Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria Informatica, Gestionale e dell'Automazione

Computational Intelligence Techniques for Energy Management in Industrial and Residential Systems

Ph.D. Dissertation of:
Gabriele Foresi

Advisor:
Chiar.mo Prof. Sauro Longhi

Coadvisor:
Prof. Andrea Monteriù

Curriculum Supervisor:
Prof.ssa Claudia Diamantini

XVIII edition - new series

Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria Informatica, Gestionale e dell'Automazione

---

Computational Intelligence Techniques for Energy Management in Industrial and Residential Systems

Ph.D. Dissertation of:
Gabriele Foresi

Advisor:
Chiar.mo Prof. Sauro Longhi

Coadvisor:
Prof. Andrea Monteriù

Curriculum Supervisor:
Prof.ssa Claudia Diamantini

XVIII edition - new series

Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Facoltà di Ingegneria
Via Brecce Bianche – 60131 Ancona (AN), Italy

"Amor, ch'a nullo amato amar perdona
mi prese del costui piacer sì forte
che, come vedi, ancor non m'abbandona."
Divina Commedia
Dante Alighieri.

"Il destino ha la sua puntualità."
Luciano Ligabue.

To my family who supported me and to my friends who encouraged me to overcome my limits.

Acknowledgments

This work has been supported by numerous people who are obliged to thank.

First of all, I would like to thank my tutor, Prof. Sauro Longhi and my co-tutor, Prof. Andrea Monteriù for giving me the opportunity to complete this research program and to carry out a period of foreign internship in the prestigious Shibaura Institute of Technology (SIT) in Tokyo.

Furthermore, all the results obtained during the research activity were made possible thanks to the supervision of two key people: Lucio and Francesco. I would like to thank them for all their precious and tireless help for everything, especially during the writing of our publications. However, the most important thing I received from them is the passion for this work, which in most cases requires a lot of sacrifice and motivation.

I would like to thank Prof. Chinthaka Premachandra, who welcomed me into his research group and supported my studies during my visit to Japan. From this experience, I learned the organization and methodology that he has always shown in his work. Furthermore, I would like to thank all the colleagues I have worked with and who have made my time in Japan really enjoyable.

I would like to thank my department colleagues, who have also become my friends. They have always supported me, with their professional experience in order to improve the quality of my research activity, especially at the beginning of this PhD course. I think that the results of my research would not have been such without the enthusiasm of Alessandro B., Alessandro F., Alex, Antonio, Daniele D., Daniele P.P. (with whom I also started the university course since September 2011), Davide, Eleonora, Emanuele, Enrico, Giulia, Luca, Marco, Sabrina, and Riccardo.

Ancona, Marzo 2020

Gabriele Foresi

Abstract

In the digitalization era, Energy Management (EM) has become one of the most important topics in both industrial and residential scenarios. The importance of solving and improving some tasks in this epoch leads to the need to apply some Computational Intelligence (CI) and Artificial Intelligence (AI) methods.

The objectives and contributions of this thesis are related to the EM in i) industrial systems (with reference to the Industry 4.0) by acting on the control system design and ii) residential systems by giving the user a role active in a flexibility scenario.

In the first scenario, the author presents two CI methodologies. The first approach consists of applying a meta-heuristic algorithm to reconfigurable systems in order to find a sub-optimal controller parameter set. The performance of this technique is based on the choice of a suitable function to be optimized. The second methodology is the application of a similarity detection technique as a control system supervisor. This is implemented to overcome the limitations of the first methodology. Both of these approaches are tested on a real system.

In the second scenario, the author proposes the application of a CI technique aiming to forecast home appliances usage. This information, shared with the energy supplier, is could be very useful to fed flexibility programs. The obtained results show how the performance of the proposed algorithm is better than the classic approaches.

Sommario

Nell'era della digitalizzazione, l'Energy Management (EM) è diventato uno degli argomenti più importanti in sia in ambito industriale che residenziali. L'importanza di risolvere e migliorare alcuni compiti in questa era porta alla necessità di applicare alcuni metodi di intelligenza computazionale (CI) e di intelligenza artificiale (AI).

Gli obiettivi e i contributi di questa tesi sono legati all'EM in i) sistemi industriali (con riferimento all'Industria 4.0) agendo sulla progettazione del sistema di controllo e ii) sistemi residenziali dando all'utente un ruolo attivo in uno scenario di flessibilità.

Nel primo scenario, l'autore presenta due metodologie CI. Il primo approccio consiste nell'applicare un algoritmo meta-euristico a sistemi industriali riconfigurabili al fine di trovare un set di parametri del controllore ottimale. Le prestazioni di questa tecnica si basano sulla scelta di un opportuno funzionale da ottimizzare. La seconda metodologia è l'applicazione di una tecnica di rilevamento della somiglianza tra segnali come supervisore del sistema di controllo. Questo è implementato per superare i limiti della prima metodologia. Entrambi questi approcci sono testati su un sistema reale.

Nel secondo scenario, l'autore propone l'applicazione di una tecnica CI volta a prevedere l'utilizzo degli elettrodomestici da parte degli utenti. Queste informazioni, condivise con il fornitore di energia, potrebbero essere molto utili per alimentare programmi di flessibilità. I risultati ottenuti mostrano come le prestazioni dell'algoritmo proposto siano migliori degli approcci classici.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

With the advent of the digital era, the cost of energy has undergone a considerable increase and it is expected to grow continuously. Since energy is a commodity of primary importance, Energy Management (EM) is a topic of a great discussion both in industrial (e.g., factories, plants, etc.) and residential scenarios (e.g., hotels, homes, buildings). Due to the importance of this topic, there is a growing need to design and develop new techniques making EM as efficient as possible. Computational Intelligence (CI) techniques can be a viable solution to face with this topic. Particularly, two kinds of applications in the EM scenario where CI techniques are used can be identified: i) the knowledge extraction from historical data (for making decisions and predictions) and ii) the design of optimization algorithms.

EM can be defined as a set of operations related to energy production and consumption aiming to conserve resources, protect the climate and save costs [1]. Then, through EM systems many objectives can be reached (e.g., monitoring of devices and appliances, the optimization for energy saving, real-time smart pricing, and peak load reduction) [2]. This definition highlights the importance of EM in its field of applications. In particular, regarding the industrial scenario, the main task of EM is to reduce as much as possible the energy consumed by systems such as robots, electric motors and reconfigurable systems (typical elements of Industry 4.0) [3]; for what concern the residential scenario, the most important goal is to save costs (e.g., by exploiting the photovoltaic production, by accepting Demand Side Flexibility policies, etc.) [4]. The concept of Demand Side Flexibility (DSF), detailed in 1.1.2, is related to the user's willingness to act on the electricity consumption in response to variable energy prices or market incentives. However, the design and development of EM techniques increasingly efficient is a still open challenge in both scenarios. The need to improve these tasks in the Artificial Intelligence (AI) era leads to the application of new techniques in computer science and machine learning scenario.

Recently, a report of Kumba S., entitled "Artificial Intelligence for Energy Efficiency and Renewable Energy – 6 Current Applications" [5] points out how the changes introduced by the new AI and CI technologies have improved the Energy Forecasting, the Energy Efficiency, and the Energy Accessibility. For this reason, the AI technologies and CI approaches can be easily used to improve the EM performance both in industries and in residential systems.

The contributions of this thesis are strictly related to the research activities carried out on the following two main topics:

- Design and Development of an automated procedure **for reducing energy consumption in industrial systems** by taking into account the concept of **Reconfigurable Industrial System**;
- Design and Development of an AI technique **for estimating users' behaviour in terms of energy consumptions** by considering the concept of **Demand Side Flexibility** (DSF).

The discovery of new CI and AI methodologies permits to solve these two problems efficiently and at the same time promises a suitable design, implementation, interpretation, and validation of these methods from a computer scientist and engineering perspective. For this reason, the title of this thesis is *Computational Intelligence Techniques for Energy Management in Industrial and Residential Systems*. The remainder of this chapter is organized as follows:

- Section 1.1 provides a background and motivations for the topics of this thesis. Author motivates the research study and highlights its significances.
- Section 1.2 presents the thesis statement, where the problem is formally defined with a list of specific research questions answered in this thesis.
- Section 1.3 resumes the index of the thesis.

1.1 Background and Motivations

Computational Intelligence (CI) and Artificial Intelligence (AI) are quickly becoming a part of our Energy industries and Energy management, helping to develop more efficient and safe energy production techniques [6]. In this scenario, machine learning techniques could i) solve problems difficult to deal with other approaches and/or ii) achieve higher average performance than obtained with other methods.

Regarding industrial scenario, manufacturers must continually look for waste reduction, process improvement, and supply chain efficiency to meet competitive pressures and their customers' cost reduction requirements. Different programs (e.g., Leans) have become a popular means to develop a culture of simplification and constant improvement. However, even though these programs provide an excellent basis for managing energy costs, these costs are often left out of an efficiency drive due to three main reasons: i) energy costs are not well understood ii) energy costs are considered uncontrollable iii) energy is not well managed. Then, energy consumption can be controlled when organizations develop measurable and progressive management processes and AI can play a crucial role in this direction [7].

Regarding the energy sector in a residential scenario, the electricity system can look to benefit from AI development. In particular, some areas, where AI could benefit the electricity system, include predicting consumption and grid management. Since maintaining a balance between supply and demand becomes increasingly difficult, grid management also becomes more complex [8]. AI could assist in designing grid control algorithms that would help deal with this problem. Optimizing grid assets and predicting their maintenance can also help systems become more efficient and economical.

According to [9], five main areas where AI in the Energy Sector is beneficial can be defined:

- **Realiability**: self-healing grids, operations improvement and efficient use of renewable resources and energy storage.
- **Safety**: Outage prediction and outage response
- **Cybersecurity of systems**: Threat detection and response.
- **Optimization**: Asset, maintenance, workflow and portfolio management.
- **Enhancements for the customer experience**: Faster and more intuitive interactive voice response, personalization, product and service matching.

1.1.1 Industry 4.0: Components, Goals and Challenges

The sentence "Fourth Industrial Revolution" was firstly introduced by Klaus Schwab, the executive chairman of the World Economic Forum, in 2015 [10]. The theme of the World Economic Forum Annual Meeting 2016 in Davos-Klosters, Switzerland was "Mastering the Fourth Industrial Revolution" [11]. In this fourth era, according to [12], technologies combining hardware, software, and biology are included and advances in communication and connectivity are emphasized. It is expected that this era will be marked by breakthroughs in different fields such as robotics, artificial intelligence, nanotechnology, quantum computing, biotechnology, the internet of things (IoT), decentralized consensus, fifth-generation wireless technologies (5G), 3D printing and fully autonomous vehicles [13].

Although the terms "Industry 4.0" and "Fourth Industrial Revolution" are often used interchangeably, Industry 4.0 is the subset of the fourth industrial revolution concerning industry because in the fourth industrial revolution areas not normally classified as "industry", such as smart cities are included. In essence, Industry 4.0 is the trend towards automation and data exchange in manufacturing technologies and processes including Cyber-Physical Systems (CPS), IoT, Cognitive Computing (CC), AI, Machine-to-Machine (M2M) communication, Radio Frequency Identification (RFID) Technology, Internet of Services (IoS), Cloud Computing (CCP), CI, Data Mining (DM), Decision-making/supporting system and Predictive Maintenance (PdM).

Industry 4.0: Key Components

Among all above-mentioned components concerning Industry 4.0, 4 of these can be considered the main ones: CPS [14], IoT [15], DM [16] and IoS [17].

The development of CPSs is becoming more and more widespread. Within these systems, the information flow coming from all the manufacturing system parts is closely monitored and managed between the physical layer and the Cyber-Space [18]. For this reason, a CPS can be defined as a set of technologies for the control and the management of interconnected systems. The last generation of CPS is able to store and analyse data, is equipped with many sensors and is network compatible. In such an environment, companies can bring their performance to a new level.

The concept of IoT can be defined as a tool allowing "Things" (or Objects) to interact with each other and to cooperate with their intelligent components for reaching a common goal [19]. Therefore, IoT can be considered a network where each CPS cooperates with each other.

The consequence of the higher use of sensors and network systems led to the generation of high volumes of data, knowns as Big Data (BD). According to IBM, 1.6 Zetabytes of digital data are now available and this number is expected to increase [20]. The development of CPS is very useful to manage BD and the interconnectivity of machines. Furthermore, the term "Data Mining" is used to define all methodologies and techniques aiming to extract useful information from big amount of data. In particular, automatic methods (Statistics, Artificial Intelligence, Machine Learning) are often used [21]. Lastly, DM allows the user to analyse and discover patterns, rule, and knowledge from data collected from many sources.

The aim of IoS is to enable service vendors to offer their services through Internet (web platforms). Generally, the IoS consists of business models, infrastructures for services, the real services and participants. These services are offered and combined into other value-added services and are communicated to users and consumers. They can access them via different channels.

According to the previous concepts, a global definition of Industry 4.0 can be given: it is a collective term for technologies and concepts of value chain organization [22]. Within the Smart Factories of Industry 4.0, a CPS monitors physical processes, creates a virtual copy of the physical world and makes decisions decentralized. Over the IoT, each CPS communicates and cooperates with each other and humans in real-time. DM discovers knowledge to support the decision-making process. Through the IoS, both internal and cross-organizational services are offered and utilized by participants of the value chain.

Industry 4.0: Principles and goals

According to [23], four design principles allowing companies to identify and implement Industry 4.0 scenarios are defined:

- **Interconnection**. It is defined as the ability of machines, devices, sensors, and people to connect and communicate with each other via IoT or the Internet of People (IoP).
- **Information transparency**. Industry 4.0 technology affords transparency which provides operators great amounts of useful information needed to make appropriate decisions. In particular, the concept of inter-connectivity allows operators to collect big amounts of data and information from all points in the manufacturing process, thus aiding functionality and identifying key areas that can benefit from innovation and improvement.
- **Technical assistance**. This concept incorporates two aspects: i) the ability of assistance systems to support humans by collecting and visualizing information in a comprehensive way in order to make decisions and solve urgent problems on short notice and ii) the ability of CPS to physically support humans by conducting tasks that are unpleasant, too exhausting, or unsafe for humans.
- **Decentralized decisions**. It is defined as the ability of CPS to make decisions on their own and to perform their tasks as autonomously as possible. Only in the case of exceptions, interferences, or conflicting goals, are tasks delegated to a higher level.

Industry 4.0 Drivers

Once all the principles and key elements have been defined, it is possible to explain which are the 3 guidelines driving the Industry 4.0 [24]:

- **Digitization and integration of vertical and horizontal value chains**. Vertically, Industry 4.0 integrates processes across the entire organization (e.g., processes in product development, manufacturing, logistics and service). However, horizontally, Industry 4.0 includes internal operations from suppliers to customers plus all key value chain partners.
- **Digitization of product and service offerings**. Integrating new methods of data collection and analysis (e.g., through the expansion of existing products, via the creation of new digitized products) helps companies to generate data on product use and thus, to refine products in order to meet best the customers' needs.
- **Digital business models and customer access**. Reaching customer satisfaction is a multi-stage, never-ending process that needs to be modified currently as customers' needs change all the time. Therefore, companies expand their offerings by establishing disruptive digital business models to provide their customers digital solutions that meet their needs best.

Challenges: Mass Customization and Reconfigurable Systems

The race to adopt elements of Industry 4.0 is already under way among companies in Europe, U.S. and Asia [25]. In the next five to ten years, Industry 4.0 is expected to transform the design, operation, and service of products and production systems [26]. Connectivity and interaction among parts, machines, and humans will enable production systems to become faster and more efficient and will lift mass customization to new levels [27]. Mass customization is a production strategy aiming to satisfy the individual needs of customers and, at the same time, to preserve the efficiency of mass production, in terms of production low costs and low selling prices. Concerning the production industries, this concept means that they will be able to orient all main value-adding processes toward the customer's requirements. Integrated products and the development of customizable production system will increase the exchange between departments and companies. Moreover, this new revolution will enable smart and flexible production control by using IT-based intercommunicating and interacting machines, equipment and tools [28].

The advent of this new era may introduce a different set of requirements, including the drastic increase of varieties, very small batch size, random arrival of orders, and wide spread of customization on system control for manufacturing operations [29–31]. The introduced reconfigurable manufacturing systems [32–34] can be a viable solution to achieve this high competitiveness, allowing to re-use the system for developing customized products with varying lot sizes. The principal goal of a reconfigurable manufacturing system is to enhance the responsiveness of manufacturing systems to unforeseen changes in product demand. These systems are cost-effective because they boost productivity and increase the lifetime of the manufacturing system. Moreover, a reconfigurable manufacturing system has an open system architecture that enables adding machines to existing operational systems very quickly, in order to respond (1) rapidly, and (2) economically to unexpected surges in market demand. The most salient feature of reconfigurable manufacturing systems is that they are capable of rapid change in structures as well as in hardware and software modules, allowing a faster adjustment of production capacity and functionality [35, 36]. However, control systems design needs innovative ideas to face this revolution. A crucial issue in control design is the definition of a set of control parameters which provide near-optimal performances w.r.t. specific criteria. This process, typically performed in the design stage as a trade off between conflicting factors (e.g., improving tracking performance, reducing energy consumptions, etc.), often produces imperfect result. Thus, there was a need to introduce automatic tuning methods to enhance machine performances and dynamically adapt to different control objectives while preserving at the same time stability and robustness properties.

1.1.2 Energy Management in Residential Scenario

According to Eurostat data, as depicted in Fig 1.1, on 2017, lighting, smart home appliances and water heating represent more than 70% of the residential electricity consumption [37]. Due to this high level of energy consumption, the concept of EM has gained more and more importance. According to [38], given a number of electrical tasks N (e.g., appliances turned on) to arrange in M time samples, the EM problem can be mathematically expressed as the minimization of an objective function J defined as:

$$\min J = \sum_{k=1}^{N} \sum_{i=0}^{M} \omega_k(i) \cdot L_k(i) \cdot C_k(i) \tag{1.1}$$

where $\omega_k(i) \in \{0, 1\}$ is a binary variable expressing if the k-th appliance is running or not at time i, $L_k(i)$ is the energy consumed by the task k-th in the time interval i and $C_k(i)$ is the energy cost of task k-th at time i. A detailed classification of home appliances is described in 1.1.2. Among them, in the above-mentioned EM problem, periodical use appliances without human interaction (e.g., dishwasher, washing machine, cooker hood and hvac), called "shiftable loads", have the most important role since their $\omega_k(i)$ can be managed by the EM algorithm. Then, by "shifting" their electricity demand within the daily profile it is possible to maximize cost-savings. In this context, the concept of Demand Side Flexibility (DSF) could lead to important benefits.

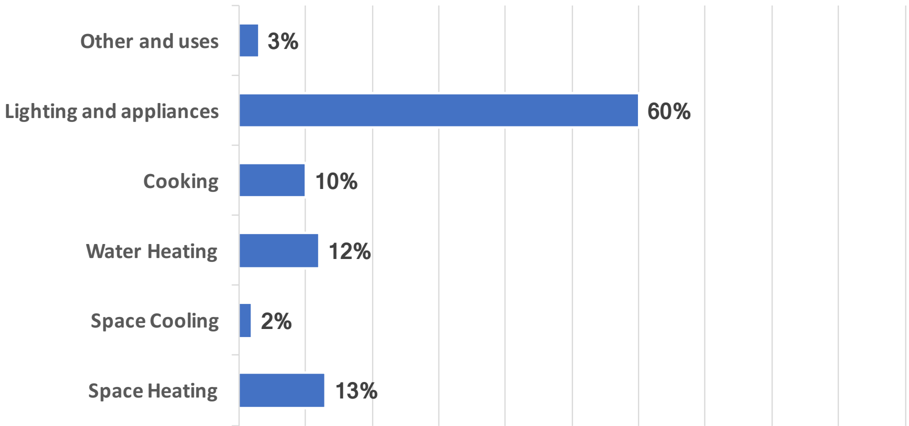


Figure 1.1 Eurostat: Electricy consumption in a residential scenario, EU-28, 2017

The concept of Demand Side Flexibility

Nowadays several trends are re-shaping the energy sector: an ubiquitous penetration of the digitalization, the ever growing number of connected devices, the availability of Big-Data and their analysis through Artificial Intelligence techniques, will change our perception of energy demand. All these technologies will enable consumers to take a more active role in the energy market by producing their own energy, selling the surplus, adjusting their energy consumption profiles and participating in demand flexibility programs [39, 40]. We talk about demand side flexibility (DSF) when a consumer adapts his energy consumption behaviour in response to variable energy prices or market incentives.

Until today the majority of the electricity demand is inflexible causing a higher cost of the overall system. An increased flexibility level can be achieved by sector coupling, for example in form of electrification of the mobility (electric vehicles) and the heating sector (power to heat) or via smart appliances. Integrating electric vehicles in the electricity grid can provide short-term flexibility because the installed batteries usually undergo daily cycles of charging [41]. Connecting a large amount of electric cars provides flexibility depending on the habits of the user, the vehicle usage and the charging profiles [42]. Another viable technique is the coupling of the heating sector and the electricity sector which can provide flexible short-term demand by using heat-pumps in combination with heat networks, heat storages and electric cooling loads. Finally, DSF can be obtained through residential demand-side management in smart homes.

To enable residential DSF, we may distinguish two main approaches: direct load control and price-based. In the first case consumers agree to accept certain conditions imposed by an energy supplier to automatically adjust their consumption. This includes for example direct load control, interruptible service and emergency demand response. On the other hand, a price-based system encourages customers to actively participate in demand response according to price information (e.g., real-time pricing, time of use, critical and peak time pricing). The customer can either shift the program manually or via a home energy manager system, controlling the consumption of several appliances [43]. This approach can be performed on the major appliances, such as electric water heaters, heating, ventilation and air conditioning (HVAC) systems, refrigerators, washing machines, washer-dryers and dishwashers.

Nowadays, it is not clear how big the future potential for demand-side flexibility based on emerging technologies (like e-mobility) will be, as this depends a lot on their penetration. On the other hand, smart homes and smart appliances are a reality and they can easily enable DSF in a shorter time. Furthermore, the availability of data coming from smart appliances and smart meters and AI techniques make possible the estimation of appliance usage patterns and then the forecasting of the user's energy behaviour, a key point for the success of DSF techniques.

The Role of smart home appliances

Smart home appliance can be defined as "capable of automatically changing and optimising their consumption patterns in response to external stimuli and system's need". Today appliances, depending on their usage patterns and functions can be classified in 4 categories:

- Major appliances (white goods) such as washing machines, dishwasher, tumble dryers, refrigerator, freezers, microwave oven, electric oven and electric boilers
- Multimedia devices (brown goods), such as TVs, computers, radios or games consoles
- Small appliances such as lamp, electric kettle, electric cooker and small electric space heaters
- Lighting

In general, the appliances allowing flexibility actions are those belonging to the white goods category. However some of them, sub-classified as "continuous use appliances" [44] as refrigerators and freezers, having a continuous use of electricity, cannot be interrupted neither shifted over time. Thus, among white goods, flexibility programs can be implemented by employing the so called "periodical use appliance" [44] as water heating, air conditioning, space heating and heat pumps (the ones possessing thermal inertia), washing machines, ovens, driers and dishwashers, which consume electricity during working cycles and they are used with a variable frequency depending on users habits. Possible demand side flexibility actions can be performed by: i) interrupting for short periods the demand of appliances with thermal inertia by minimizing the impact on consumer comfort ii) shifting (anticipating or postponing) the appliance cycles.

It is worth to notice that these actions have to be performed according to specific criteria (e.g., optimizing an objective function) in order to exploit all the potential benefits. As an example, if appliances with thermal inertia are interrupted, when they are reconnected an undesirable rebound effect may occur. On the same time, when appliances cycles are shifted, a demand reduction occurs and it is recovered later, when the operation of the appliance is re-scheduled.

1.2 Problems statement

Thesis statement: Through computational techniques, including artificial intelligence algorithms, the main objective is to design and develop i) an automated procedure aiming to improve performance (with focus on energy consumption) in Reconfigurable Industrial Systems and ii) a clustering and forecasting algorithm for exploiting the Demand Side Flexibility programs.

1.2.1 Problem 1: Reconfigurable Industrial Systems

Problem 1 is addressed to enhance the performance of Reconfigurable Industrial Systems (mainly in terms of energy consumption) by acting on the control system: **design and development of an automated procedure able to find control parameters that optimize a suitable objective function.**

Given the mathematical model of an industrial process, the research questions regarding the development of the CI technique are summarized below:

1. Which control technique could ensure the best possible robustness to the system?
2. Which index (or indices) can be used to define the objective function to be optimized?
3. Among all the parameters of the control law, which ones influence system performance the most?
4. How can the CI technique be embedded in the control loop?

Questions related to the evaluation procedure include:

1. Which references can be applied to the system in order to evaluate the proposed solution?

2. Does the proposed technique outperform the performance of standard controllers (e.g., the one provided by the system manufacturer)?

3. Can the controller found by the algorithm on a reference have good performance even on similar references?

1.2.2 Problem 2: Demand Side Flexibility

Problem 2 is addressed to estimate the home appliances usage habits to be used in flexibility programs: **design and development of an AI-based clustering and forecasting algorithm useful to create a two-way communication between an energy supplier and a customer.**

The research questions regarding the AI algorithm for the appliance usage estimation are summarized below:

1. How can AI model be applied to estimate the users habits and model their variability over time?

2. How can AI technique be applied to analyse the behaviour of the users and model of consumption profiles at the individual level?

. Questions related to the evaluation procedure include:

1. Does the proposed method outperform classic clustering and forecasting approaches?

2. Is the ML method reliable for the home appliances usage estimation task towards the real-world usage?

1.3 Thesis Overview

This thesis tries to answer the questions reported above by designing and developing computational intelligence and machine learning algorithms for the energy consumption reduction on industrial systems and for the estimation of the home appliances usage.

The following list shows the organization and an overview of the rest of the thesis.

- **Chapter 2** reviews the state of art of two research fields: Reconfigurable Industrial Systems and Demand Side Flexibility Scenario.

- **Chapter 3** describes the proposed methods. In particular, the author presents the proposed methodologies for achieving the set goals.

- **Chapter 4** explains the case studies where the proposed techniques are applied.
- **Chapter 5** firstly presents the Experimental Protocol including the hardware setup and the experimental settings. Then, the author provides the experimental results for evaluating the performance of the proposed methods.
- **Chapter 6** presents conclusions and future works.

Chapter 2

State of Art

2.1 State of art: Reconfigurable Industrial Systems

As a consequence of the adoption of Reconfigurable Industrial Systems, able to support different kinds of processing for developing customized products, one of the challenges still open is to find a set of control parameters that guarantee the achievement of the desired performance for each input reference (or set-point). Recently, many researchers faced with this problem by implementing different techniques. In the following, a survey on the developed techniques is reported.

2.1.1 PID and classic approaches

The most widely used controller in industries is the Proportional-Integrative-Derivative (PID). It is considered as the best controller for complex industrial systems [45]. A lot of studies have dealt with parameters tuning to improve the performance of PI and PID controllers [46, 47]. However, tuning the PID parameters for achieving desired performance is a complicated task due to a large number of performance indices (e.g., steady-state error, overshoot, peak time, settling time, rise time, etc). Generally, a combination of these performance indices is considered when tuning the controller parameters. For this reason, a multi-objective optimization problem has to be formally defined. Since the relationship between the above-mentioned performance indices and PID parameters is unknown, it is very challenging to tune PID parameters for satisfying given system performance, especially for complex systems. To solve the PID parameter tuning problem, some classic rule-based methods are generally developed (e.g., Ziegler-Nichols method, Tyreus-Luyben method, C-H-R method, Internal Model Control (IMC) method, Cohen and Coon method, Ciancone-Marline method, Root-Locus (RL), Frequency Response (FR)) [48]. However, these methods may have many disadvantages: i) difficulties with system affected by disturbances ii) difficulty to achieve optimal system performance iii) they are valid for a few types of systems iv) multi-objective problems cannot be solved v) difficulties with complex systems (e.g., systems with time delay).

Since in real cases the measured process variables are affected by disturbances, noises, and uncertainties, their effect must be considered when tuning the controller parameters. Generally, the above-mentioned classic techniques do not guarantee the desired performance. Moreover, the system dynamics of a complex process may differ in several operating ranges and this causes more difficulties in tuning parameters process. Therefore, many techniques have been used to explore optimal controller parameters set in real-time to satisfy multi-objective performance indices and to overcome these drawbacks.

2.1.2 Frequency Response-based techniques

Even though the FR analysis has many disadvantages, many works have used this technique to tune PID parameters.

As shown in [49, 50], the Gain-Phase-Margin (GPM) method based on FR analysis is implemented. It has been demonstrated that GPM is more efficient than the other methods in particular when it is applied to PID controller tuning for positioning control systems such as for Computer Numerical Control (CNC) machines and industrial robots. The most important advantage of this method is the providing of information about the relative and absolute system stability. Moreover, due to this method is general and versatile, it can be applied to automatically compute the PID parameters controller, as some available commercial controllers such as Galil Motion Control do [51].

In [52], a simulation software is developed for PID tuning. In order to obtain the PID coefficients both the open and closed loops models, including the PID structure in a Laplace form, are evaluated in the interest frequencies. The presented software is tested on simulated models up to the third order. Authors in [53] propose a controller design methodology based on process FR data. These data are identified through relay feedback tests and using multiple points on the Nyquist curve. The Least Squares Method (LSM) is used to obtain the controller model and the proposal validation has been carried out via simulations over linear systems and compared with classical ZN and GPM methods.

On the other hand, an alternative approach for an adaptive control for PI controllers is presented in [54]. The proportional and integral gains are set using a Nelder-Mead algorithm. Moreover, open-loop gain and phase margin constraints are included in the proposed tuning algorithm. Simulations and experimental tests are performed on a simple pilot column distillation loop with a commercial controller but using large sample periods for the tuning process.

In [55], the FR methodology is developed to efficiently design a feed-forward compensator for an industrial motion stage in a transmission electron microscope. The proposed approach does not necessarily provide optimal tracking behaviour and an additional control action may be required. Lastly, as seen in [56,57], the GPM method is applied in tuning applications tackling a specific problem in positioning control systems. However, this method is carried out off-line due to the controller tuning procedure required more time.

2.1.3 Modern Optimization Techniques

Recently, modern optimization techniques are applied in tuning PID parameters to overcome the disadvantages of FR-based techniques.

Authors in [58] proposed an optimal PID tuning algorithm using soft computing optimization method HC12. By comparing it with classic Ziegler-Nichols and Modulus Optimum methods, the effectiveness of the proposed method is demonstrated. However, because the next searching point is generated in the neighbourhood of possible solutions using a fixed pattern, the method may cause the system to converge to local minima.

A comparative study of Genetic Algorithms (GA) and Ants Colony Optimization (ACO) is presented in [59]. GA can be defined as a powerful searching algorithm mimicking natural genetics behaviour and natural selection [60]. Many works have dealt with GA to optimize the PID gains in control systems. The application of the GA in tuning controllers parameters is becoming a trend of great importance due to their powerful searching capabilities and heuristic characteristics [61]. The effectiveness of this technique is demonstrated in positioning control systems for simulated robotics path generation in [62–64]. Therefore, GA have also been used in control tuning applications, showing better results than classical techniques. Besides, as shown in [65, 66], the new concept of micro-GA, could be useful to reduce computational resources and to provide suitable solutions in different optimization problems when they are carefully designed. However, one of the main drawbacks of GA is the prematurity and stagnation, while it searches a globally optimal solution.

Recently, in [67] a GA parameter optimization is carried out for a small helicopter focusing on the system stability and adaptability. The performance of the system is tested and validated on the simulated model. In [68], a methodology for a PID controller design is presented. In this approach, the antibodies concept which provides population diversity and searching speed is used to improve a classic GA. Also in this case, the validation of this approach is carried out by using a simulated artificial leg. In [69], an adaptive niche GA is proposed to find the optimal PID parameters. It is an elitist strategy ensuring stable convergence. Moreover, the niche ideology keeps the population diversity and the adaptive mutations and crossover probabilities improve the local search ability. The proposed methodology is tested on four simulated models of first and second order.

In [70], the GA and chaos optimizing concept are integrated for PID parameter optimization. In this case, the initial population is generated by a logical sequence and an adaptive mutation probability is used to jump the local optima. Simulation tests are carried out on a third-order proposed plant model. A Real-Coded Genetic Algorithm (RGA) approach using floating-point variables representation is implemented in [71] to optimize the PID parameters of a temperature system model, obtained by software identification tools; the system response is simulated and compared to ZN and CC methods. In [72], the RGA technique is applied to a simulated hybrid tank system for i) identifying the model and i) tuning PID parameters. Moreover, an alternative approach is developed in [73] for self-tuning PID controller based on GA. In particular, a dominant selection and cyclic mutation operators are used to improve the fitness of the GA population. This method is carried out by using a particular platform and it is validated with simulations.

A tuning approach for PID controllers based on GA using adaptive mutation and crossover probabilities to avoid premature convergence is developed in [74]. Authors in [60] apply an adaptive GA with variable mutation probability to optimize the PID controller gains for a simulated ideal second-order model representing a coal transportation system. Meanwhile, in [75] a fuzzy PID controller is used for high order plants with time delays. The controller parameters are tuned by using a GA-based approach. Lastly, a multi-objective non-dominated sorting GA is developed in [76] for tuning PID controller applied to a robotic manipulator. The results of simulations demonstrated the great efficiency of this approach.

From the analysis of these works, several aspects of control tuning methods can be summarized. The FR analysis has notorious advantages over time domain analysis and it can be implemented as an automatic tuner for positioning control systems. The GA is a powerful optimization technique used to avoid premature local convergence on tuning applications. In all the related works above presented, researchers have dealt with i) only PID control tuning and ii) with simulated models. It would be desirable to i) tune parameters of more complex and non-linear control techniques (e.g., Sliding Mode, Variable Structure Control, Passivity Based) and ii) implement GA approaches in real systems, not only in simulated models. These can be defined as the main contribution of the first part of this thesis.

2.2 State of art: Demand Side Flexibility

Recently, as a consequence of the re-shaping of the energy sector, many researchers have dealt with the estimation and forecasting of household appliances usage patterns from an artificial intelligence perspective [77]. In the following, for each appliance category presented in Sec. 1.1.2, a brief survey on the developed algorithms and techniques is reported. A summary is shown in Tables 2.1, 2.2 and 2.3.

2.2.1 White goods

In [78], two systematic approaches to analyse washing machine, dishwasher and tumble dryers patterns usage are described. In the first methodology, given a typical customer behavior, appliances starting time are identified by a clustering method (G-means). In the second approach, a bivariate Gaussian mixture model (GMM) is developed in order to model the customer demand profile related to these appliances. A spectral decomposition (SD) to analyze the patterns usage of washing machine has been described in [79]. Within this technique, the learned patterns contain likelihood measures to predict if it is active at the present instant. Authors in [80] propose an unsupervised progressive incremental data mining mechanism applied to smart meters energy consumption data to estimate the usage of the washing machine. This algorithm can be considered as an extension of frequent pattern (FP)-growth and K-means clustering algorithms.

The approach proposed in [81] consists of an algorithm (both knowledge-based and data-driven) aiming to predict whether the washing machine and electric oven will start at a certain time or not. Regarding the data-driven side, Bayesian networks (BNs) are used. In [82], the prediction of the pattern usage of washing machine and microwave oven through classification approaches by taking into account the correlation between the various domestic appliances is described. In particular they implemented two artificial intelligence algorithms: binary relevance problem (BR) and Rakel algorithm with label powerset (LP).

Authors in [83] propose a combination of a minibatch K-means clustering and filtering approach to extract the states of dishwasher and microwave oven. Then, for each state, a maximum likelihood estimation is used to extract usage patterns of these appliances. In the work proposed in [84], authors describe a forecasting algorithm aiming to suggest the best time (of the day) to turn the electric oven on. In details, they use a graphical Bayesian model algorithm by addressing both human behaviour prediction and interdependency pattern identification to efficiently predict its usage.

Appliances	**K/G-M**	**GMM**	**SD**	**FP**	**BNs**	**BR**	**LP**
Washing Machine	[78], [80]	[78]	[79]	[80]	[81]	[82]	[82]
Dishwasher	[78], [83]	[78]					
Tumble Dryers	[78]	[78]					
Microwave Oven						[82]	[82]
Electric Oven	[80]			[80]			

Table 2.1 White goods patterns usage recognition techniques: a summary.

2.2.2 Brown goods

Among all existing brown goods, laptops and TVs are the most treated appliances in literature. The approach described in [79] is a data-driven algorithm based on likelihood measures whose aim is to predict if the TV is on in a certain instant time. The algorithm proposed in [80] extends the well-known clustering and pattern recognition algorithms (K-means and FP-growth) to identify TV and laptop pattern usage. The main characteristic of this technique is to be incremental and unsupervised. Authors in [82] proposed two different rule-based classification approaches to recognize the most common TVs and laptops patterns usage: Classifier chain algorithm with decision trees (DTs) and classifier chain using bagging (CC2). The work in [84], by considering the consumer behaviour and the dependencies between different appliances, describes a modified Bayesian model to forecast the usage of TV from power consumption data. Lastly, the work in [85] proposes a Radio Frequency Interference (RFI) emissions to recognize the Laptop activity. In particular, an eight-fit Gaussian mixture model and k-peak finder are used for feature extraction from RFI data, followed by activity recognition using k-nearest neighbour classification algorithm.

Appliances	**K/G-M**	**SD**	**FP**	**BNs**	**DTs**	**CC2**	**RFI**
TV	[80]	[79]	[80]	[84]	[82]	[82]	
Laptop	[80]	[79]	[80]		[82]	[82]	[85]

Table 2.2 Brown goods patterns usage recognition techniques: a summary.

2.2.3 Small appliances and lighting

Although this category is the less interesting in terms of flexibility, there exists some works addressing the issue. As an example, the approach proposed in [86] consists of AI tools that, starting from the load measurement data, quantify the use of an electric kettle. Particularly, an adaptive neuro-fuzzy inference system (NFI) is developed to predict the usage of the electric kettle. In [81], an hybrid approach (model-based and data-driven) are developed to understand the lamp and lighting patterns usage. In particular, DTs are considered and evaluated. The work in [83] extracts electric space heaters patterns usage by merging a clustering approach with a filtering approach. Then, the output of this fusion is used as input to a probabilistic methodology. Authors in [82] implement a multi-label k-nearest neighbours (MLk) to recognize and understand electric cooker and lighting patterns usage. Lastly, authors in [87] use the Hidden Markov Model (HMM) to recognize the state of electric kettle, electric space heater, and lamp. In particular, they apply HMMs to appliance signatures for the identification of their category and the most probable sequence of states.

Appliances	**K/G-M**	**NFI**	**DTs**	**CC2**	**MLk**	**HMM**
Electric Kettle		[86]				[87]
Lamp		[81]				[87]
Electric cooker					[82]	
Electric Space Heater	[83]					[87]
Lighting			[81]		[82]	

Table 2.3 Small appliances and lighting patterns usage recognition techniques: a summary.

Chapter 3

Methods

3.1 Performance Improvement in Reconfigurable Industrial Systems

This section in structured as below: the first proposed approach is described in 3.1.1 and the description of the automatic procedures are reported in 3.1.2 and 3.1.3. In 3.1.4 the limits of the first approach are presented and a second methodology is proposed in 3.1.5 as possible solution.

3.1.1 First Proposed Methodology

In a reconfigurable scenario, the main contribution of this thesis (as depicted in Fig. 3.1) is the introduction of an automatic controller parameter tuning methods in the control design phase of a real system. Particularly, when a reference $y^*(t)$ is set in input to the control system, an optimization algorithm automatically runs aiming to find a suitable set of control parameters according to a specific objective function. This objective function to be optimized can be set by the designer depending on the particular desired behaviour and the priorities of the manufacturing process (e.g., tracking error, consumptions, current overshoot minimization or a combination of these). However, for many

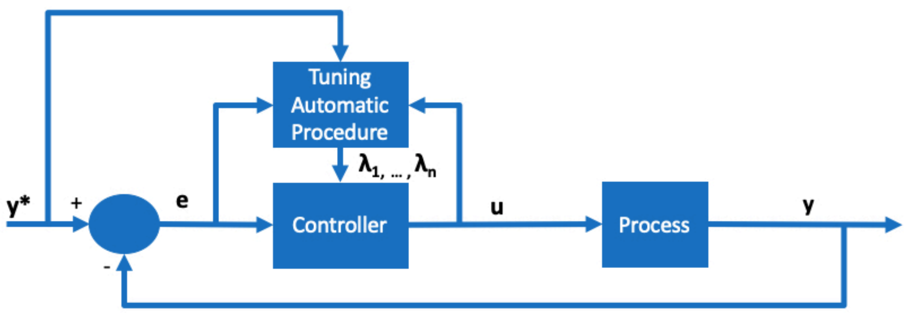


Figure 3.1 Scheme of the first proposed methodology.

control architectures, it is often very difficult to obtain a closed form solution of this optimization problem, then heuristic optimisation techniques, detailed in 3.1.2 and 3.1.3, are adopted. In particular, two different optimisation procedure are implemented: a modified version of the Artificial Bee Colony (ABC) algorithm and the Particle Swarm Optimization (PSO). At the end of the proposed procedure, the best controller found is associated with the set reference and stored in a database.

3.1.2 Artificial Bee Colony Algorithm

Original Version

The ABC algorithm is a meta-heuristic bounded optimisation process inspired by the intelligent foraging behaviour of the bees proposed by Derviş Karaboğa (Erciyes University) [88]. In this algorithm, a possible solution of the problem is represented by the position of a food source in the $\mathbb{R}^{\mathrm{M}}$ space and the nectar amount of the food source represents the fitness of the associated solution. In the ABC, the colony of artificial bees contains three groups of bees: employed bees performing a greedy search on a specific food source, onlooker bees watching the dance of employed bees and choosing a food source based on a probability function, and scout bees searching for food sources randomly. The algorithm is mainly based on five steps.

In the first step, an initial distribution of N random food source positions (i.e., solutions) is generated, where N denotes the size of onlooker bees or employed bees. Each solution $\boldsymbol{x}_i$ $(i = 1, \ldots, N)$ is a vector of M elements, where M represents the number of optimisation parameters. Then the solutions are subject to repeated cycles of the search processes of the employed, onlooker and scout bees. The number of cycles depends on a stop criterion, imposed by the user.

In the second step, employed bees search in the neighbourhood of the previous solution, and test the nectar amount (fitness value) of the new solution (new source). If the nectar amount is higher than that the previous one, the bee memorizes the new position. The search process is repeated by all employed bees. The expression used to produce the *j-th* element of *i-th* newer candidate food position v_i^j is

$$v_i^j = x_i^j + \mathrm{rand}(-1,\,1)\left(x_i^j - x_k^j\right) \tag{3.1}$$

where j and k are randomly chosen indexes according to $k \in \{1, \ldots, N\}$, $j \in \{1, \ldots, M\}$, x_i^j is the *j-th* element of *i-th* older food position and $\mathrm{rand}(-1,\,1)$ returns a single uniformly distributed random number in the interval $(-1,\,1)$. Afterwards, employed bees share their position and nectar information with the onlooker bees.

In the third step, the onlooker bees evaluate the information shared by all employed bees, and choose a food source with a probability proportional to its quality. In order to define the probability function, the structure of the fitness function $F_i(\boldsymbol{x}_i)$ for a minimization problem can be chosen as

$$F_i(\boldsymbol{x}_i) = \begin{cases} \dfrac{1}{1 + f_{\boldsymbol{x}_i}} & f_{\boldsymbol{x}_i} \geq 0 \\ 1 + |f_{\boldsymbol{x}_i}| & f_{\boldsymbol{x}_i} < 0 \end{cases} \tag{3.2}$$

where $f_{\boldsymbol{x}_i}$ is the objective function value of *i-th* solution. The probability value associated with the food source, p_i, is:

$$p_i = \frac{F_i(\boldsymbol{x}_i)}{\sum_{k=1}^{N} F_k(\boldsymbol{x}_k)} \tag{3.3}$$

where $F_i(\boldsymbol{x}_i)$ is the fitness value of the *i-th* solution $\boldsymbol{x}_i$.

As in the case of the employed bees, the onlooker bees evaluate each new position and check its nectar amount. If the nectar is higher than that the previous one, the onlooker bee keeps the new position. The expression to produce the *i-th* newer candidate food position is shown in Eq. (3.1).

In the fourth step, if the nectar of a solution does not improve after the maximum number of trials (*limit*), this solution is deleted and a scout bee is sent randomly onto a possible new food source. The expression to randomly send a bee is

$$x_i^j = x_{\min}^j + \mathrm{rand}(0,\, 1) \left(x_{\max}^j - x_{\min}^j \right) \tag{3.4}$$

where $x_{\min}^j$ and $x_{\max}^j$ are the lower bound and the upper bound of *j-th* parameter respectively, and rand(0, 1) is a function that returns a single uniformly distributed random number in the interval (0, 1).

In the last step, the best food source found so far are memorized.

Changes in the Adapted Version

The main changes applied to the original ABC algorithm are related to the definitions of fitness and probability functions. Regarding the fitness function, it has been chosen as

$$F_i(\boldsymbol{x}_i) = \begin{cases} \dfrac{1}{f_{\boldsymbol{x}_i} + A} + B & 0 \leq f_{x_i} < \sigma_{\max} \\ 0 & f_{x_i} \geq \sigma_{\max} \end{cases} \tag{3.5}$$

where $\sigma_{\max}$ is an upper bound of the objective function. The A and B coefficients can be found imposing $F_i(\boldsymbol{x}_i)|_{f_{\boldsymbol{x}_i}=0} = 1$ and $F_i(\boldsymbol{x}_i)|_{f_{\boldsymbol{x}_i}=\sigma_{\max}} = 0$ and

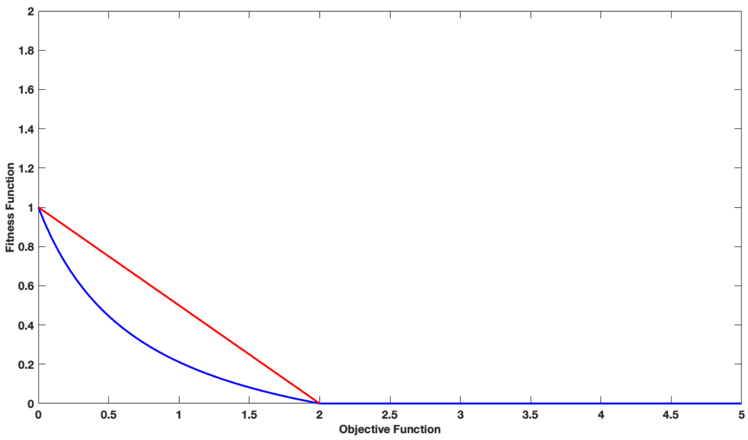


Figure 3.2 Example of Fitness Function according to 3.5 (blue signal) with $\sigma_{\max} = 2$ compared with a Linear Function (red signal).

then solving this linear system

$$\begin{cases} A = -\dfrac{1}{B} - \sigma_{\max} \\ B = 1 - \dfrac{1}{A} \end{cases} \tag{3.6}$$

On the other hand, the probability function has been chosen as

$$p_i = \begin{cases} 0 & F_i(\boldsymbol{x}_i) \leq 0.2 \\ \dfrac{\sqrt{F_i(\boldsymbol{x}_i) - 0.2}}{\sqrt{F_{\max} - 0.2}} & 0.2 < F_i(\boldsymbol{x}_i) < F_{\max} \\ 1 & F_i(\boldsymbol{x}_i) = F_{\max} \end{cases} \tag{3.7}$$

As depicted in Fig. 3.2, the chosen fitness function (in Eq. 3.7) has been preferred to a linear one in order to ensure lower values in the interval $[0, \sigma_{\max}]$. In a similar way, as shown in Fig. 3.3, the probability function has been chosen instead of a linear one so that higher probability values are provided in the interval $[0.2, F_{\max}]$.

3.1.3 Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is a computational method proposed by Kennedy and Eberhart [89] aiming to optimize a problem by iteratively trying to improve a candidate solution according to a given measure of quality. It solves a problem by having a population of candidate solutions (i.e., particles)

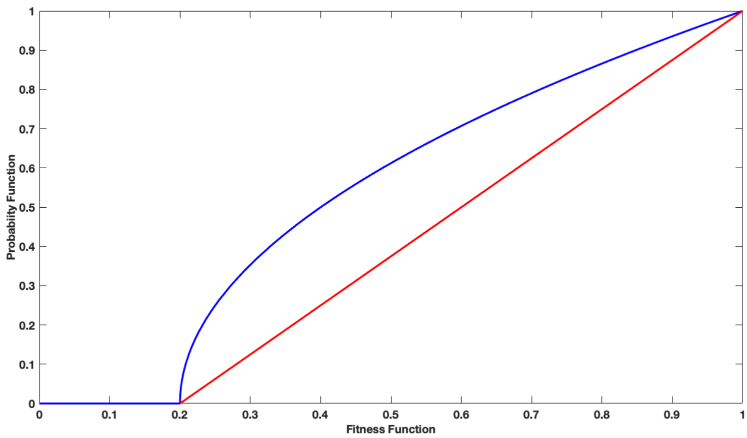


Figure 3.3 Example of Probability Function according to 3.7 (blue signal) with $F_{\max} = 1$ compared with a Linear Function (red signal).

and moving them around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle keeps track of its local best position ($\mathbf{pbest_i}$) and the best position in the search-space (**gbest**), which is updated when other particles find better solutions. In particular, each particle modifies its position according to: i) its current position ii) its current velocity iii) the distance between its current position and $\mathbf{pbest_i}$ and iv) the distance between its current position and **gbest**. This is expected to move the swarm toward the best solutions. In a formal way, let $f : \mathbb{R}^{\mathrm{N}} \Rightarrow R$ an objective function to be minimize, the goal is to find a solution $\mathbf{a}$ for which $f(\mathbf{a}) \leq f(\mathbf{b})$ for all $\mathbf{b}$ in the search-space. Then, $\mathbf{a}$ is the global minimum. By defining

- S: the number of particles in the swarm
- $\mathbf{x_i}$: position of particle s_i
- $\mathbf{v_i}$: velocity of particle s_i
- $\mathbf{b_{lo}}$: search-space lower boundaries
- $\mathbf{b_{up}}$: search-space upper boundaries

it is possible to divide this algorithm in 3 steps. In the first step, the position of the each particle x_i is initialized with an uniformly distributed random vector

$$\mathbf{x_i} \sim U(\mathbf{b_{lo}}, \mathbf{b_{up}})$$

and its $\mathbf{pbest_i}$ is initialized to its initial position $\mathbf{x_i}$. In the second phase, the objective function f is evaluated on each particle's position and the **gbest** is updated. Then, the velocity of each particle $\mathbf{v_i}$ is initialized with an uniformly distributed random vector

$$\mathbf{v_i} \sim U(-|\mathbf{b_{up}} - \mathbf{b_{lo}}|, |\mathbf{b_{up}} - \mathbf{b_{lo}}|)$$

. In the third step, until a termination criteria is not met, these phases are repeated

- the velocity of each particle is updated by using

  $$\mathbf{v_i} \leftarrow \mathbf{v_i} + c_1\text{rand}(0{,}1)(\mathbf{pbest_i} - \mathbf{x_i}) + c_2\text{rand}(0{,}1)(\mathbf{gbest} - \mathbf{x_i})$$

  where c_1 is the weight of local information, c_2 is the weight of global information and rand(0,1) is a random value $\in (0, 1)$

- each particle is moved in a new position through

  $$\mathbf{x_i} \leftarrow \mathbf{x_i} + \mathbf{v_i}$$

- if $f(\mathbf{x_i}) < f(\mathbf{pbest_i})$
  - $\mathbf{pbest_i}$ is updated ($\mathbf{pbest_i} \leftarrow \mathbf{x_i}$)
  - if $f(\mathbf{pbest_i}) < f(\mathbf{gbest})$
    * **gbest** is updated ($\mathbf{gbest} \leftarrow \mathbf{pbest_i}$)

The output of PSO is the **gbest** variable.

3.1.4 Limitations of the First Methodology

Even though the proposed approach can be applied to each industrial system and its efficiency is proven by experimental results, showed in Section 5.1, it has a strong limitation which could compromise the production capacity of the process. Since for each reference set to the control system the controller tuning procedure runs in automatic way, it may use a lot of time and the plant production could suffer a sharp decrease. Then, a trade-off between the optimization time and the production time is needed. Then, a second methodology aiming to find this trade-off is proposed.

3.1.5 Solution: Second Proposed Methodology

As the controller performance strongly depends on the shape of the reference signal provided, it is crucial to quantify the novelty of new references. When

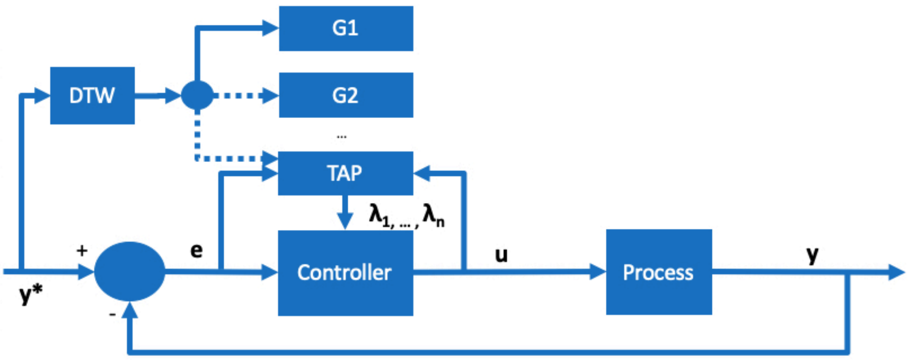


Figure 3.4 Scheme of the second proposed methodology.

a new reference is set to the control system, it is compared with the previous provided reference signals and it is determined whether a stored set of controller parameters set can be applied preserving good performance. As depicted in Fig. 3.4, a control system supervisor is used as "Similarity Detector" in order to evaluate the novelty of the reference signals. In particular, the automatic tuning procedure runs only if the Similarity Detector recognizes the set reference as "novel" (i.e, there is no previous reference similar to it). On the other hand, if the novelty detection strategy finds at least one past reference similar to the set one, the tuning algorithm is not needed and a past controller parameters is used. In order to evaluate the novelty of the reference signals, two techniques have been implemented and compared: Euclidean Distance and Dynamic Time Warping.

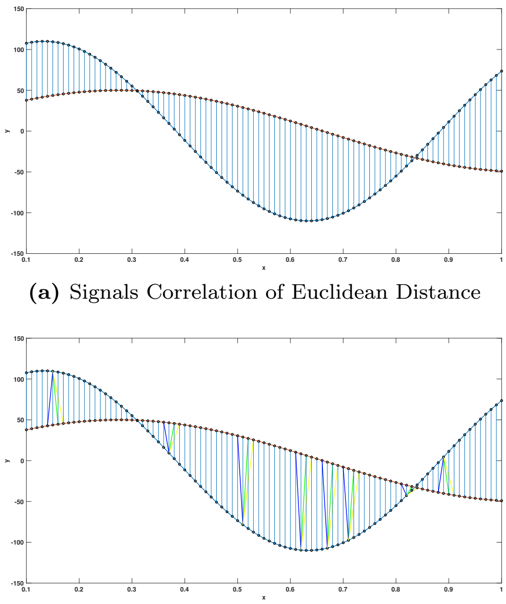
Euclidean Distance

In this technique, given two time-series with the same length $x = [x_1, \cdots, x_n]$ and $y = [y_1, \cdots, y_n]$, the distance measure d between them is computed as follows:

$$d = \sqrt{\sum_{i=0}^{n}(x_i - y_i)^2} \tag{3.8}$$

According to 3.8, it is worth to highlight that this technique relates in an univocal way the i-th point of x with the i-th point of y. For this reason, both signals must have the same sample frequency and the same duration. Furthermore, the value d is related to the number of samples and the amplitude of the signals and, then, it can be normalized as follows:

$$\widetilde{d} = \frac{d}{as} \tag{3.9}$$



(a) Signals Correlation of Euclidean Distance

(b) Signals Correlation of DTW technique

Figure 3.5 Comparison between the proposed similarity detection techniques

where d is the Euclidean distance, a is the maximum amplitude of the reference signal and s is the number of samples.

Dynamic Time Warping

In this second technique, the similarity detection among the new reference signal provided, r, and the past references, r_i is based on the DTW algorithm [90]. DTW returns a distance measure d depending on the difference in the shape, amplitude and frequency of two signals. In particular, the correspondence between the i-th point of x and the i-th point of y is not biunivocal and this entails a more intuitive 'elastic' comparison. In Figure 3.5, a comparison between the proposed techniques in terms of signals correlation is shown. As the previous technique, the value is strongly related to the number of samples and the amplitude of the signals and can be normalized according to 3.9. Moreover, we assume that both signals having the same sample frequency and the same duration (one second).

Similarity value

Both the above described techniques provide a distance measure between two signals. It is possible to convert it into a similarity measure $s \in [0\,,1]$ by using the following equation:

$$s = \frac{1}{1 + k\widetilde{d}} \tag{3.10}$$

where k is a weighting factor. In particular, a greater value of k involves a lower similarity interval and vice-versa. Two signals are assumed similar if the similarity value s exceeds an established threshold (T_1). If the new reference r is not similar to any other signal in the database, then the controller parameters tuning procedure starts and the resulting controller parameter set $\widetilde{c}$ is applied to the process. On the contrary, if there is at least one stored reference signal similar to r, controller parameter sets c_i of each similar signal r_i are evaluated on the reference r. The controller parameter set c_k with the best performance is then selected. Algorithm steps are listed in Algorithm 1.

Algorithm 1: Novelty Detection Algorithm.

foreach *signal in the database* **do**
    Computation of the similarity value s_i among the new reference r and the signals r_i in the database;
end
if $\exists i : s_i > T_1$ **then**
    foreach $i : s_i > T_1$ **do**
        Performance evaluation of the controller c_i applied to the new reference r ;
    end
    Selection of the controller c_k with the best performance $\widehat{f_{x_k}}$;
    Output: Controller c_k;
else
    Controller parameters tuning procedure;
    Output: Controller $\widetilde{c}$ obtained by optimization algorithm;
end

3.2 Home Appliances Pattern Recognition in a Flexibility Scenario

The description of DSF procedure is reported in 3.2.1, while the DSF techniques are described in 3.2.2.

3.2.1 Demand Side Flexibility Procedure

In a flexibility scenario, a two-way communication between the energy supplier and a customer is created. The success of the DSF procedure, depicted in Fig. 3.6, is strongly related to the customer's willingness to act on the electricity consumption and to the estimation of appliance usage patterns. In particular,

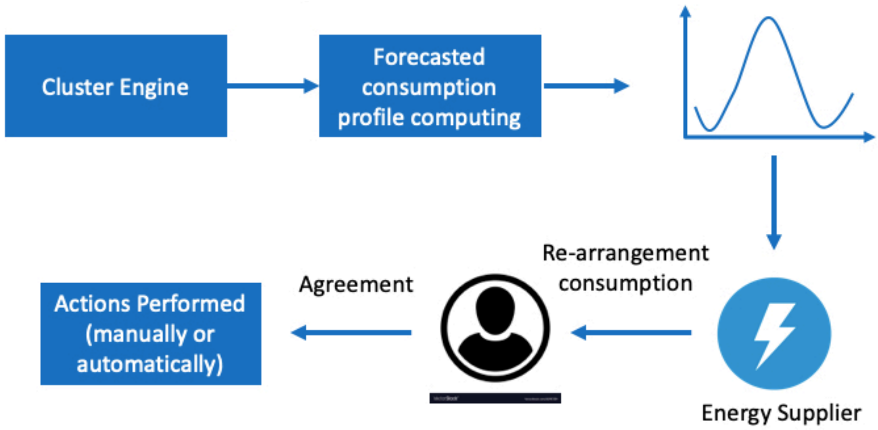


Figure 3.6 DSF Procedure.

once the clusters are found, the whole DSF procedure may be divided in three main stages:

- The output of the first stage is the forecasted consumption profile for a certain user and a certain day. This profile is obtained by: measuring/extracting the appliance profile (averaged for a selected time period e.g., last day, last 5 working days, etc.), computing the membership values by the clustering engine and using these memberships together with the cluster shapes in order to build the final forecasted consumption pattern.

- The forecasted profile can be computed by the energy supplier or by a third party (e.g., the appliance manufacturer in a proprietary cloud). The second stage starts when the energy supplier receives the forecasted profile of the different appliances of the users participating to DSF programs. In this stage the energy supplier may ask users their will to re-arrange consumptions (switching off/shifting/starting appliances in particular time periods) according to the techniques described in Subsection 3.2.2.

- When a user agrees, DSF actions can be performed in two ways: i) the user respects the agreement by manually adjusting its consumptions ii) the technique is automatically carried out by a home energy management system or by a direct remote control of particular appliances.

3.2.2 Residential Flexibility Approaches

Once the appliances usage patterns are properly estimated and recognized, this information, shared with the energy supplier, can enable flexibility actions. The most frequently used techniques, as shown in Fig. 3.7, include peak reduction

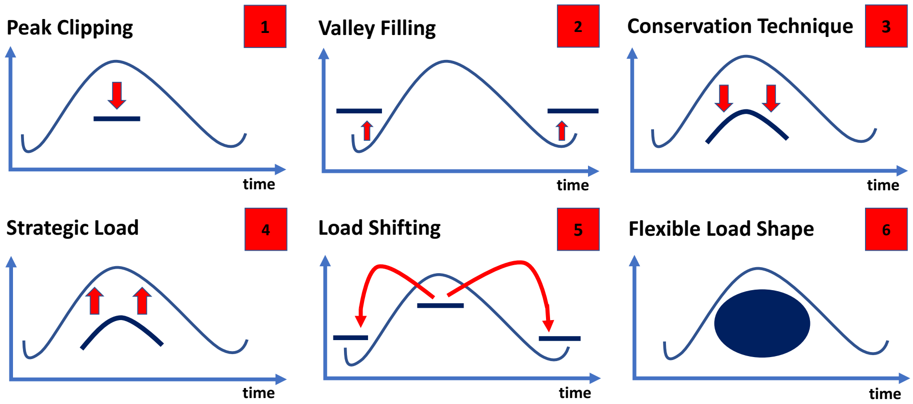


Figure 3.7 The most frequently demand side flexibility used techniques.

techniques, filling valleys, moving tips, conservation strategy, strategic growth, and flexible modelling techniques [91], [92]. These techniques mainly differ in the way the electricity is used. Peak clipping (1) is a basic form of load management and it can be defined as a reduction of a load during peak demand. This technique could be performed by directly controlling consumers energy smart appliances (e.g., turning down the thermostat of heaters and/or increasing the temperature of refrigerators).

This comes hand in hand with another technique, called valley filling (2). In this action, consumption is stimulated during off-peak periods. This strategy may be desirable when the long-term average price is lower than the cost of load building in the off-peak hours. Due to the decrease of the cost of production, the consumer benefits from more favourable price and this contributes to better energy efficiency of the whole system. Various incentives can be executed to motivate consumer to change their energy patterns. This technique can be usually performed through new off-peak electric loads previously relying on other energy networks, such as overnight charging of electric vehicles and thermal energy storage.

Conservation technique (3) is a sort of a reduction in both energy demand and consumption by consumers and it can be done mostly via implementation of new technologies and uptake of energy efficient home appliances (particularly, Heating, Ventilation and Air Conditioning (HVAC) system and pumps) [93]. It is also can be defined as the load shape change occurring from various targeted conservation activities. It is not considered as load management option as it involves a reduction in sales not necessarily accompanied with peak reduction.

Strategic load (4) growth is a strategy aiming to increase the load level, going beyond the valley filling. It also refers to the spontaneous effects of economic growth. To reach this goal it is possible to use electric vehicles and, among existing appliances, a water heating system or HVAC [93]. Other means for increase in energy intensity in industrial and commercial sectors are included.

Load shifting (5) is also one of the classic forms of load management. Its aim, on the other hand, is to shift loads from peak to off-peak period. Space heating and cooling storage as well as domestic hot water storage have a considerable potential to enable load shifting keeping the overall consumption. Moreover, lighting and TV are occasionally recommended to implement this technique.

When it comes to flexible load shape (6), a consumer accepts to limit his energy demand at certain times, depending on the real-time needs and system conditions and includes variability in reliability of energy. This might include the possibility for a utility to interrupt loads if necessary. Regarding this last technique, appliances as Heating and Air Conditioning are the most used. Among the above-mentioned techniques, load management techniques and demand response in particular have become increasingly interesting. This is mostly driven by smart grid system implementation.

The Peak Clipping, Conservation Technique and Valley Filling strategies are traditional load management approaches used by the utilities to altering the load shapes. The utilities provide incentives to target customers for more specific load shape changes to avoid construction of new generation units of relatively low usage at the time of high system loads. Whereas Strategic load, Load Shifting and Flexible Load Shape strategies offer more systematic and large scale changes than the first three and the goal is not only to alter the peak valley structure, but also to change the ways in which electricity is used.

Chapter 4

Case Studies

4.1 Performance Improvement in Reconfigurable Industrial Systems

The approaches described in 3.1.1 and 3.1.5 can be applied to all industrial processes. However, in the high performance applications scenario due to the fourth industrial revolution, the use of Permanent-Magnet Synchronous Motors (PMSMs) and Robot Manipulators has gained more and more importance [94, 95]. In 4.1.1 the mathematical model of a PMSM is described, 4.1.2 explains the implemented control technique, 4.1.3 the joint model of a robot manipulator and its control architecture are presented while in 4.1.4 the settings of the optimization algorithms are specified.

4.1.1 Process: Permanent Magnets Synchronous Motor (PMSM)

According to the Park Transform, in the $(d,\, q)$ reference frame, synchronously rotating with the rotor of the motor, the PMSM electrical equations of motion can be written as [96]

$$\frac{\mathrm{d}\, i_d}{\mathrm{d}\, t} = -\frac{R}{L} i_d + \omega_e i_q + \frac{1}{L} u_d \tag{4.1}$$

$$\frac{\mathrm{d}\, i_q}{\mathrm{d}\, t} = -\frac{R}{L} i_q - \omega_e i_d - \frac{1}{L} \lambda_0 \omega_e + \frac{1}{L} u_q \tag{4.2}$$

where i_d and i_q are the $d - axis$ and $q - axis$ stator currents, respectively; u_d and u_q are the $d - axis$ and $q - axis$ stator voltages, respectively; R is the winding resistance and $L = L_d = L_q$ is the winding inductance on axis d and q; λ_0 is the flux linkage of the permanent magnet and ω_e is the electrical angular rotor speed. The electrical torque τ_e and the mechanical power P of the motor are given by

$$\tau_e = K_t i_q \tag{4.3}$$

$$P = \tau_e \omega_r \tag{4.4}$$

where $K_t = \frac{3}{2}\lambda_0 N_r$ is the torque constant, with N_r the number of pole pairs and ω_r is the mechanical angular rotor speed. The developed torque of the motor is proportional to the i_q current due to the assumption that there is no reluctance torque in the considered PMSM.

The mechanical motion equation of the PMSM motor is described by:

$$J\frac{\mathrm{d}\,\omega_r}{\mathrm{d}\,t} + B\omega_r = \tau_e - \tau_\ell \tag{4.5}$$

$$\frac{\mathrm{d}\,\theta_r}{\mathrm{d}\,t} = \omega_r \tag{4.6}$$

where J is the mechanical inertia of the motor and load, B is the coefficient of viscous friction, τ_ℓ is the load torque and θ_r denotes the mechanical angular rotor position.

For the electrical angular and mechanical angular position/speed, these relations hold: $\omega_e = N_r\omega_r$ and $\theta_e = N_r\theta_r$.

Discretized Model

The PMSM continuous-time model in the (d, q) reference-frame, is composed by Eqs. (4.1)-(4.6). The discretization of this model is based on the choice of a suitable sampling time T_c and, according to the well-known techniques [97], gives these equations:

$$\omega_e(k+1) = A_\omega\omega_e(k) + B_\omega(K_t i_q(k) - \tau_\ell) \tag{4.7}$$

$$i_d(k+1) = A_i i_d(k) + B_i u_d(k) + f_1(\omega_e, i_q, k) \tag{4.8}$$

$$i_q(k+1) = A_i i_q(k) + B_i u_q(k) - f_2(\omega_e, i_d, k) \tag{4.9}$$

where

$$A_\omega = e^{-\frac{B}{J}T_c} \qquad B_\omega = \frac{1}{J}\int_0^{T_c} e^{-\frac{B}{J}\tau}\,d\tau$$

$$A_i = e^{-\frac{R}{L}T_c} \qquad B_i = \frac{1}{L}\int_0^{T_c} e^{-\frac{R}{L}\tau}\,d\tau$$

$$f_1(\omega_e, i_q, k) = \int_{kT_c}^{(k+1)T_c} \omega_e(\tau)i_q(\tau)\,d\tau \simeq \omega_e(k)i_q(k)T_c$$

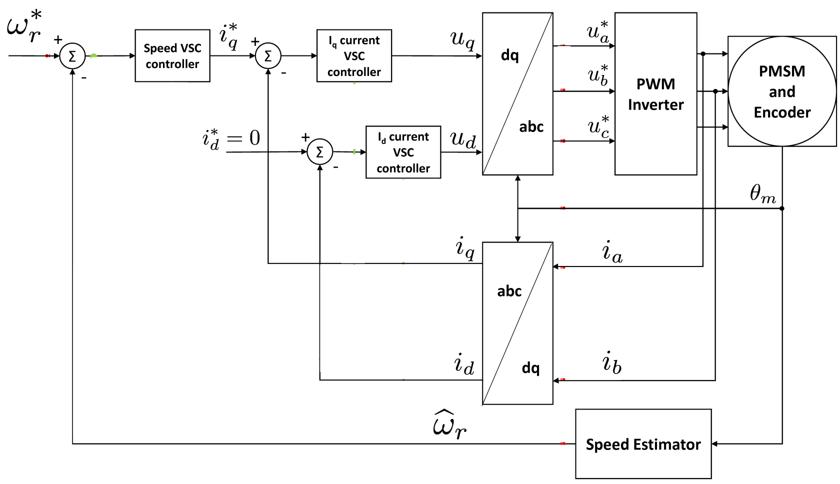


Figure 4.1 Scheme of the FOC technique.

$$f_2(\omega_e, i_d, k) = \int_{kT_c}^{(k+1)T_c} \omega_e(\tau) \left(i_d(\tau) + \frac{\lambda_0}{L} \right) d\tau \simeq \omega_e(k) \left(i_d(k) + \frac{\lambda_0}{L} \right) T_c$$

To consider possible model uncertainties, it is assumed that model parameters may differ from their nominal values only for some bounded quantities:

$$\begin{aligned} A_\omega &= \bar{A}_\omega + \Delta A_\omega & B_\omega &= \bar{B}_\omega + \Delta B_\omega \\ |\Delta A_\omega| &\leq \rho_{A_\omega} & |\Delta B_\omega| &\leq \rho_{B_\omega} \\ A_i &= \bar{A}_i + \Delta A_i & B_i &= \bar{B}_i + \Delta B_i \\ |\Delta A_i| &\leq \rho_{A_i} & |\Delta B_i| &\leq \rho_{B_i} \end{aligned} \tag{4.10}$$

where $\bar{A}_\omega$, $\bar{B}_\omega$, $\bar{A}_i$ and $\bar{B}_i$ are the nominal values, while ΔA_ω, ΔB_ω, ΔA_i and ΔB_i are their uncertainties which are bounded by the constants ρ_{A_ω}, ρ_{B_ω}, ρ_{A_i} and ρ_{B_i}, respectively.

4.1.2 Control Technique: Variable Structure Control (VSC) Discrete

Fig. 4.1 shows the control architecture of a PMSM, called Field-Oriented Control (FOC). In particular, the speed controller generates the control effort i_q^* which must be applied to the motor to track the desired speed reference ω_e^*. Since the control effort on the q-axis current can not be directly applied to the motor, it is used as a reference to a cascade internal I_q current controller, whose task is to generate the control effort on the q-axis voltage. The u_q reference can be applied to the motor via $dq - abc$ transformation and PWM inverter.

Actually, most of the PMSM systems used in industrial applications, are controlled with Proportional - Integral (PI) or Proportional - Integral - Derivative (PID) controllers [98]. In order to evaluate the efficiency of the proposed approaches an alternative and advanced methodology ensuring robustness to the system is used: the Variable Structure Control (VSC) with quasi-sliding mode. VSC has been applied with very promising results to electric servo motors [99], permanent-magnet synchronous motors [100] and induction motor drives [101]. Although the sliding mode control is well established for continuous-time control systems [102], in the last decades researchers focused their attention on the implementation of discrete sliding mode in commercial Digital Signal Processors (DSPs) [103].

For each FOC controller, a second-order discrete-time sliding surface has been defined as below:

$$\begin{split} s_\omega(k) = \big(\hat{\omega}_e(k) - \omega_e^*(k)\big) + c_{11}\big(\hat{\omega}_e(k-1) - \omega_e^*(k-1)\big) + \\ + c_{12}\big(\hat{\omega}_e(k-2) - \omega_e^*(k-2)\big) \end{split} \tag{4.11}$$

$$\begin{split} s_{iq}(k) = \big(i_q(k) - i_q^*(k)\big) + c_{21}\big(i_q(k-1) - i_q^*(k-1)\big) + \\ + c_{22}\big(i_q(k-2) - i_q^*(k-2)\big) \end{split} \tag{4.12}$$

$$s_{id}(k) = i_d(k) + c_{31} i_d(k-1) + c_{32} i_d(k-2) \tag{4.13}$$

where $\hat{\omega}_e(k)$ is the estimation of $\omega_e(k)$ provided by a speed estimator block (which is usually a simple encoder position difference block over one sampling period of the speed control loop), $\omega_e^*(k)$ is the given reference value for the angular velocity, whereas $i_q^*(k)$ is the reference value for the i_q current, which is provided by the speed controller. Now, let define the following parameters:

$$\begin{aligned} c_{11} &= -(\lambda_{11} + \lambda_{12}) \\ c_{12} &= \lambda_{11}\lambda_{12} \\ c_{21} &= -(\lambda_{21} + \lambda_{22}) \\ c_{22} &= \lambda_{21}\lambda_{22} \\ c_{31} &= -(\lambda_{31} + \lambda_{32}) \\ c_{32} &= \lambda_{31}\lambda_{32} \end{aligned} \tag{4.14}$$

where λ_{11}, λ_{12}, λ_{21}, λ_{22}, λ_{31} and λ_{32} are the roots of sliding surfaces defined in Eqs. (4.11), (4.12) and (4.13).

A quasi sliding motion on the surface $s_\omega(k) = 0$ can be achieved if

$$\lim_{k\to+\infty} s_\omega(k) = 0 \tag{4.15}$$

which can be satisfied by imposing

$$|s_\omega(k+1)| < |s_\omega(k)| \tag{4.16}$$

and, defining $\Delta s_\omega(k+1) = s_\omega(k+1) - s_\omega(k)$, this relation can be obtained

$$s_\omega(k)\Delta s_\omega(k+1) < -\frac{1}{2}\Delta s_\omega^2(k). \tag{4.17}$$

It can be verified that this condition is ensured by the control law $i_q^*(k) = i_q^{eq}(k) + i_q^n(k)$, where the equivalent control is given by:

$$\begin{aligned} i_q^{eq}(k) = \frac{1}{\bar{B}_\omega}\Big[\omega_e^*(k) - \bar{A}_\omega\hat{\omega}_e(k) - c_{11}\Big(\hat{\omega}_e(k) - \omega_e^*(k)\Big)+ \\ - c_{12}\Big(\hat{\omega}_e(k-1) - \omega_e^*(k-1)\Big)\Big] \end{aligned} \tag{4.18}$$

The discontinuous control i_q^n is such that the sliding condition can be imposed exactly outside a given sector, while inside such sector the sliding condition can be imposed only approximately. This can be improved adopting the approach known as Time Delay Control, obtaining

$$i_q^n(k) = \begin{cases} -\dfrac{s_\omega(k) - \bar{B}_\omega i_q^n(k-1)}{\bar{B}_\omega} & |s_\omega(k)| \le \rho_\omega \\ \theta_\omega \dfrac{|s_\omega(k)| - \rho_\omega}{\bar{B}_\omega} & |s_\omega(k)| > \rho_\omega \end{cases} \tag{4.19}$$

where $|\theta_\omega|$ is an auxiliary variable and

$$\rho_\omega(\rho_{B_\omega}, \rho_{A_\omega}) = \left(|\bar{B}_\omega| + \rho_{B_\omega}\right)\rho_\tau + \rho_{A_\omega}\omega_e^{\max} + \rho_{B_\omega} i_q^{\max} \tag{4.20}$$

is the maximum value of the system uncertainty. It is important to note that $\omega_e^{\max}$ and $i_q^{\max}$ are the largest speed achievable by the motor and the largest current, respectively, which can be supplied depending on its constructive limits. The control law $i_q^*(k)$ is fed as reference value, which is the required motor torque, to one of the two inner current control loops. The tracking of such reference is ensured imposing a quasi sliding motion on the surface $s_{iq}(k) = 0$. Following the same lines as before, it can be verified that the sliding condition on $s_{iq}(k) = 0$ is ensured by the control law $u_q(k) = u_q^{eq}(k) + u_q^n(k)$, where:

$$u_q^{eq}(k) = \frac{1}{\bar{B}_i}\Big[i_q^*(k) - \bar{A}_i i_q(k) - c_{21}\Big(i_q(k) - i_q^*(k)\Big) + - c_{22}\Big(i_q(k-1) - i_q^*(k-1)\Big)\Big] \quad (4.21)$$

and

$$u_q^n(k) = \begin{cases} -\dfrac{s_{iq}(k) - \bar{B}_i u_q^n(k-1)}{\bar{B}_i} & |s_{iq}(k)| \leq \rho_q \\ \theta_q \dfrac{|s_{iq}(k)| - \rho_q}{\bar{B}_i} & |s_{iq}(k)| > \rho_q \end{cases} \quad (4.22)$$

where $|\theta_q|$ is an auxiliary variable and the maximum uncertainty value of this subsystem is given by

$$\rho_q(\rho_{B_i}, \rho_{A_i}) = \rho_{A_i} i_q^{\max} + \rho_{B_i} u_q^{\max} + \rho + \omega_e^{\max}\left(i_d^{\max} + \frac{\lambda_0}{L}\right) T_c \quad (4.23)$$

Finally, the achievement of a quasi sliding motion on $s_{id}(k) = 0$ guarantees the vanishing of the variable $i_d(k)$, and is ensured by the following control law:

$$u_d^{eq}(k) = -\frac{(\bar{A}_i + c_{31}) i_d(k) + c_{32} i_d(k-1)}{\bar{B}_i} \quad (4.24)$$

and

$$u_d^n(k) = \begin{cases} -\dfrac{s_{id}(k) - \bar{B}_i u_d^n(k-1)}{\bar{B}_i} & |s_{id}(k)| \leq \rho_d \\ \theta_d \dfrac{|s_{id}(k)| - \rho_d}{\bar{B}_i} & |s_{id}(k)| > \rho_d \end{cases} \quad (4.25)$$

where $|\theta_d|$ is an auxiliary variable and

$$\rho_d(\rho_{B_i}, \rho_{A_i}) = \rho_{A_i} i_d^{\max} + \rho_{B_i} u_d^{\max} + \omega_e^{\max} i_q^{\max} T_c \quad (4.26)$$

is the maximum uncertainty value of this subsystem.

4.1.3 Process: Joint Model of a Robot Manipulator

A robotic manipulator is a mechanism composed by a chain of rigid bodies, the links, connected by N joints. As shown in Fig 4.2, each robotic joint is composed by a rigid rod (of negligible mass) and it is driven by an electric motor place in point P. At the end of the rod, a mass load M is placed. The electric motor in P generates a torque that is reflected in the application of the force $f(t)$ on the mass M. By defining

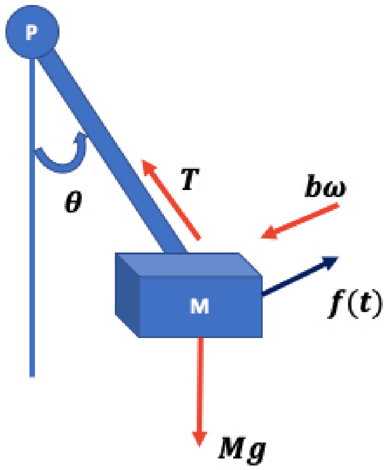


Figure 4.2 Example of robotic joint.

- θ, angular position
- $\omega = \dot{\theta}$, angula velocity
- $\alpha = \dot{\omega} = \ddot{\theta}$, angular acceleration
- $f(t)$, the torque generated by the motor and applied to the mass
- T, constraint reaction of the rod
- $b\omega = b\dot{\theta}$, air friction
- Mg, the weight force

the equations of the joint model are

$$T = Mg\cos(\theta)$$

and

$$f - Mg\sin(\theta) - b\omega = M\alpha$$

. From a control system point of view, the most important equation is the second one. By introducing the angular velocity $\omega = \dot{\theta}$, we obtain

$$f - Mg\sin(\theta) - b\omega = M\dot{\omega}$$

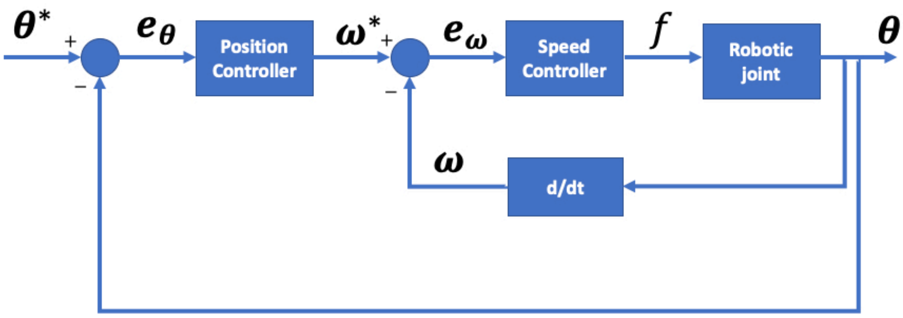


Figure 4.3 Robotic joint control scheme.

. After discretizing the model with a suitable sampling time T_c, the following equation is obtained

$$f(k) - Mg\sin(\theta(k)) - b\omega(k) = M\frac{\omega(k+1) - \omega(k)}{\Delta T_c}$$

From these equation, the discretized joint model is given by

$$\omega(k+1) = \omega(k) - g\Delta T_c \sin(\theta(k)) - \frac{b\Delta T_c}{M}\omega(k) + \frac{\Delta T_c}{M} f(k) \quad (4.27)$$

$$\theta(k+1) = \theta(k) + \Delta T_c \omega(k) \quad (4.28)$$

The most common control scheme used for a robotic joint is shown in Fig 4.3. It is composed by two kinds of control: the external controller is related to the position, while the inner controller is related to the velocity. In industrial applications, both of these controllers are usually implemented as PIs or PIDs.

4.1.4 Optimization Algorithms Settings

Parameters Bounds

A solution of the tuning optimization algorithm is composed of N bounded parameters, i.e., the roots of the sliding surfaces, the auxiliary variables and the maximum value of the uncertainties affecting the system. In order to guarantee the stability of their surfaces, the roots of the sliding surfaces, namely λ_{11}, λ_{12}, λ_{21}, λ_{22}, λ_{31} and λ_{32}, have to be in range $(-1, 1)$. The auxiliary variables (θ_ω, θ_q and θ_d), introduced in the definition of the control laws, allow to choose suitable values for $i_q^n(k)$, $u_q^n(k)$ and $u_d^n(k)$, respectively, as defined in Eqs. (4.19), (4.22) and (4.25), and they vary in $[-1, 1]$. It is assumed that model uncertainties ρ_{A_ω}, ρ_{B_ω}, ρ_{A_i} and ρ_{B_i}, introduced in Eq. (4.10), may vary between 1% and 20% with respect to their nominal values. Consequently, ρ_ω

bounds are $[\rho_{\omega_{\min}}, \rho_{\omega_{\max}}]$ computed according to Eq. (4.20)

$$\rho_{\omega_{\min}} \triangleq \rho_\omega(\rho_{B_{\omega_{\min}}}, \rho_{A_{\omega_{\min}}}) \tag{4.29}$$

$$\rho_{\omega_{\max}} \triangleq \rho_\omega(\rho_{B_{\omega_{\max}}}, \rho_{A_{\omega_{\max}}}). \tag{4.30}$$

Upper and lower bound for ρ_q and ρ_d can be computed according to Eq. (4.23) and Eq. (4.26)

$$\rho_{q_{\min}} \triangleq \rho_q(\rho_{B_{i_{\min}}}, \rho_{A_{i_{\min}}}) \tag{4.31}$$

$$\rho_{q_{\max}} \triangleq \rho_q(\rho_{B_{i_{\max}}}, \rho_{A_{i_{\max}}}) \tag{4.32}$$

$$\rho_{d_{\min}} \triangleq \rho_d(\rho_{B_{i_{\min}}}, \rho_{A_{i_{\min}}}) \tag{4.33}$$

$$\rho_{d_{\max}} \triangleq \rho_d(\rho_{B_{i_{\max}}}, \rho_{A_{i_{\max}}}) \tag{4.34}$$

Tuning Algorithm Settings

The FOC technique proposed in this paper has been implemented using variable structure (sliding mode) controllers, shown in Fig. 4.1. Each controller has four parameters which have to be optimized by the ABC algorithm procedure, that are:

$$\begin{aligned} \boldsymbol{\omega}_c &\triangleq [\lambda_{11} \;\; \lambda_{12} \;\; \theta_\omega \;\; \rho_\omega] \\ \boldsymbol{i}_{q_c} &\triangleq [\lambda_{21} \;\; \lambda_{22} \;\; \theta_q \;\; \rho_q] \\ \boldsymbol{i}_{d_c} &\triangleq [\lambda_{31} \;\; \lambda_{32} \;\; \theta_d \;\; \rho_d] \end{aligned} \tag{4.35}$$

The solution $\boldsymbol{x}$ of the optimisation problem is defined by

$$\boldsymbol{x} \triangleq [\boldsymbol{\omega}_c \;\; \boldsymbol{i}_{q_c} \;\; \boldsymbol{i}_{d_c}] \tag{4.36}$$

Even though the focus of this thesis is on the energy management, in control applications the tracking performance are not negligible. For this reason, the objective function to minimize has been chosen as

$$f_{\boldsymbol{x}} = K_1 \frac{IAE}{IAE_m} + K_2 \frac{IAU}{IAU_m} \tag{4.37}$$

where IAE and IAU are the actual Integral Absolute Error and the Integral Absolute Control Action, normalized by the same indexes obtained by using the PIDs manufacturer controller (namely IAE_m and IAU_m). In particular, IAE is defined as

$$IAE = \int_0^t |e(\tau)| \, d\tau \tag{4.38}$$

where $e(\tau)$ is the tracking error between the speed reference and the estimated velocity, namely $e(\tau) = \hat{\omega}_e(\tau) - \omega_e^*(\tau)$. The IAU index, instead, is defined as

$$IAU = \int_0^t |u(\tau)|\, d\tau \tag{4.39}$$

where $u(\tau)$ is the control effort value, which correspond to the i_q current, namely $u(\tau) = i_q(\tau)$. K_1 and K_2 are two factors (with $K_1 < K_2$ and $K_1 + K_2 = 2$) which permit to weigh the importance of tracking performances and energy consumption in the tuning procedure. In this case, $K_1 = 0.95$ and $K_2 = 1.05$ are fixed. Generally, it is possible to opt for a different objective function according to the desired features to minimize. As an example, if the optimization procedure needs to focus on reducing steady state oscillations rather than decreasing rise time and overshoot, one can consider the Integral Time Absolute Error (ITAE) instead of IAE.

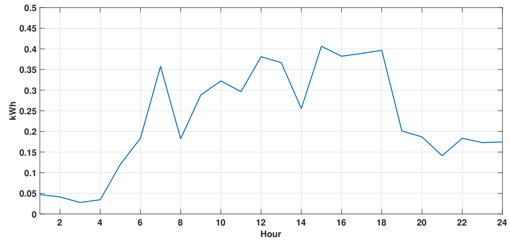
Regarding the ABC algorithm, in Eq. (3.6), τ_{max} is set equal to 2 (i.e. the objective function value when $IAE = IAE_m$ and $IAU = IAU_m$) and, consequently, the A and B values are $A = -1 + \sqrt{3}$ and $B = \frac{1}{2} - \frac{\sqrt{3}}{2}$.

The stop criterion used for both algorithms is based on the elapsed time by defining a suitable $time_{max}$. This value indicates the time the tuning procedure runs. Obviously, with a higher value of $time_{max}$ there are further possibilities to obtain a solution with a better objective function value and vice versa. At the end of the tuning procedure, the best solution found is stored in the database, together with its relative reference signal r and the objective function value f_x, and applied to the motor. Lastly, in the Algorithm 1, $T_1 = 80\%$ is used and in Eq. (3.10) $k = 1$ is set.

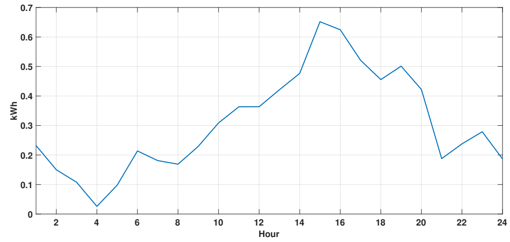
4.2 Home Appliances Pattern Recognition in a Flexibility Scenario

Although electric boilers may have a considerable flexibility potential, to the best of our knowledge, a reliable approach to extract their usage patterns has not been investigated in literature. Generally, the water temperature of electric boilers is kept at a set-point of 70 ° C. However, by knowing the usage patterns, it is possible to set the lowest required temperature ensuring consumer's comfort and use the electric boiler as a thermal storage.

In the following a case study to extract and forecast an average real-life usage pattern for electric boilers is presented.



(a)



(b)

Figure 4.4 Example of electric boiler energy consumption: weekday (a); weekend (b).

4.2.1 Electric Boilers Data

Data were collected by 38 electric boilers with a volume of 80 litres, installed in Italy and used by families composed on average by 3.3 people and standard deviation 1.1. The boilers are located in cities (of 200k to 500k inhabitants) ranging from 44° north latitude to 38° north latitude, situated not over 300 meters above the sea level and belonging to the same Mediterranean climate regime. Particularly, the geographical distribution of the electric boilers is 15 electric boilers installed in the north of Italy, 10 in the center and the remaining 13 in the south. Data were acquired by a smart meter and stored in a cloud for processing. The sampling time is 1 minute and the data acquisition campaign lasted for 11 months from January to November 2018. Among all the signals acquired, energy consumption is the most significant for the goal to be achieved.

Figure 4.4 shows an example of daily electric boiler energy consumption on a weekday 4.4(a) and 4.4(b) on weekend.

4.2.2 Fuzzy C-Means (FCM)

In order to analyse the behaviour of the users, we adopted the clustering technique Fuzzy C-means (FCM), which was proposed by [104] and it is frequently used in pattern recognition problems [105]. FCM is based on the minimization of the following objective function:

$$J_p = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^p \|\boldsymbol{x}_i - \boldsymbol{c}_j\|^2 \tag{4.40}$$

where N is the number of data points, C is the number of clusters, $\boldsymbol{x}_i$ is the i-th d-dimensional data point, $\boldsymbol{c}_j$ is d-dimensional center of the j-th cluster, p is the fuzziness index for controlling the degree of fuzzy overlap, with $1 < m < \infty$ and μ_{ij} is the degree of membership of $\boldsymbol{x}_i$ in the j-th cluster. The FCM is considered to extract the clusters regarding the daily consumption profile that most represent the usage of the electric boilers. The acquired power supply of each electric boiler was processed to calculate the energy with 24 discretized steps of 1 hour and the data was divided into two datasets regarding the daily energy consumption during weekdays and holidays. The optimal number of clusters is two and it was set considering p=1.4 and using the well-known Xie-Beni fuzzy clustering validity index [106].

4.2.3 Fuzzy Gustafson-Kessel Algorithm (GK)

Gustafson and Kessel [107] extended the standard FCM algorithm by employing an adaptive distance norm, in order to detect clusters of different geometrical shapes in one data set. Each cluster has its own norm inducing matrix $\mathbf{A}_j$, which yields the following inner-product norm:

$$D_{ij\mathbf{A}_j}^2 = (\mathbf{x}_i - \mathbf{c}_j)^T \mathbf{A}_j (\mathbf{x}_i - \mathbf{c}_j)$$

The matrices $\mathbf{A}_j$ are used as optimization variables in the c-means functional, thus allowing each cluster to adapt the distance norm to the local topological structure of the data. The objective functional of the GK algorithm is defined by

$$J_p = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^p D_{ij\mathbf{A}_j}^2 \tag{4.41}$$

This objective function cannot be directly minimized with respect to $\mathbf{A}_j$, since it is linear in $\mathbf{A}_j$. To obtain a feasible solution, $\mathbf{A}_j$ must be constrained in some way. The usual way of accomplishing this is to constrain the determinant of $\mathbf{A}_j$:

$$|\mathbf{A}_j| = \rho_j > 0 \; \forall j$$

Allowing the matrix $\mathbf{A}_j$ to vary with its determinant fixed corresponds to optimizing the cluster's shape while its volume remains constant. By using the

Lagrange-multiplier method, the following expression for $\mathbf{A}_j$ is obtained:

$$\mathbf{A}_j = [\rho_j \det(\mathbf{F}_j)^{\frac{1}{C}}]\mathbf{F}_j^{-1}$$

where $\mathbf{F}_j$ is the fuzzy covariance matrix of the j-*th* cluster given by

$$\mathbf{F}_j = \frac{\sum_{i=1}^{N} \mu_{ij}^p (\mathbf{x}_i - \mathbf{c}_j)(\mathbf{x}_i - \mathbf{c}_j)^T}{\sum_{i=1}^{N} \mu_{ij}^p}$$

4.2.4 Comparison and Comments

The GK algorithm is computationally more involved than FCM, since the inverse and the determinant of the cluster covariance matrix must be calculated in each iteration. For this reason, although the GK algorithm has a great advantage against the other clustering algorithms as it adapts the clusters according to the real shape of the cluster, FCM is chosen for the proposed case study. In this context, by knowing the user's energy usage patterns, an electricity supplier may request the user (or remotely control the boiler) to shift from one pattern to another, always maintaining the lowest required temperature to ensure consumers comfort.

Chapter 5

Results

5.1 Performance Improvement in Reconfigurable Industrial Systems

This section is structured as the following: in 5.1.1 and 5.1.2 the experimental protocol is described, while in 5.1.3 and 5.1.4 the results of the two proposed methodology are respectively reported.

5.1.1 Hardware Setup

The hardware setup used to evaluate the proposed approaches is composed of an external PC imposing the speed reference to the motor and the Technosoft MCK28335-Pro DSP motion control kit [108]. It is available in the Robotics Laboratory at the Department of Information Engineering of Università Politecnica delle Marche (Italy). This motion control kit includes a DSP-based controller board, a PM50 power module, a PMS motor equipped with an encoder and a software platform developing motion control applications. In particular, the Similarity Detector has been implemented in the PC, while the Controller Parameter Tuning Procedure has been carried out on the motion control kit. The controller board is based on the high-performance Texas Instruments DelfinoTM TMS320F28335 DSP motion controller [109]. The power module includes a three-phase inverter, the protection circuits and the measurement circuits for the DC-bus voltage and the motor currents. The PC and DSP communicate through the RS-232 interface using a serial communication monitor located in the DSP flash. The chosen experimental setup is commonly used in rapid prototyping scenarios, as it permits to easily deploy (and test) control laws on real PMSM motors [110]. The experimental setup is shown in Fig. 5.1.

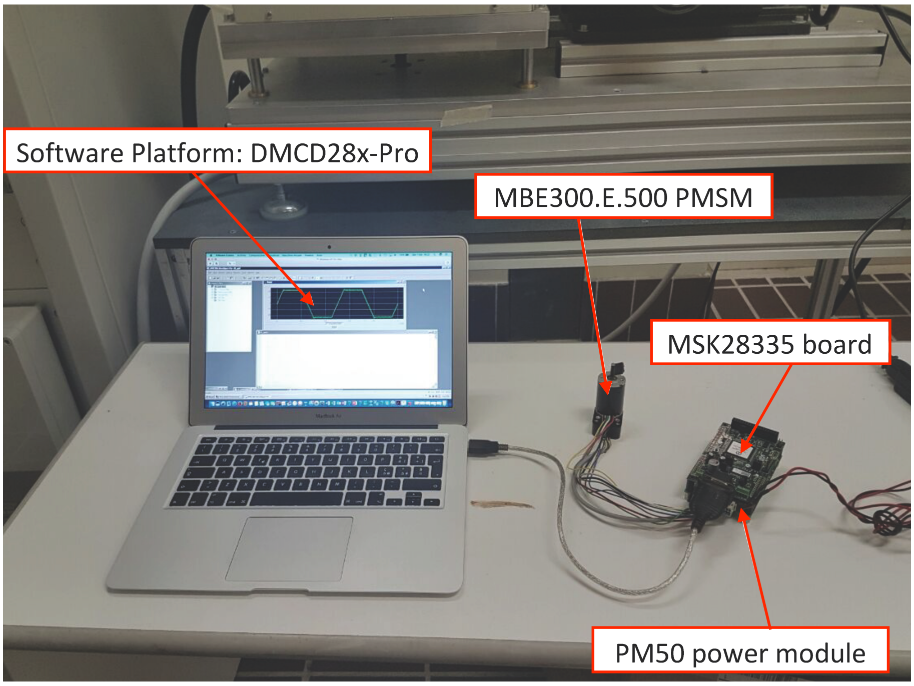


Figure 5.1 Hardware setup.

5.1.2 Experimental Settings

Experimental tests have been performed by taking into account different reference signals: square, sine and trapezoidal waves at the frequency of 1 Hz and 2 Hz and amplitude of 110 rad/s, which are common for this kind of motor applications. However, different values could be chosen keeping similar results. One of the main advantages of the proposed architecture is that the parameters can be easily tuned when the reference signal changes (both in shape, frequency and amplitude), and the overall performances are kept to near-optimal values. In order to evaluate the efficiency of the proposed methodology, a comparison between the performance (according to IAE and IAU) of tuned and manufacturer controllers on the above-mentioned references is performed. The original PMSM manufacturer controller is composed by three PI regulators for the speed and current. PIs are designed and tuned using a frequency technique, as typically performed in industrial scale, and the proportional and integral gains

Controller	K_{p_ω}	K_{i_ω}	K_{p_q}	K_{i_q}	K_{p_d}	K_{i_d}
Manufacturer	170.16	30.38	14.94	0.95	14.94	0.95

Table 5.1 Parameters of manufacturer PI controllers.

Parameter	Value
Optimisation parameters (M)	12
Number of food sources (N)	5
Limit cycle to abandon a food source (*limit*)	5
Time limit ($time_{max}$) [minutes]	5

Table 5.2 ABC algorithm parameters.

are:

$$\begin{aligned} K_{p_\omega} &= \frac{2\theta_s\omega_s - a_s}{b_s} \\ K_{i_\omega} &= \frac{\omega_s^2 h_s}{b_s} \\ K_{p_q} &= \frac{2\theta_c\omega_c - a_c}{b_c} \\ K_{i_q} &= \frac{\theta_c h}{b_c} \end{aligned} \tag{5.1}$$

where θ_s and ω_s are the damping factor and the passband of the closed loop transfer function of the speed system, respectively. Moreover, θ_c and ω_c are the damping factor and the passband of the closed loop transfer function of the current system, respectively. Finally, a_s, b_s, a_c and b_c are parameters which depend on the physical structure of the system. The two current controllers have the same gains. Furthermore, each controller obtained by the tuning procedure is named with the reference signal employed during the tuning phase (i.e. 'Square 1' is the controller obtained by the tuning algorithm when the reference is a square wave with amplitude of 110 rad/s at frequency of 1 Hz.), instead the controller named 'Manufacturer' is the one provided by the motor manufacturer. Table 5.1 reports the parameters value of the manufacturer controller.

5.1.3 First Proposed Methodology

Artificial Bee Colony

The ABC tuning algorithm parameters are shown in Table 5.2 while the parameters of each ABC-optimized controller are reported in Table 5.3. The first

Parameter	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
λ_{11}	0.27	0.38	0.55	0.65	0.60	0.57
λ_{12}	0.13	0.29	0.87	0.59	0.85	0.81
λ_{21}	0.40	0.13	0.88	0.91	0.95	0.65
λ_{22}	0.56	0.51	0.86	0.72	0.47	0.86
λ_{31}	0.31	0.31	0.41	0.64	0.90	0.86
λ_{32}	0.71	0.35	0.67	0.23	0.95	0.61
ρ_ω	0.5	1.22	14.28	11.45	17.91	18.67
ρ_q	3.16	2.04	4.06	0.73	4.68	1.33
ρ_d	4.20	2.80	3.48	0.53	3.6	1.34
θ_ω	-0.18	-0.02	0.45	0.37	-0.49	0.68
θ_q	-0.14	0.83	-0.21	-0.83	0.68	-0.11
θ_d	-0.39	-0.88	-0.89	0.66	0.12	0.23

Table 5.3 Parameters of ABC-tuned VSC controllers.

term of the objective function value (Eq. 4.37) is reported in Tab. 5.4, while the second term is reported in Tab. 5.5.

Particle Swarm Optimization

The PSO tuning algorithm parameters are shown in Table 5.6 while the parameters of each PSO-optimized controller are reported in Table 5.7. The first term of the objective function value (Eq. 4.37) is reported in Tab. 5.8, while the second term is reported in Tab. 5.9.

Comparison and Evaluation

Results show that, for both algorithms, a controller optimized on a particular reference presents the best tracking performance and the lowest current consumption on that signal as highlighted from the diagonal values of the tables 5.4,5.5, 5.8 and 5.9. By using the ABC algorithm, the tracking performance improvement (w.r.t. the manufacturer controller) varies from 5%, when the reference is a sine wave at frequency of 1 Hz to 56%, when the reference is a trapezoidal wave at frequency of 2 Hz and the current consumption reduction varies from 8% to 57%. On the other hand, by applying the PSO, the tracking performance improvement (w.r.t. the manufacturer controller) varies from 9%, when the reference is a sine wave at frequency of 1 Hz to 58%, when the reference is a trapezoidal wave at frequency of 2 Hz and the current consumption reduction varies from 11% to 60% on the same references. It is possible to notice that, due to its ease of implementation, PSO presents greater improvements than ABC algorithm. Tracking performance and current consumptions

Controller	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
Square 1 Hz	**0.86**	0.95	1.16	1.29	1.22	0.91
Square 2 Hz	0.88	**0.92**	1.38	1.65	1.42	1.16
Sine 1 Hz	2.18	2.74	**0.95**	0.71	0.78	0.52
Sine 2 Hz	1.26	1.21	1.05	**0.69**	0.78	0.44
Trap. 1 Hz	1.91	1.97	0.97	0.71	**0.72**	0.48
Trap. 2 Hz	1.51	1.58	1.00	0.71	0.81	**0.44**
Manuf.	1.00	1.00	1.00	1.00	1.00	1.00

Table 5.4 Normalized IAE values (according to Eq. (4.37)) of controllers ABC-tuned on the reference signals listed in the header column and tested on the ones listed in the header row. Waveforms, with a fixed amplitude, are identified by their shape (i.e., square, sine and trapezoidal) and frequency.

Controller	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
Square 1 Hz	**0.84**	0.93	1.31	1.23	1.42	0.98
Square 2 Hz	0.91	**0.89**	1.31	1.77	1.38	1.26
Sine 1 Hz	2.29	2.83	**0.92**	0.89	0.81	0.69
Sine 2 Hz	1.37	1.26	1.15	**0.66**	0.81	0.48
Trap. 1 Hz	1.98	1.91	0.96	0.77	**0.70**	0.52
Trap. 2 Hz	1.67	1.49	1.02	0.82	0.75	**0.43**
Manuf.	1.00	1.00	1.00	1.00	1.00	1.00

Table 5.5 Normalized IAU values (according to Eq. (4.37)) of controllers ABC-tuned on the reference signals listed in the header column and tested on the ones listed in the header row. Waveforms, with a fixed amplitude, are identified by their shape (i.e., square, sine and trapezoidal) and frequency.

Parameter	Value
Optimisation parameters (M)	12
Number of particles (S)	20
c_1	2
c_2	2
Time limit ($time_{max}$) [minutes]	5

Table 5.6 PSO algorithm parameters.

Parameter	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
λ_{11}	0.21	0.49	0.75	0.79	0.65	0.87
λ_{12}	0.17	0.38	0.71	0.67	0.91	0.82
λ_{21}	0.43	0.28	0.89	0.83	0.93	0.54
λ_{22}	0.48	0.51	0.77	0.62	0.51	0.92
λ_{31}	0.26	0.41	0.51	0.74	0.88	0.89
λ_{32}	0.75	0.28	0.87	0.51	0.94	0.67
ρ_ω	0.61	2.12	17.48	12.59	18.97	19.21
ρ_q	2.91	2.18	5.16	0.95	5.34	1.98
ρ_d	5.31	2.21	4.92	0.78	3.44	1.74
θ_ω	-0.27	-0.18	0.58	0.49	-0.89	0.74
θ_q	-0.45	0.91	-0.61	-0.67	0.88	-0.19
θ_d	-0.12	-0.73	-0.24	0.89	0.43	0.58

Table 5.7 Parameters of PSO-tuned VSC controllers.

Controller	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
Square 1 Hz	**0.81**	0.91	1.09	1.17	1.11	0.99
Square 2 Hz	0.83	**0.88**	1.42	1.53	1.21	1.29
Sine 1 Hz	2.31	2.51	**0.91**	0.81	0.91	0.59
Sine 2 Hz	1.37	1.43	1.15	**0.62**	0.89	0.48
Trap. 1 Hz	1.99	1.91	0.98	0.73	**0.69**	0.51
Trap. 2 Hz	1.62	1.82	1.01	0.77	0.87	**0.42**
Manuf.	1.00	1.00	1.00	1.00	1.00	1.00

Table 5.8 Normalized *IAE* values (according to Eq. (4.37)) of controllers PSO-tuned on the reference signals listed in the header column and tested on the ones listed in the header row. Waveforms, with a fixed amplitude, are identified by their shape (i.e., square, sine and trapezoidal) and frequency.

Controller	Square		Sine		Trapezoidal	
	1 Hz	2 Hz	1 Hz	2 Hz	1 Hz	2 Hz
Square 1 Hz	**0.78**	0.84	1.08	1.12	1.31	0.96
Square 2 Hz	0.83	**0.85**	1.41	1.56	1.71	1.26
Sine 1 Hz	2.02	2.41	**0.89**	0.77	0.87	0.54
Sine 2 Hz	1.31	1.44	1.07	**0.59**	0.82	0.49
Trap. 1 Hz	1.98	1.82	0.94	0.69	**0.67**	0.51
Trap. 2 Hz	1.72	1.89	1.03	0.74	0.79	**0.40**
Manuf.	1.00	1.00	1.00	1.00	1.00	1.00

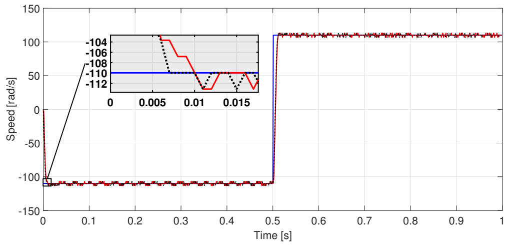
Table 5.9 Normalized IAU values (according to Eq. (4.37)) of controllers PSO-tuned on the reference signals listed in the header column and tested on the ones listed in the header row. Waveforms, with a fixed amplitude, are identified by their shape (i.e., square, sine and trapezoidal) and frequency.

of PSO-tuned and manufacturer controllers are depicted in Figures 5.2, 5.3, 5.4 and 5.5, respectively.

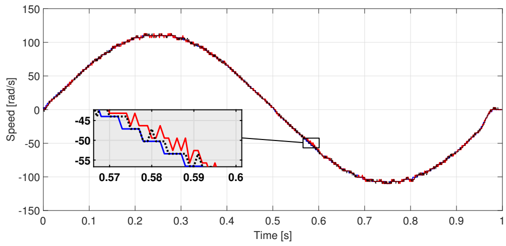
The controller tuned on the square wave, as shown in Figures 5.2(a) and 5.3(a), presents a lower rise time and the same steady-state performance with respect to the manufacturer one. In particular, the integral of tracking error for the PSO-VSC on this waveform at frequencies 1 Hz and 2 Hz is 19% and 12% lower than the manufacturer controller, respectively. As depicted in 5.2(b) and 5.3(b), the improvement of the PSO-VSC on the sine wave is an evident faster dynamic tracking of the reference which numerically consists in an improvement of 9% on the 1 Hz signal and 38% on the 2 Hz one. The controller tuned on the trapezoidal wave shows an improved ramp tracking performance and the same steady state accuracy (Figures 5.2(c) and 5.3(c)). This behaviour provides improvements of 31% and 58%, respectively. On the other hand, the improvement of the PSO-VSC controllers consists of a significant lowering of current peaks (Figures 5.4(a),5.5(a),5.4(b), 5.5(b), 5.4(c) and 5.5(c)).

5.1.4 Second Proposed Methodology

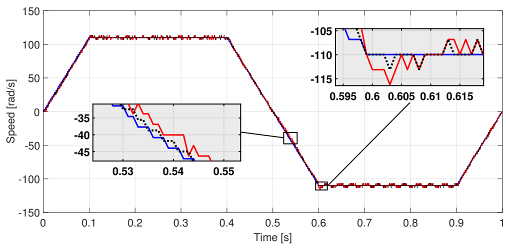
By analysing the performance of the tuning automatic procedure (Tables5.4,5.5, 5.8 and 5.9), it is possible to notice that the controller tuned on the square waves (step-like) shows bad performances on the other waveforms (ramps-like), and vice versa. Then, in order to evaluate the procedure described in Algorithm 1, a reference signal r is chosen and the similarity s is computed by varying the shape, the amplitude and the frequency of a generic signal r_i. Figure 5.6 depicts the trend of the similarity value s computed with the the Euclidean Distance and the DTW-based procedure, according to 3.10.



(a) Square wave (1 Hz)

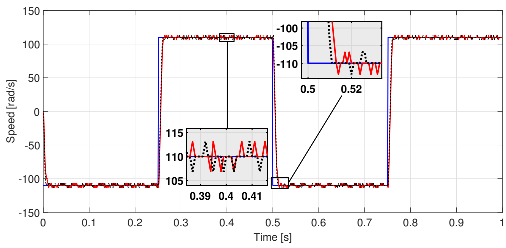


(b) Sine wave (1 Hz)

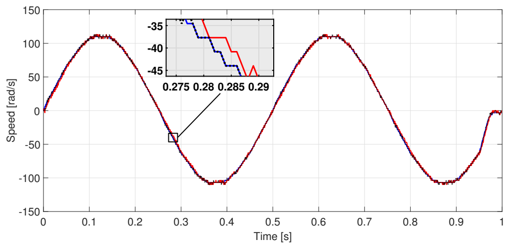


(c) Trapezoidal wave (1 Hz)

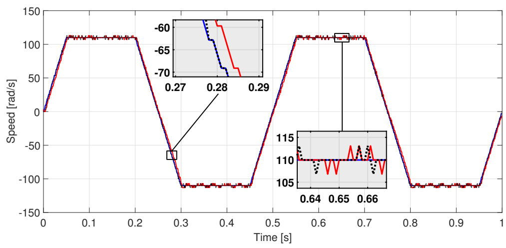
Figure 5.2 Tracking performance of PSO-tuned and manufacturer controllers on a square, sine and trapezoidal references at frequency of 1 Hz. Blue continuous lines are the reference signals, red continuous lines are the manufacturer controllers and the black dotted lines are the tuned controllers.



(a) Square wave (2 Hz)

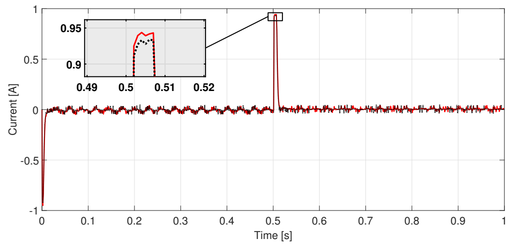


(b) Sine wave (2 Hz)

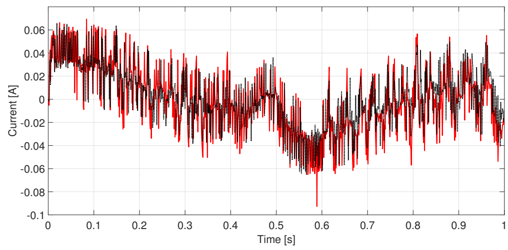


(c) Trapezoidal wave (2 Hz)

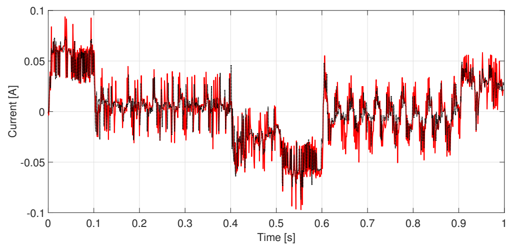
Figure 5.3 Tracking performance of PSO-tuned and manufacturer controllers on a square, sine and trapezoidal references at frequency of 2 Hz. Blue continuous lines are the reference signals, red continuous lines are the manufacturer controllers and the black dotted lines are the tuned controllers.



(a) Square wave (1 Hz)

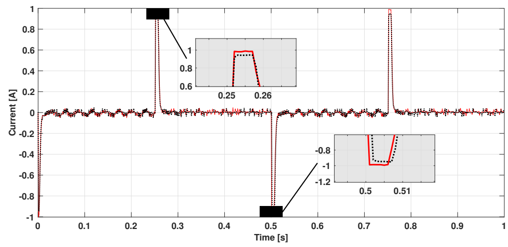


(b) Sine wave (1 Hz)

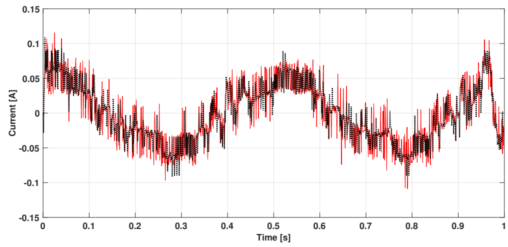


(c) Trapezoidal wave (1 Hz)

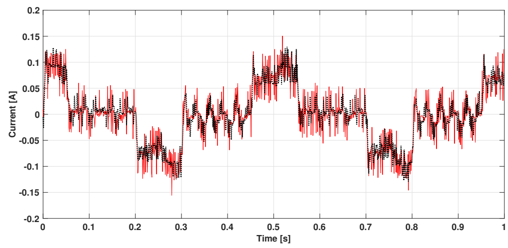
Figure 5.4 Current Consumptions of PSO-tuned and manufacturer controllers on a square, sine and trapezoidal references at frequency of 1 Hz. Red continuous lines are the manufacturer controllers and the black dotted lines are the tuned controllers.



(a) Square wave (2 Hz)



(b) Sine wave (2 Hz)



(c) Trapezoidal wave (2 Hz)

Figure 5.5 Current Consumptions of PSO-tuned and manufacturer controllers on a square, sine and trapezoidal references at frequency of 2 Hz. Red continuous lines are the manufacturer controllers and the black dotted lines are the tuned controllers.

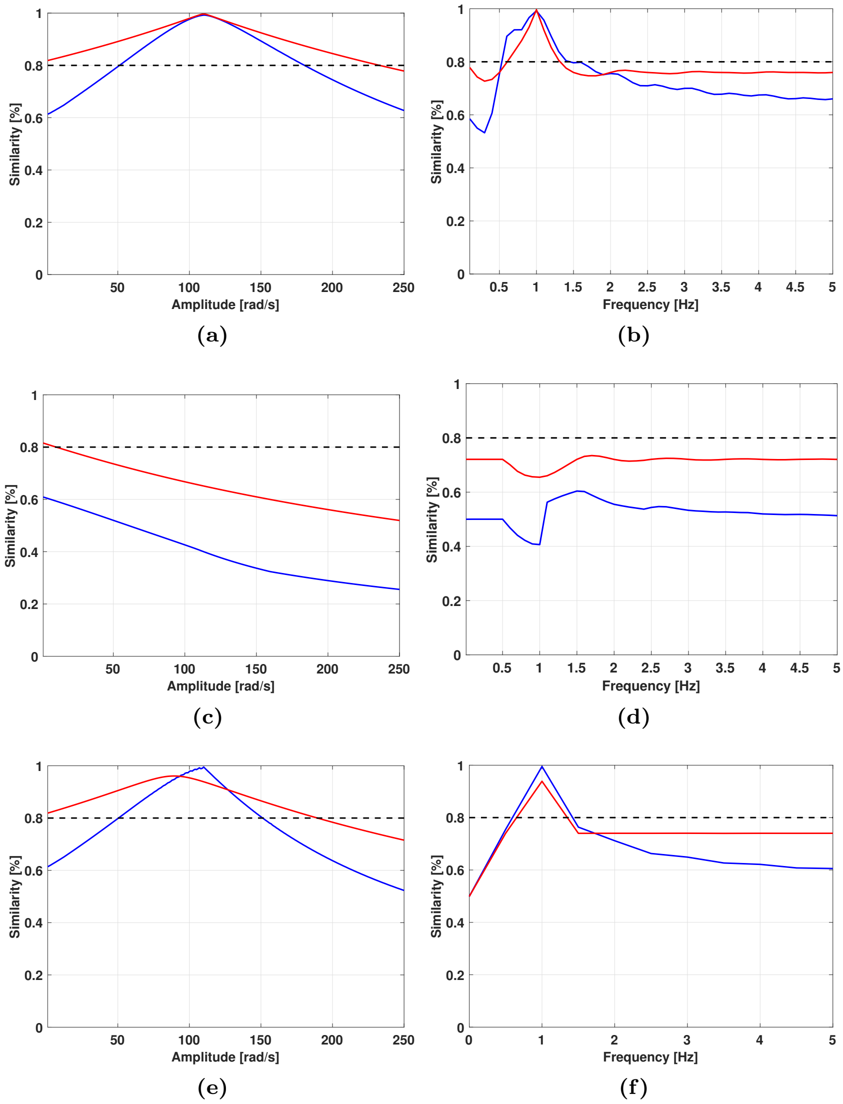


Figure 5.6 Variation of the similarity value s computed via the Euclidean distance with $k = 10$ (red continuous line) and DTW-based procedure with $k = 1$ (blue continuous line). Black dashed line is the threshold T_1. The reference signal r is a sine wave of amplitude of 110 rad/s and frequency of 1 Hz, with $T_1 = 80\%$.

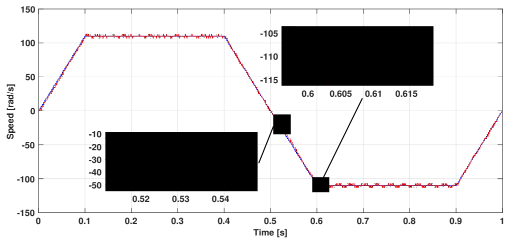


Figure 5.7 Tracking Performance of PSO-sine-tuned (black dotted line) and manufacturer controllers (red continuous line) on a trapezoidal references (blue continuous lines) at frequency of 1 Hz.

The reference signal r is a sine wave with amplitude of 110 rad/s and frequency of 1 Hz. As shown in Figures 5.6(a) and 5.6(b), the similarity value is 100% for both approaches when the amplitude is 110 rad/s and the frequency is 1 Hz, respectively, as it was expected. Furthermore, the DTW-based similarity value exceeds the threshold T_1 in the following intervals

- between 50 rad/s and 180 rad/s
- between 0.5 Hz and 1.5 Hz.

while the Euclidean distance-based similarity value

- always exceeds the threshold T_1 for what concerns the amplitude
- exceeds the threshold T_1 between 0.6 Hz and 1.4 Hz.

The similarity values of both approaches between r and a square signal with frequency of 1 Hz and variable amplitude, as shown in Figure 5.6(c), never exceeds the threshold T_1. However, the DTW-based similarity value between r and a trapezoidal signal with frequency of 1 Hz and variable amplitude overcomes the threshold T_1 in the interval between 50 rad/s and 150 rad/s. For this reason, the Controller Tuning Algorithm on the trapezoidal wave within this interval is not necessary. On the other hand, the Euclidean distance-based similarity value between r and a trapezoidal signal with frequency of 1 Hz and variable amplitude overcomes the threshold T_1 up to 180 rad/s (see Figure 5.6(e)). According to this comparison and to the characteristics of the proposed approaches, the DTW technique is more suitable for the particular application described in this thesis, since in control systems the correlation between the shape of the two signals is more important than the correlation between the individual samples.

In Figures 5.7 and 5.8 the tracking performance and current consumption of PSO-sine-tuned controller on trapezoidal wave is shown, respectively. The improvement of the sine-tuned controller on the trapezoidal waveform is a better ramp tracking performance, a lower undershoot and significant lowering of

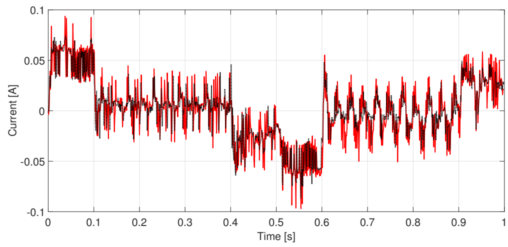


Figure 5.8 Current Consumption of PSO-sine-tuned (black dotted line) and manufacturer controllers (red continuous line) on a trapezoidal references at frequency of 1 Hz.

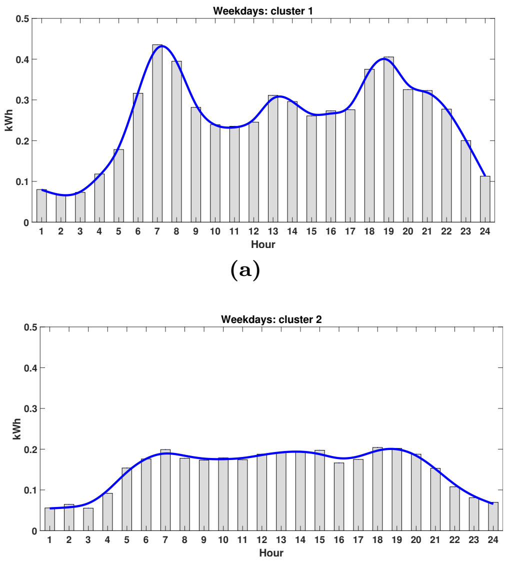
current peaks. As reported in Tables 5.8 and 5.9, the use of 'Sine 1' controller on the trapezoidal reference at frequency of 1 Hz shows a 9% tracking performance improvement and a 13% consumptions reduction compared with the manufacturer one ($\frac{IAE}{IAE_m} = 0.91$ and $\frac{IAU}{IAU_m} = 0.87$). Then, by using the same controller (as imposed by the the novelty detection algorithm), both tracking performance and current consumptions still results to be improved without the need of the parameter tuning.

5.2 Home Appliances Pattern Recognition in a Flexibility Scenario

This section is structured as the following: in 5.2.1 the results of the proposed clustering approach are described, in 5.2.2 the advantages of FCM with respect to the classic AI approach are listed and in 5.2.3 a FCM-based seasonality analysis is carried out.

5.2.1 FCM Clustering and Forecasting

Figures 5.9 and 5.10 show the FCM clustering results obtained for weekdays and holidays, respectively. In particular, the figures 5.9(a) and 5.9(b) show the daily energy distribution of weekdays for cluster 1 and cluster 2, respectively. It is worth to note that cluster 1 highlights how the highest energy consumption is concentrated before and after the working time, from 6 a.m. to 9 a.m. and from 6 p.m to 9 p.m.; cluster 2 highlights how from midnight to 4 a.m. the energy consumption is low, whereas the energy is mainly used up from 5 a.m. to 9 p.m, definitively, the usage of the electric boilers is focused from 6 a.m. to 9 a.m. and from 6 p.m to 9 p.m. during the weekdays and especially from 7 a.m. to 8 a.m. Figure 5.10(a) shows the daily energy distribution in kWh of the cluster 1 of holidays and the figure 5.10(b) shows the daily energy distribution in kWh of the cluster 2 of holidays. It is worth to note that cluster 1 highlights how



(a)

,

(b)

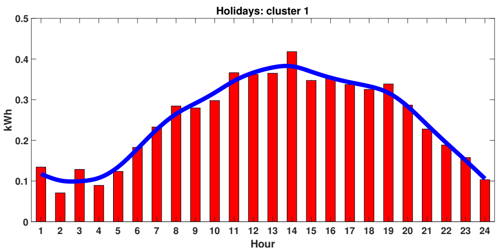
Figure 5.9 FCM clustering of energy consumption during weekdays: cluster 1 (a); cluster 2 (b).

from midnight to 5 a.m. the energy consumption is low, whereas the energy is mainly used up from 11 a.m. to 11 p.m; cluster 2 highlights how the highest energy consumption are gathered from 7 a.m. to 10 a.m. Differently, during holidays cluster 1 discloses more energy consumption during the night and the scales of cluster 1 and cluster 2 are similar, thus highlighting that people tends to use the electric boiler equally distributed during the day and less focused from 6 a.m. to 9 a.m. and from 8 p.m to 11 p.m. By knowing the user's energy usage patterns, an electricity supplier may request the user (or remotely control the boiler) to shift from one pattern to another, always maintaining the lowest required temperature to ensure consumers comfort.

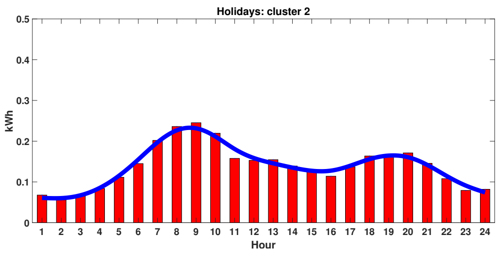
5.2.2 Peculiarity of a fuzzy clustering appoach

The peculiarity of a fuzzy clustering approach, Fuzzy C-Means (FCM) in this case, is that it allows one individual profile to belong to two or more clusters. On the contrary with a standard k-means approach, each profile is associated to a specific centroid and, thus, a specific cluster. By using FCM, since a profile can be placed in a middle way between two clusters (through the "membership" concept), it becomes possible to:

- model the "fuzziness" of human habits
- reduce the number of clusters (with only 2 clusters it is possible to model



(a)



(b)

Figure 5.10 FCM clustering of energy consumption during weekend: cluster 1 (a); cluster 2 (b).

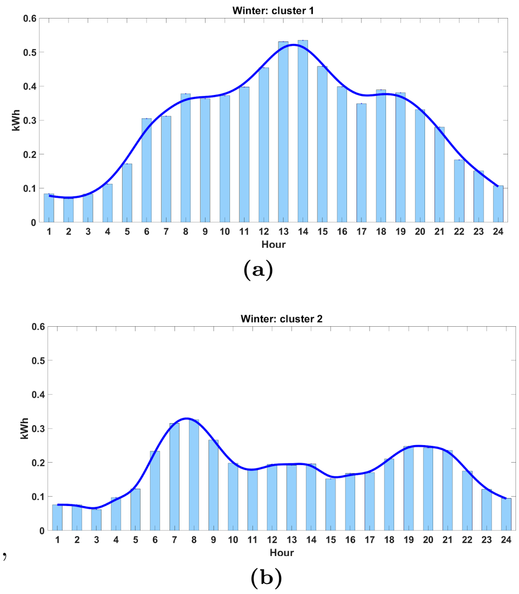
more than two behaviours)

- neglect data with extreme variability (implicitly considering them as outliers)
- to use a single clustering procedure for different seasons, as described in 5.2.3

Due to the membership concept, FCM clustering allows the modelling of consumption profiles at individual level (e.g., User A has a pattern belonging 0.6 to cluster 1 and 0.4 to cluster 2 while User B has a pattern belonging 0.2 to cluster 1 and 0.8 to cluster 2) and, for the same user, the membership of different patterns of the same user may vary over time, according, as an example, to seasonality (e.g., the same User A, in January may have a consumption pattern belonging 0.2 to cluster 1 and 0.8 to cluster 2, while in June is 0.7 to cluster 1 and 0.3 to cluster 2). In this context, the prediction of the consumption at individual level is possible and will result as a "smoother" one (with an hourly time resolution and partially influenced by the aggregated consumption).

5.2.3 Analysis of Seasonality

In this subsection, the results of the clustering performed for the winter and summer seasons are described. Results, as shown in Figures 5.11 and 5.12



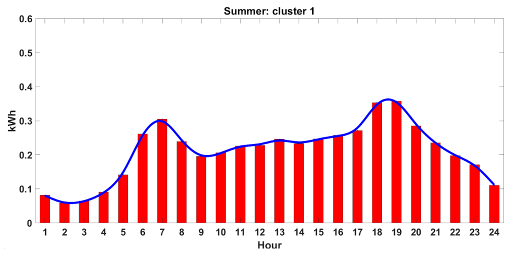
,

Figure 5.11 FCM winter clustering of energy consumption: cluster 1 (a); cluster 2 (b).

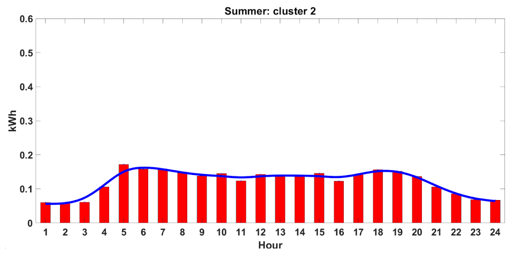
, reveal that the seasonality does not affect, in this specific case study, the clustering results considering the whole year. In detail, the cluster 1 of Winter is similar to the cluster shown in Fig. 5.10(a), the clusters 2 of Winter and 1 of Summer are similar to the clusters shown in Fig 5.9(a) and Fig. 5.10(b), finally, the cluster 2 of Summer is similar to the cluster shown in Fig.5.9(b).

Although these results show that clusters do not significantly differ between seasons, this condition may happen. However the use of FCM allows to take into account seasonality, with a single clustering procedure, since it is possible to find the optimal number of clusters for the whole year and then exploiting the concept of "membership" (e.g., we may obtain a total of 4 clusters, 2 of them related to winter and the remaining to summer conditions; when evaluating the membership values for an individual pattern measured in January, the result will be higher for the "winter behaviour" clusters).

A new/different clustering procedure is needed only when users' profiles do not belong any more to the clusters with a high degree of membership (the sum of membership is lower than 0.5).



(a)



(b)

Figure 5.12 FCM summer clustering of energy consumption: cluster 1 (a); cluster 2 (b).

Chapter 6

Conclusions and Future Works

The main contribution of this thesis is the application of different computational intelligence and artificial intelligence algorithms for the Energy Management in industrial and residential scenarios. Particularly, two problems were addressed and solved:

- performance improvement in reconfigurable industrial systems: on-line controller parameter tuning and reference similarity detection.
- home appliances pattern recognition in a flexibility scenario: clustering and forecasting approach to exploit the demand side flexibility programs.

. The GA-based (modified-ABC and PSO) automated tuning procedure is applied to a real industrial system in order to find a near-optimal controller parameters set according to a specific objective function (based on energy consumption and tracking performance). In control design stage, the proposed technique resulted a viable solution to solve multi-objective optimization and to achieve good performance (e.g., energy consumption reduction and tracking improvement) for each input reference. However, this method may use a lot of time and, then, the production time may suffer a huge decrease. Then, a DTW-based similarity detection algorithm is developed in order to evaluate the "novelty" of the reference signals.

Additionally, the whole proposed approach

- can be efficiently applied to all industrial control systems;
- can be efficiently applied to all control techniques;
- outperforms the results (in terms of energy consumption and tracking performance) obtained with classic controllers (e.g., the one provided by the manufacturer) on each reference where it is tested;
- outperforms the results (in terms of energy consumption and tracking performance) obtained with classic controllers (e.g., the one provided by the manufacturer) on each reference similar (according to DTW) to those in which it is tested;

- finds the best trade-off between the optimization time and production time.

A fuzzy clustering approach (FCM) is developed to estimate and forecast the electric boilers usage patterns. This information, sent to the energy supplier can enable flexibility actions in order to have benefits in terms of energy costs-savings. Through this algorithm, by exploiting the concept of "fuzzy membership", it is possible to obtain average forecasting performances higher than those obtained with classical AI approaches. This result permits to make the estimation of a user's future behaviours faster and more effective and the energy management policies more accurate. In particular, it could be possible to i) model the "fuzziness" of human habits and ii) reduce the number of clusters iii) use a clustering procedure for different seasons.

By summarizing, the adoption of CI and AI techniques can be a turning point for managing energy consumption and its costs in the industrial and residential sectors.

Due to the use of increasingly complex industrial systems and the increasing amount of data available, future works may be addressed to these aspects:

- application of different types of GA by taking into account model constraints (not only variables constraints);
- analysis of GA convergence time in order to reach a given performance level;
- application of GA in several motor benches in order to make the optimization parallel;
- application of Deep Learning approaches for the similarity and novelty detection;
- study and development of Deep Learning approaches to make the clustering and forecasting more efficient and reliable.

Bibliography

[1] K. Blok and E. Nieuwlaar, *Introduction to energy analysis.* Routledge, 2016.

[2] A. A. Khan, M. Naeem, M. Iqbal, S. Qaisar, and A. Anpalagan, “A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids,” *Renewable and Sustainable Energy Reviews*, vol. 58, pp. 1664–1683, 2016.

[3] R. Alizadeh, P. D. Lund, A. Beynaghi, M. Abolghasemi, and R. Maknoon, “An integrated scenario-based robust planning approach for foresight and strategic management with application to energy industry,” *Technological Forecasting and Social Change*, vol. 104, pp. 162–171, 2016.

[4] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, “Optimal home energy management under dynamic electrical and thermal constraints,” *IEEE Transactions on Industrial Informatics*, vol. 9, no. 3, pp. 1518–1527, 2012.

[5] “Artificial intelligence for energy efficiency and renewable energy – 6 current applications,” https://emerj.com/ai-sector-overviews/artificial-intelligence-for-energy-efficiency-and-renewable-energy/.

[6] D. Lee and C.-C. Cheng, “Energy savings by energy management systems: A review,” *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 760–777, 2016.

[7] H. S. Kang, J. Y. Lee, S. Choi, H. Kim, J. H. Park, J. Y. Son, B. H. Kim, and S. Do Noh, “Smart manufacturing: Past research, present findings, and future directions,” *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 3, no. 1, pp. 111–128, 2016.

[8] Z. Vale, H. Morais, and H. Khodr, “Intelligent multi-player smart grid management considering distributed energy resources and demand response,” in *IEEE PES General Meeting.* IEEE, 2010, pp. 1–7.

[9] S. Kalogirou, K. Metaxiotis, and A. Mellit, “Artificial intelligence techniques for modern energy applications,” in *Intelligent information systems and knowledge management for energy: Applications for decision*

support, usage, and environmental protection. IGI Global, 2010, pp. 1–39.

[10] K. Schwab, *The fourth industrial revolution.* Currency, 2017.

[11] "New forum center to advance global cooperation on fourth industrial revolution," https://www.weforum.org/press/2016/10/new-forum-center-to-advance-global-cooperation-on-fourth-industrial-revolution/.

[12] "The fourth industrial revolution: what it means, how to respond," https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/.

[13] J. Bloem, M. Van Doorn, S. Duivestein, D. Excoffier, R. Maas, and E. Van Ommeren, "The fourth industrial revolution," *Things Tighten*, vol. 8, 2014.

[14] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, 2015.

[15] F. Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in industry 4.0: A review of the concept and of energy management approached in production based on the internet of things paradigm," in *Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on.* IEEE, 2014, pp. 697–701.

[16] J. Lee, E. Lapira, B. Bagheri, and H.-a. Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," *Manufacturing Letters*, vol. 1, no. 1, pp. 38–41, 2013.

[17] "The internet of services – industry 4.0 as an opportunity," 2017. [Online]. Available: https://www.cidaas.com/internet-services-industry-4-0-opportunity/

[18] A. Ahmadi, C. Cherifi, V. Cheutet, and Y. Ouzrout, "A review of cps 5 components architecture for manufacturing based on standards," in *SKIMA, International Conference on Software, Knowledge, Intelligent Management and Applications*, 2017.

[19] K. K. Patel, S. M. Patel *et al.*, "Internet of things-iot: definition, characteristics, architecture, enabling technologies, application & future challenges," *Int. J. Eng. Sci. Comput*, vol. 6, no. 5, 2016.

[20] R. D. Snee and R. Hoerl, *Leading Holistic Improvement with Lean Six Sigma 2.0.* FT Press, 2018.

[21] F. Chen, P. Deng, J. Wan, D. Zhang, A. V. Vasilakos, and X. Rong, "Data mining for the internet of things: literature review and challenges," *International Journal of Distributed Sensor Networks*, vol. 11, no. 8, p. 431047, 2015.

[22] H. Wang, "A survey of maintenance policies of deteriorating systems," *European journal of operational research*, vol. 139, no. 3, pp. 469–489, 2002.

[23] M. Hermann, T. Pentek, and B. Otto, "Design principles for industrie 4.0 scenarios," in *2016 49th Hawaii international conference on system sciences (HICSS)*. IEEE, 2016, pp. 3928–3937.

[24] M. Gubán and G. Kovács, "Industry 4.0 conception," *Acta Technica Corviniensis-Bulletin of Engineering*, vol. 10, no. 1, p. 111, 2017.

[25] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, "Industry 4.0," *Business & Information Systems Engineering*, vol. 6, no. 4, pp. 239–242, Aug 2014.

[26] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, no. Supplement C, pp. 18 – 23, 2015.

[27] F. S. Fogliatto, G. J. da Silveira, and D. Borenstein, "The mass customization decade: An updated review of the literature," *International Journal of Production Economics*, vol. 138, no. 1, pp. 14 – 25, 2012.

[28] D. Gorecky, M. Schmitt, M. Loskyll, and D. Zühlke, "Human-machine-interaction in the industry 4.0 era," in *Industrial Informatics (INDIN), 2014 12th IEEE International Conference on*. Ieee, 2014, pp. 289–294.

[29] H. Tieng, C. F. Chen, F. T. Cheng, and H. C. Yang, "Automatic virtual metrology and target value adjustment for mass customization," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 546–553, April 2017.

[30] D. Mourtzis, "Challenges and future perspectives for the life cycle of manufacturing networks in the mass customisation era," *Logistics Research*, vol. 9, no. 1, p. 2, 2016.

[31] D. Mourtzis, M. Doukas, and F. Psarommatis, "A toolbox for the design, planning and operation of manufacturing networks in a mass customisation environment," *Journal of Manufacturing Systems*, vol. 36, pp. 274–286, 2015.

[32] Y. Koren, *General RMS Characteristics. Comparison with Dedicated and Flexible Systems.* Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 27–45.

[33] M. G. Mehrabi, A. G. Ulsoy, and Y. Koren, “Reconfigurable manufacturing systems: Key to future manufacturing,” *Journal of Intelligent Manufacturing*, vol. 11, no. 4, pp. 403–419, 2000.

[34] C. Rösiö and K. Säfsten, “Reconfigurable production system design – theoretical and practical challenges,” *Journal of Manufacturing Technology Management*, vol. 24, no. 7, pp. 998–1018, 2013.

[35] C. Renzi, F. Leali, M. Cavazzuti, and A. O. Andrisano, “A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems,” *The International Journal of Advanced Manufacturing Technology*, vol. 72, no. 1, pp. 403–418, 2014.

[36] R. J. Urbanic and R. W. Hedrick, “A matrix-based framework for assessing machine tool reconfiguration alternatives,” *The International Journal of Advanced Manufacturing Technology*, vol. 81, no. 9, pp. 1893–1919, 2015.

[37] “Regulation eu 2017/1369,” https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32017R1369.

[38] L. Ciabattoni, M. Grisostomi, G. Ippoliti, D. P. Pagnotta, G. Foresi, and S. Longhi, “Residential energy monitoring and management based on fuzzy logic,” in *2015 IEEE International Conference on Consumer Electronics (ICCE).* IEEE, 2015, pp. 536–539.

[39] R. Chang, Y. Yuan, H. Lv, W. Yin, and S. X. Yang, “Selling the smart grid—part 1: Why consumers must buy in for the smart grid to succeed,” *IEEE Consumer Electronics Magazine*, vol. 1, no. 2, pp. 24–31, 2012.

[40] Y. Yuan, R. Chang, H. Lv, W. Yin, and S. X. Yang, “Selling the smart grid-part 2: How consumers will interact with the smart grid,” *IEEE Consumer Electronics Magazine*, vol. 1, no. 3, pp. 20–28, 2012.

[41] Y. Wi, J. Lee, and S. Joo, “Electric vehicle charging method for smart homes/buildings with a photovoltaic system,” *IEEE Transactions on Consumer Electronics*, vol. 59, no. 2, pp. 323–328, 2013.

[42] S. K. Rastogi, A. Sankar, K. Manglik, S. K. Mishra, and S. P. Mohanty, “Toward the vision of all-electric vehicles in a decade [energy and security],” *IEEE Consumer Electronics Magazine*, vol. 8, no. 2, pp. 103–107, 2019.

[43] S. Singh, A. Roy, and M. P. Selvan, "Smart load node for nonsmart load under smart grid paradigm: A new home energy management system," *IEEE Consumer Electronics Magazine*, vol. 8, no. 2, pp. 22–27, 2019.

[44] L. Ciabattoni, F. Ferracuti, M. Grisostomi, G. Ippoliti, and S. Longhi, "Fuzzy logic based economical analysis of photovoltaic energy management," *Neurocomputing*, vol. 170, pp. 296–305, 2015.

[45] S. Bennett, *A history of control engineering, 1930-1955.* IET, 1993, no. 47.

[46] B. Adhavan, A. Kuppuswamy, G. Jayabaskaran, and V. Jagannathan, "Field oriented control of permanent magnet synchronous motor (pmsm) using fuzzy logic controller," in *IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 2011, pp. 587–592.

[47] M. Tursini, F. Parasiliti, and D. Zhang, "Real-time gain tuning of pi controllers for high-performance pmsm drives," *IEEE Transactions on Industry Applications*, vol. 38, no. 4, pp. 1018–1026, 2002.

[48] K. M. Hussain, R. A. R. Zepherin, and M. S. Kumar, "Comparison of tuning methods of pid controllers for foptd system," *IJIREEICE*, vol. 2, no. 3, pp. 1177–80, 2014.

[49] R. A. Osornio-Rios, R. de Jesus Romero-Troncoso, G. Herrera-Ruiz, and R. Castañeda-Miranda, "The application of reconfigurable logic to high speed cnc milling machines controllers," *Control Engineering Practice*, vol. 16, no. 6, pp. 674–684, 2008.

[50] J. R. Rivera-Guillen, R. de Jesus Romero-Troncoso, R. A. Osornio-Rios, A. Garcia-Perez, and G. Herrera-Ruiz, "Design methodology for fully dynamic-controlled polynomial profiles and reduced tracking error in cnc machines," *The International Journal of Advanced Manufacturing Technology*, vol. 51, no. 5-8, pp. 723–737, 2010.

[51] "Galil motion,dmc-18x2usermanual, galil motion control inc,(2005),," www.galilmc.com/.

[52] C. S. Atchiraju and T. Nagraja, "A computer software for pid tuning by new frequency domain design method," *Computers & Electrical Engineering*, vol. 29, no. 1, pp. 251–257, 2003.

[53] X.-j. Zhu *et al.*, "A simple auto-tuner in frequency domain," *Computers & chemical engineering*, vol. 30, no. 4, pp. 581–586, 2006.

[54] K. Natarajan, A. Gilbert, B. Patel, and R. Siddha, "Frequency response adaptation of pi controllers based on recursive least-squares process identification," *ISA transactions*, vol. 45, no. 4, pp. 517–528, 2006.

[55] D. Rijlaarsdam, P. Nuij, J. Schoukens, and M. Steinbuch, "Frequency domain based nonlinear feed forward control design for friction compensation," *Mechanical Systems and Signal Processing*, vol. 27, pp. 551–562, 2012.

[56] R. A. Osornio-Rios, R. d. J. Romero-Troncoso, L. Morales-Velazquez, J. J. de Santiago-Perez, R. d. J. Rivera-Guillen, and J. de Jesus Rangel-Magdaleno, "A real-time fpga based platform for applications in mechatronics," in *2008 International Conference on Reconfigurable Computing and FPGAs*. IEEE, 2008, pp. 289–294.

[57] L. Morales-Velazquez, R. de Jesus Romero-Troncoso, R. A. Osornio-Rios, G. Herrera-Ruiz, and J. J. de Santiago-Perez, "Special purpose processor for parameter identification of cnc second order servo systems on a low-cost fpga platform," *Mechatronics*, vol. 20, no. 2, pp. 265–272, 2010.

[58] R. Matousek, P. Minar, S. Lang, and P. Pivonka, "Hc12: Efficient method in optimal pid tuning," in *Proceedings of the World Congress on Engineering and Computer Science*, vol. 1, 2011, pp. 19–21.

[59] B. Nagaraj and N. Murugananth, "A comparative study of pid controller tuning using ga, ep, pso and aco," in *2010 International Conference On Communication Control And Computing Technologies*. IEEE, 2010, pp. 305–313.

[60] D. Lu, L. Zhu, and X. Li, "Pid parameter optimization of shunting and winch control system in coal transportation based online adaptive genetic algorithm," in *2010 International Conference on E-Product E-Service and E-Entertainment*. IEEE, 2010, pp. 1–4.

[61] G. Renner and A. Ekárt, "Genetic algorithms in computer aided design," *Computer-Aided Design*, vol. 35, no. 8, pp. 709–726, 2003.

[62] Z. S. Abo-Hammour, O. M. Alsmadi, S. I. Bataineh, M. A. Al-Omari, and N. Affach, "Continuous genetic algorithms for collision-free cartesian path planning of robot manipulators," *International Journal of Advanced Robotic Systems*, vol. 8, no. 6, p. 74, 2011.

[63] A. Ghanbari and S. Noorani, "Optimal trajectory planning for design of a crawling gait in a robot using genetic algorithm," *International Journal of Advanced Robotic Systems*, vol. 8, no. 1, p. 6, 2011.

[64] X. Wang, T. Lu, and P. Zhang, "State generation method for humanoid motion planning based on genetic algorithm," *International Journal of Advanced Robotic Systems*, vol. 9, no. 1, p. 23, 2012.

[65] B. H. Dennis and G. S. Dulikravich, "Optimization of magneto-hydrodynamic control of diffuser flows using micro-genetic algorithms and least-squares finite elements," *Finite Elements in Analysis and Design*, vol. 37, no. 5, pp. 349–363, 2001.

[66] C. A. C. C. Coello and G. T. Pulido, "A micro-genetic algorithm for multiobjective optimization," in *International Conference on Evolutionary Multi-Criterion Optimization.* Springer, 2001, pp. 126–140.

[67] W. Zhao, D. Yu, and Z. Hu, "Parameters optimization for small helicopter highly controller based on genetic algorithm," in *World Automation Congress 2012.* IEEE, 2012, pp. 1–4.

[68] G. Tan, B. Jiang, and L. Yang, "A novel immune genetic algorithm-based pid controller design and its application to cip-i intelligent leg," in *Third International Conference on Natural Computation (ICNC 2007)*, vol. 4. IEEE, 2007, pp. 282–286.

[69] H.-Y. Li, "The adaptive niche genetic algorithm for optimum design of pid controller," in *2007 International Conference on Machine Learning and Cybernetics*, vol. 1. IEEE, 2007, pp. 487–491.

[70] T. Wu, Y. Cheng, J. Tan, and T. Zhou, "The application of chaos genetic algorithm in the pid parameter optimization," in *2008 3rd International Conference on Intelligent System and Knowledge Engineering*, vol. 1. IEEE, 2008, pp. 230–234.

[71] A. J. A. Nazir, R. Surajan, L. Binu *et al.*, "A simplified genetic algorithm for online tuning of pid controller in labview," in *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC).* IEEE, 2009, pp. 1516–1519.

[72] K. A. Mohideen, G. Saravanakumar, K. Valarmathi, D. Devaraj, and T. Radhakrishnan, "Real-coded genetic algorithm for system identification and tuning of a modified model reference adaptive controller for a hybrid tank system," *Applied Mathematical Modelling*, vol. 37, no. 6, pp. 3829–3847, 2013.

[73] J. Zhang, J. Zhuang, H. Du *et al.*, "Self-organizing genetic algorithm based tuning of pid controllers," *Information Sciences*, vol. 179, no. 7, pp. 1007–1018, 2009.

[74] G. Lin and G. Liu, "Tuning pid controller using adaptive genetic algorithms," in *2010 5th International Conference on Computer Science & Education*. IEEE, 2010, pp. 519–523.

[75] I. Pan, S. Das, and A. Gupta, "Tuning of an optimal fuzzy pid controller with stochastic algorithms for networked control systems with random time delay," *ISA transactions*, vol. 50, no. 1, pp. 28–36, 2011.

[76] H. V. H. Ayala and L. dos Santos Coelho, "Tuning of pid controller based on a multiobjective genetic algorithm applied to a robotic manipulator," *Expert Systems with Applications*, vol. 39, no. 10, pp. 8968–8974, 2012.

[77] D. Koolen, N. Sadat-Razavi, and W. Ketter, "Machine learning for identifying demand patterns of home energy management systems with dynamic electricity pricing," *Applied Sciences*, vol. 7, no. 11, p. 1160, 2017.

[78] N. Sadeghianpourhamami, T. Demeester, D. Benoit, M. Strobbe, and C. Develder, "Modeling and analysis of residential flexibility: Timing of white good usage," *Applied energy*, vol. 179, pp. 790–805, 2016.

[79] S. Welikala, C. Dinesh, M. P. B. Ekanayake, R. I. Godaliyadda, and J. Ekanayake, "Incorporating appliance usage patterns for non-intrusive load monitoring and load forecasting," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 448–461, 2017.

[80] S. Singh and A. Yassine, "Mining energy consumption behavior patterns for households in smart grid," *IEEE Transactions on Emerging Topics in Computing*, 2017.

[81] K. Basu, L. Hawarah, N. Arghira, H. Joumaa, and S. Ploix, "A prediction system for home appliance usage," *Energy and Buildings*, vol. 67, pp. 668–679, 2013.

[82] K. Basu, V. Debusschere, and S. Bacha, "Appliance usage prediction using a time series based classification approach," in *IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society*. IEEE, 2012, pp. 1217–1222.

[83] S. Zhai, Z. Wang, X. Yan, and G. He, "Appliance flexibility analysis considering user behavior in home energy management system using smart plugs," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 2, pp. 1391–1401, 2018.

[84] N. C. Truong, J. McInerney, L. Tran-Thanh, E. Costanza, and S. Ramchurn, "Forecasting multi-appliance usage for smart home energy management," in *Twenty-Third International Joint Conference on Artificial Intelligence*, 2013.

[85] M. Gulati, V. K. Singh, S. K. Agarwal, and V. A. Bohara, "Appliance activity recognition using radio frequency interference emissions," *IEEE Sensors Journal*, vol. 16, no. 16, pp. 6197–6204, 2016.

[86] D. Murray, J. Liao, L. Stankovic, and V. Stankovic, "Understanding usage patterns of electric kettle and energy saving potential," *Applied Energy*, vol. 171, pp. 231–242, 2016.

[87] A. Ridi, C. Gisler, and J. Hennebert, "Appliance and state recognition using hidden markov models," in *2014 International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2014, pp. 270–276.

[88] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (abc) algorithm," *Applied soft computing*, vol. 8, no. 1, pp. 687–697, 2008.

[89] J. Kennedy and R. Eberhart, "Particle swarm optimization (pso)," in *Proc. IEEE International Conference on Neural Networks, Perth, Australia*, 1995, pp. 1942–1948.

[90] D. J. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series." in *KDD workshop*, vol. 10, no. 16. Seattle, WA, 1994, pp. 359–370.

[91] P.-H. Li and S. Pye, "Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective," *Applied energy*, vol. 228, pp. 965–979, 2018.

[92] N. Javaid, S. Javaid, W. Abdul, I. Ahmed, A. Almogren, A. Alamri, and I. Niaz, "A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid," *Energies*, vol. 10, no. 3, p. 319, 2017.

[93] V. Harish and A. Kumar, "Planning and implementation strategy of demand side management in india," in *2014 First International Conference on Automation, Control, Energy and Systems (ACES)*. IEEE, 2014, pp. 1–6.

[94] J. Rodriguez, R. M. Kennel, J. R. Espinoza, M. Trincado, C. A. Silva, and C. A. Rojas, "High-performance control strategies for electrical drives: An experimental assessment," *IEEE Transactions on Industrial Electronics*, vol. 59, no. 2, pp. 812–820, Feb 2012.

[95] I. Hahn, "Heuristic structural optimization of the permanent magnets used in a surface mounted permanent-magnet synchronous machine," *IEEE Transactions on Magnetics*, vol. 48, no. 1, pp. 118–127, 2012.

[96] P. C. Krause, O. Wasynczuk, and S. D. Sudhoff, *Modern Analysis of Electric Machinery and Drive Systems.* John Wiley and Sons, New York, USA, 2002.

[97] P. Vaclavek and P. Blaha, "Pmsm model discretization for model predictive control algorithms," in *IEEE/SICE International Symposium on System Integration (SII)*, 2013, pp. 13–18.

[98] Y. Joshi, K. Parikh, and V. K. Yadav, "Field oriented control of pmsm using improved space vector modulation technique," *International Journal of Digital Application and Contemporary research*, vol. 2, no. 8, 2014.

[99] Y.-F. Li and J. Wikander, "Model reference discrete-time sliding mode control of linear motor precision servo systems," *Mechatronics*, vol. 14, no. 7, pp. 835 – 851, 2004.

[100] S. Li, M. Zhou, and X. Yu, "Design and implementation of terminal sliding mode control method for pmsm speed regulation system," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 4, pp. 1879–1891, Nov 2013.

[101] T. Orlowska-Kowalska, G. Tarchala, and M. Dybkowski, "Sliding-mode direct torque control and sliding-mode observer with a magnetizing reactance estimator for the field-weakening of the induction motor drive," *Mathematics and Computers in Simulation*, vol. 98, pp. 31 – 45, 2014.

[102] V. I. Utkin, "Sliding mode control design principles and applications to electric drives," *IEEE Transactions on Industrial Electronics*, vol. 40, no. 1, pp. 23–36, Feb 1993.

[103] B. Veselic, B. Perunicic-Drazenovic, and C. Milosavljevic, "High-performance position control of induction motor using discrete-time sliding-mode control," *IEEE Transactions on Industrial Electronics*, vol. 55, no. 11, pp. 3809–3817, Nov 2008.

[104] J. C. Dunn, "A fuzzy relative of the isodata process and its use in detecting compact well-separated clusters," *Journal of Cybernetics*, vol. 3, no. 3, pp. 32–57, 1973.

[105] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms.* Norwell, MA, USA: Kluwer Academic Publishers, 1981.

[106] X. L. Xie and G. Beni, "A validity measure for fuzzy clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 8, pp. 841–847, Aug 1991.

[107] D. E. Gustafson and W. C. Kessel, "Fuzzy clustering with a fuzzy covariance matrix," in *1978 IEEE conference on decision and control including the 17th symposium on adaptive processes.* IEEE, 1979, pp. 761–766.

[108] "Documentation of the mck28335-pro motion control kit," last access: January 16, 2018. [Online]. Available: http://www.technosoftmotion.com/de/tools/motion-control-kits/mck28335

[109] "Datasheet of the delfino tms320f28335 dsp motion controller," last access: January 16, 2018. [Online]. Available: http://www.ti.com/product/TMS320F28335/datasheet

[110] K. Hong, W.-S. Gan, Y. K. Chong, K. Chew, C. Lee, and T. Koh, "An integrated environment for rapid prototyping of dsp algorithms using matlab and texas instruments' tms320c30," *Microprocessors and Microsystems*, vol. 24, no. 7, pp. 349–363, 2000.