neural network training with data collected in open loop and with data collected in closed loop, respectively. For each approach, a neural network model was used to estimate the concentration of influent, expressed by COD_{in} . The proposed neural network has a multilayered architecture consisting of two neural layers, the hidden layer having 10 neurons.

The data for the training and validation of developed neural networks are collected through the cloud component (data sent by PLC to the cloud), over a period of 3500 hours. For the training process, the data was randomly divided: 90% for the training process, 5% for testing and 5% for validation.

5.3.2 Neural estimator for the concentration of the influent built with date collected in open loop

For the training of the neural network considering the case in which the anaerobic digester operates in open loop, an evolution of the command variable was considered, Q_{ad} . Here, two cases were analyzed: a case in which there were considered as input variables Q_{ad} , CH_4 and COD, respectively Q_{ad} , CH_4 and TSS.

Therefore, the results obtained for the first case are illustrated in Figure 5.8.





As it can be seen, the output of the neural network follows the output of the process very well, which denotes the ability of the neural network to provide very good results on estimating the concentration of influent.

5.3.3 Neural estimator for the concentration of the influent build with data collected in closed loop

To train the neural network considering the case where the anaerobic digester is operating in closed loop, a new dataset has been collected. In this case, too, an evolution of the command

variable was considered, Q_{ad} , resulting from the use of an PI-type controller. Two cases were analyzed to estimate the amount of COD_{in} : case in which there were considered as input variables the Q_{ad} , CH_4 and COD, respectively Q_{ad} , CH_4 and TSS Thus, the results obtained for the first case of the use of the neural network NN3 are illustrated in Figure 5. 9.



Fig. 5.9 Graphical representation of the neural network NN3 (Q_{ad} , CH_4 and COD) compared to the evolution of COD_{in}

As it can be seen, the output of the neural network follows very well the concentration of influent recorded from the process, the result of the analyzed estimator being thus very good.

5.3.4 Testing a control solution applied on the HILS platform

The following are the results of applying an PI controller implemented to validate the developed testing platform. The design of the PI controller took into account the nonlinear character of the process, the nonlinear model was linearized around an operating point given by the control variable Q_{ad} . Therefore, the anaerobic digestion process control system operates under the stabilization regime of the COD_{out} to a required reference variation, when the disturbance S_{1in} is constant. Figure 5.10 illustrates the operation of the control system when the effluent concentration reference COD_{out} , has a step variation followed by a stabilization regime.





5.4 Conclusions

The developed platform is efficient because: it allows thorough testing in extreme situations, it allows repeatability of tests, it reduces the possibility of disastrous situations and, finally, it reduces time and costs compared to experiments carried out on a real process. The built-in cloud computing component has proven its practical usefulness because it has the ability to store a significant amount of data and at the same time it allows the synchronization of data, which can be accessed by the user through several remote devices through the Internet.

Both the control component, implemented within the programmable device, and the cloud component were tested, by a neural network used to estimate the concentration of the influent. The results presented show the very good performance of the testing platform based on the HILS principle and thus they certify the approach taken.

Chapter 6: CONCLUSIONS

Within the doctoral thesis entitled "CONTRIBUTIONS REGARDING THE AUTOMATIC CONTROL OF ANAEROBIC DIGESTION PROCESSES", the problem of adopting advanced control methods in the case of an important category of biotechnological processes was approached. Thus, it started from the analysis of the state of the art which revealed that two types of automatic control applications had been developed: classical structures or those based on artificial intelligence, which were validated on the physical process or by numerical simulation on a complex mathematical model of ADM1 type, and advanced control structures, which were validated on simplified mathematical models. However, given the "distance" existing between the simple mathematical models and the complex mathematical model ADM1, the approach assumed by the doctoral thesis to find advanced methods of control that can be used for the problem of automatic control of the anaerobic digestion process is justified.

6.1 Original contributions

Within the thesis, the following original contributions may be considered:

Chapter 2:

- Presentation of the main mathematical models existing for anaerobic digestion processes, the complex model ADM1 and the simplified model AM2, as well as the compatibility between these models.

Chapter 3:

- Study and development of a control structure based on the Model Free Control method for anaerobic digestion processes;

- Starting from the observation that in real applications the load regime (concentration of influent) of the anaerobic digester is variable in time, a method of tuning the parameters of the controller is proposed to ensure the stability of the system in a wide range of operating regimes;

- Validation by numerical simulation of the control structure based on the Model Free Control method using the complex mathematical model ADM1 as a virtual plant.

Chapter 4:

- The study and development of a control structure based on the Virtual Reference Feedback Tuning method for anaerobic digestion processes, considering both the usual variant of the method and a simplified variant of it;

- Validation by numerical simulation of the control structure based on the Virtual Reference Feedback Tuning method using the complex mathematical model ADM1 as a virtual plant;

- Study and development of a control structure based on the Internal Model Control method for anaerobic digestion processes;

- Validation by numerical simulation of the control structure based on the Internal Model Control method using the complex mathematical model ADM1 as a virtual plant;

- Study and development of a control structure based on the Fictitious Reference Iterative Tuning method for anaerobic digestion processes;

- Validation by numerical simulation of the control structure based on the Fictitious Reference Iterative Tuning method using the ADM1 complex mathematical model as a virtual plant.

Chapter 5:

- Design and development of a platform based on the Hardware In the Loop Simulation principle for testing control solutions implementable on a programmable logic controller;

- Development of a Cloud Computing component for the development of applications at the higher hierarchical level of the automatic control structure and its connection with the platform based on the HILS principle;

- Testing of the HILS-based platform and the Cloud Computing component for the anaerobic digestion process.

6.2 Dissemination of the obtained results

Some of the research presented in the doctoral thesis were published in the following scientific articles:

Articles in ISI rated journals:

1.Larisa Condrachi, Ramon Vilanova, Montse Meneses, Marian Barbu, Anaerobic Digestion Process Control Using a Data-Driven Internal Model Control Method, Energies 2021, Vol 14(20), 6746, (Impact factor calculated by ISI for 2021: 3.004).

- Articles presented in indexed international conferences:

2.Larisa Condrachi, Ramon Vilanova, Marian Barbu, Data-Driven Internal Model Control of an Anaerobic Digestion Process, 25th International Conference System Theory, Control an Computing (ICSTCC), 20-23 October 2021, Iași, România (Articol indexat SCOPUS).

3.Irina Luca, **Larisa Condrachi**, Laurențiu Luca, Ramon Vilanova, Marian Barbu, Testing Platform for Real-time Controllers Based on Hardware In the Loop Simulation, 26th IEEE International Conference on Emerging Technologies and Fcatory Automation (ETFA), 7-10 September 2021, Vasteras, Sweden (Article indexed ISI Proceedings).

4.Larisa Condrachi, Emil Ceangă, Ramon Vilanova, Cezar Bichescu, Marian Barbu, The Anaerobic Digestion Process Control Using Data Driven Methods, 23th International Conference on System Theory, Control and Computing (ICSTCC), 9-11 October 2019, Sinaia, România (Article indexed ISI Proceedings).

5.Larisa Condrachi, Ramon Vilanova, Emil Ceangă, Marian Barbu, The Tuning of a Model-Free Controller for an Anerobic Digestion Process using ADM1 as Virtual Plant, 7th IFAC Symposium on System Structure and Control SSSC, 9-11 September 2019, Sinaia, România, Vol 52, Issue 17, Pages 99-104 (Article indexed ISI Proceedings).

6.Larisa Condrachi, Emil Ceangă, Lucian Puiu Georgescu, Gabriel Murariu, Ramon Vilanova, Marian Barbu, Model-Based Optimization of an Anaerobic Digestion Process, 22nd International Conference on System Theory, Control and Computing (ICSTCC) 10-12 October 2018, Sinaia, România (Article indexed ISI Proceedings).).

7.Larisa Condrachi, Marian Barbu, Anaerobic Digestion Processes Controller Tuning Using Fictitious Reference Iterative Method, 13Th IFAC Symosium on Dynamic and Control of Process System, including Biosystems (DYCOPS 2022) 14-17 June 2022, Republic of Korea (The article was accepted to be presented within the symposium).

- Articles presented in international conferences:

1.Larisa Condrachi, Marian Barbu, Fictitious reference iterative tuning method applied for an anaerobic digestion process controller, 11th International Conference on Environmental Engineering and Management, 8-10 September 2021, Munttenz, Switzerland.

6.3 Future research directions

The present research carried out within this doctoral thesis can be continued as follows:

- The use of artificial intelligence techniques for the development of software sensors and advanced structures for the automatic control of anaerobic digestion processes.
- Expanding the HILS-based testing platform by including new validation elements, and consideration may also be given to issues that ensure the cyber security of the connection of the elements and the cybersecurity of data transmission in the cloud.

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