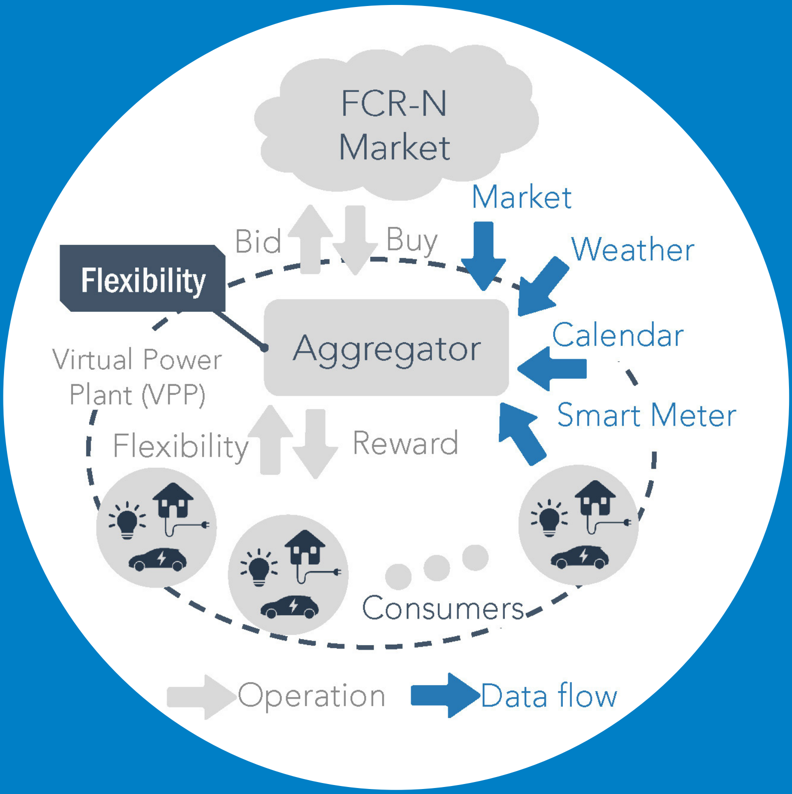
Department of Electrical Engineering and Automation

Aggregating domestic energy storage resources to participate in frequency containment reserves

Christian Giovanelli



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Aggregating domestic energy storage resources to participate in frequency containment reserves

Christian Giovanelli

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Abstract

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Abstract
The power grid is expected to undergo major transformations due to the increased penetration of renewable variable energy sources and electric vehicles. Uncertainty caused by the volatility of renewable energy production requires the adoption of new measures to maintain the balance between supply and demand, thus guaranteeing the reliability and stability of the grid. These challenges require the active engagement of consumer-side energy production and consumption to provide sufficient flexibility for the power grid through a mechanism known as demand response (DR). This dissertation focuses on DR, and more specifically on enabling residential consumers to participate in the balancing of the grid by providing frequency containment reserves.
To provide frequency containment reserves, the dissertation determines the functional and non-functional requirements for using domestic energy storage resources. The functional requirements are identified in two use cases. The first use case defines the requirements for the planning phase of the DR, while the second specifies the requirements for the frequency reserves provision. In addition, non-functional requirements are specified for the developed DR system.
The dissertation proposes the design of a DR system for providing frequency containment reserves based on the specified requirements. The design defines a hybrid ICT architecture capable of functioning during both the planning and execution of DR. For DR planning, the dissertation employs a partially distributed optimization algorithm to enable the day-ahead scheduling of consumer-owned energy storage resources. For frequency reserve provision, the dissertation contributes by integrating the proposed ICT architecture with a hybrid coordination algorithm. This auction-based task allocation algorithm enables consumer-owned energy storage resources to be allocated for the provision of frequency containment reserves. The developed DR system is validated through simulations in the two use cases.
The dissertation investigates the required market intelligence for enabling a virtual power plant (VPP) to profitably exploit distributed energy resources. In the future, the VPP could exploit its resources on various markets, including frequency containment reserves. In order to bid intelligently on such markets, VPP should be capable of predicting market prices. Therefore, the dissertation focuses on providing a solution for predicting the prices of the frequency containment reserve for normal operation market. The dissertation provides a data-driven solution, analyzing the market prices and providing a methodology for predicting the day-ahead prices through the design and implementation of various machine learning regression models, including an artificial neural network model. The designed models are evaluated by comparing the prediction performance in an experimental setup.

Keywords demand response, smart grid, ICT architecture, ancillary markets, price prediction

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Preface

This dissertation outlines the research conducted in the Department of Electrical Engineering and Automation at Aalto University between 2015 and 2018. During this time, I had the opportunity to meet and work with many people, who in disparate ways have supported me along this special journey.

The first person I would like to express my gratitude is Prof. Valeriy Vyatkin. Valeriy, I am really grateful that you gave me the opportunity to work in the ITiA group. Thank you also for your consistent and constructive support in my research and beyond; for putting your trust in me, and for allowing me to develop international collaborations that took me far from Finland.

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I would like to thank my advisor Ilkka Seilonen for guiding me through the scientific world since my day zero at Aalto (starting by showing how a dissertation "should look like"). Further, thank you for promptly reminding me to keep the focus on the objectives in our long-lasting meetings in which scientific and off-topics talks were regularly alternated.

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This dissertation would not have been possible without the cooperation of several co-authors: Olli Kilkki, Seppo Sierla, Ilkka Seilonen, Ryutaro Ichise, Valeriy Vyatkin, Xin Liu, Antti Alahäivälä, and Matti Lehtonen. Thank you for your collaboration, it has been a pleasure working with all of you!

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For the indirect supporters, I have to start expressing my deepest gratitude with the TUAS Club members, that filled my days with "scientific" discussions of not-so-scientific topics. Thank you guys for creating such an entertaining environment, as promised I will list you based on the paid bribe: Sergio Samokhin, Navid Khajehzadeh, Gerardo Santillan, Ville Liimatainen, Kha Nguyen, Kourosh Latifi, Zoran Cenev, Evgeny Nefedov, Ferdi Kusumah, Jean Antoine Seon, Matti Hokkanen, and The Boss (Jari-Pekka Ruonio for the registry office). A separate note of recognition goes to Prof. Emeritus Heikki Koivo for sharing wise stories and anecdotes combined with diverse sports chats during the not-so-short breaks.

Then, I am gratified to have so many good friends that have accompanied me during this adventure providing genuine and unconditional support. From the friend that found me a house in Helsinki, to the friend that hosted me in Tokyo while I was homeless, going through the friends that traveled here and there to meet and spend some valuable time filled with joy, to the friends that gave me their indispensable aid in the challenging moments. And yes, also to my childhood friends also known as "Bad boys" that still ask me "When are you going to have a real job?". Thank you all for the many beautiful ways that you touch my life.

Finally, I have to thank my family, that is my father Giuliano, mother Elisabetta, sister Martina, and brother Michele for backing me up with love and affection in every single moment of this fantastic roller coaster ride called life.

Espoo, January 2019.

Christian Giovanelli

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I Olli Kilkki, Christian Giovanelli, Ilkka Seilonen, Valeriy Vyatkin. Optimization of decentralized energy storage flexibility for frequency reserve. In *Industrial Electronics Society, IECON 2015-41st Annual Conference of the IEEE*, Yokohama, Japan, 002219–002224, November 2015.

II Christian Giovanelli, Olli Kilkki, Ilkka Seilonen, Valeriy Vyatkin. Distributed ICT architecture and an application for optimized automated demand response. In *PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2016 IEEE*, Ljubljana, Slovenia, October 2016.

III Christian Giovanelli, Olli Kilkki, Antti Alahäivälä, Ilkka Seilonen, Matti Lehtonen, Valeriy Vyatkin. A distributed ICT architecture for continuous frequency control. In *6th International Conference on Smart Cities and Green ICT Systems, SMARTGREENS 2017*, Porto, Portugal, April 2017.

IV Christian Giovanelli, Olli Kilkki, Seppo Sierla, Ilkka Seilonen, Valeriy Vyatkin. Towards a task allocation algorithm for frequency containment reserves. In *Industrial Informatics (INDIN), 2017 IEEE 15th International Conference on*, Emden, Germany, 765–768, July 2017.

V Christian Giovanelli, Olli Kilkki, Seppo Sierla, Ilkka Seilonen, Valeriy Vyatkin. Task Allocation Algorithm for Energy Resources Providing Frequency Containment Reserves. *IEEE Transactions on Industrial Informatics*, April 2018.

VI Christian Giovanelli, Xin Liu, Seppo Sierla, Valeriy Vyatkin, Ryutaro Ichise. Towards an aggregator that exploits big data to bid on frequency containment reserve market. In *Industrial Electronics Society, IECON 2017-43rd Annual Conference of the IEEE*, Beijing, China, 7514–7519, November 2017.

VII Christian Giovanelli, Seppo Sierla, Ryutaro Ichise, Valeriy Vyatkin. Exploiting Artificial Neural Networks for the Prediction of Ancillary Energy Market Prices. *Energies*, July 2018.

Author's Contribution

Publication I: "Optimization of decentralized energy storage flexibility for frequency reserve"

The author was involved as a co-author, writing parts of the publication, mainly those related to coordination logic.

Publication II: "Distributed ICT architecture and an application for optimized automated demand response"

This publication presents research by the author who designed and developed the ICT architecture and wrote most of the publication.

Publication III: "A distributed ICT architecture for continuous frequency control"

The author has designed and simulated the DR system, as well as written a larger part of the manuscript.

Publication IV: "Towards a task allocation algorithm for frequency containment reserves"

This article presents research by the author who modelled and simulated the system as well as wrote most of the publication.

Publication V: "Task Allocation Algorithm for Energy Resources Providing Frequency Containment Reserves"

The author contributed to the formulation, development and simulation of the task allocation algorithm, and wrote most of the two publication.

Publication VI: "Towards an aggregator that exploits big data to bid on frequency containment reserve market"

The author contributed to the publication by designing the models and executing the experiments. In addition, the author wrote most of the publication.

Publication VII: "Exploiting Artificial Neural Networks for the Prediction of Ancillary Energy Market Prices"

The author contributed to the publication by designing the models and executing the experiments. In addition, the author wrote most of the publication.

List of Symbols

Acronyms

UCII	Use case 2
UCI	Use case 1
aFRR	Manual frequency restoration reserve
AMQP	Advanced message queue protocol
ANN	Artificial neural network
ARIMA	Auto regressive integrated moving average
DER	Distributed energy resource
DES	Domestic energy storage resource
DR	Demand response
DROS	Demand response optimization service
DSM	Demand side management
EV	Electric vehicle
FCR	Frequency containment reserve
FCR-D	Frequency containment reserve for disturbance operation
FCR-N	Frequency containment reserve for normal operation
GBDT	Gradient boosting decision tree
HAN	Home area network
HEMS	Home energy management system
ICT	Information and communication technology

mFRR	Automated frequency restoration reserve
MIMO	Multi-input multi-output
MOM	Message-oriented middleware
MSE	Mean squared error
SGD	Stochastic gradient descent
SVM	Support vector machine
SVR	Support vector regression
TSO	Transmission system operator
V2B	Vehicle-to-building
V2H	Vehicle-to-home
VPP	Virtual power plant
WAN	Wide area network

Greek symbols

$\Delta f(t)$	Frequency deviation
Δf_{dead}	Dead-band frequency deviation
$\Delta f_{\max}$	Maximum frequency deviation
$\Delta \overline{f}(t)$	Filtered frequency deviation
δ_{cloud}	Cloud-based system communication delay
δ_{han}	Home area network communication delay
$\delta_{\max}$	Maximum communication delay
$\delta_{\min}$	Minimum communication delay
δ_{total}	Total communication delay
τ_1, τ_2	Under/over-frequency task

Latin symbols

$\overline{f}(t)$	Filtered frequency
$b^r(\tau)$	Bidding function of an energy resource for a task
C	Set of consumers
c	Residential consumer

$depth$	Architecture depth of the artificial neural network
$DR_{\text{desired}}(t)$	Desired control target
$f(t)$	Frequency
f_{nom}	Nominal frequency
$fa(r,\tau,t)$	Frequency allocation function
$flex(r,\tau,t)$	Power flexibility of an energy resource
$flex_{\text{target}}(\tau,t)$	Target power demand
$flex_{\text{toProvide}}(\tau,t,f)$	Flexibility required for one task
$flex_{\text{total}}(\tau,t)$	Total system flexibility
p	Dropout of the artificial neural network
R	Set of energy resources
r	Domestic energy storage resource of the demand response system
$R_{\text{allocated}}(\tau,t)$	*Allocated* function
$R_{\text{available}}(\tau,t)$	*Available* function
$R_{\text{disconnected}}(\tau,t)$	*Disconnected* function
$R_{\text{idle}}(\tau,t)$	*Idle* function
$R_{\text{inoperative}}(\tau,t)$	*Inoperative* function
$R_{\text{monitoring}}(\tau,t)$	*Monitoring* function
$R_{\text{reacting}}(\tau,t)$	*Reacting* function
T	Set of tasks
t	Time in seconds
$t_{\text{available}}(r,\tau)$	Estimated time of availability of an energy resource
$ta(r,t)$	Task allocation function
$y(\tau,r)$	Binary function that specifies the allocation of a resource to a task

1. Introduction

1.1 Background

A crucial aspect of power systems consists of maintaining a constant frequency in the electrical grid, in order to prevent the occurrence of abnormal events that can lead to severe outages and damage. In the power grid, the deviation of frequency from the nominal value is caused by power imbalances between the production and consumption of electricity. In recent years, power imbalances have rapidly increased within the power grid, mainly due to an increase in variable renewable generation [1] and changes in consumption patterns, arising from factors, such as the expansion of electric vehicles [2]. Therefore, a mechanism is needed for maintaining the production/consumption balance in the power grid. This mechanism, known as demand response (DR), requires the active involvement of consumers in balancing the power grid.

With the liberalization of the energy markets and evolution of the power grid, several market mechanisms have recently emerged for DR, including ancillary service markets [3, 4]. Ancillary services are special services provided by the power grid with the objective of supporting the maintenance of the balance between demand and supply, thus ensuring the continuous flow of electricity. In the Nordic power system, the specific ancillary service market for maintaining the grid balance is referred as the Frequency Containment Reserve (FCR). The task of FCR is to maintain the balance of the gird within the time frame of minutes or seconds and to stabilize the system frequency after the occurrence of an imbalance event. Thus, FCR has a key role in frequency coordination and the power balancing. The FCR consists of two types of reserve markets: the FCR for normal operation (FCR-N) and the FCR for disturbance operations (FCR-D).

The evolution of the smart grid has also contributed to the development of new business models and smart grid entities, with many more yet to come. Among others, one key role in the engagement of consumers to the DR will be represented by aggregators. Aggregators are new entities in the smart grid that act as mediators between consumers and utility operators [5]. They provide the technologies to execute DR and to participate in DR markets on behalf of the consumers. In addition, the aggregators coordinate the consumers during three different phases of the DR: the day-ahead phase, the intraday phase, and the actual frequency control provision phase.

One important category of distributed energy resources (DERs) is energy storage resources [6], with the focus of this dissertation being the exploitation of domestic energy storage resources (DESs) for DR, and FCR-N in particular. Since numerous types of energy storage resources exist, a categorization would be useful to define the scope of this dissertation. One major categorization is based on the type of energy that is stored. In an industrial context, many categories can be identified, including mechanical rotational energy stored in a flywheel and gravitational energy in pumped storage systems. However, in a domestic context, two main categories of DESs can be identified:

1. electricity storage, such as dedicated batteries and electric vehicle batteries, which are expected to grow in volume in the coming years due to a rapid fall of battery packs prices [7],

2. thermal energy storage, such as refrigerators, freezers, heating systems, boilers, and air conditioning systems.

Another means to categorize energy storage resources is according to their primary function:

A. dedicated storage resources enabling households to participate in the smart grid for:

   a. contributing to a greener energy system
   b. exploiting fluctuations in electricity markets such as spot and DR markets

B. storage resources that perform a useful function for the user, such as electric vehicle batteries, refrigerators, and boilers. A common characteristic of these DERs is that because they have a primary function required by the user (e.g. driving or maintaining a temperature), they can only be exploited for DR under one of the following conditions:

   a. the requirements for the primary function of the DER are not violated
   b. a separate agreement is made with the user allowing the requirements for the primary function of the DER to be altered for the purpose of DR

With respect to the above categories, this dissertation focuses on the following areas: both categories 1 and 2, as well as A. and B., are considered through case studies involving dedicated battery storage (Publications I and II) and refrigerators (Publications III, IV and V). The refrigerator is representative of most storage resources belonging to categories 2 and B., as they consume energy for heating or cooling purposes and are characterized by the requirement of maintaining the temperature between a lower and an upper limit, because of this requirement, the work in Publications III, IV and V can readily be generalized to DESs. Furthermore, as the focus is on solutions with a financial incentive for the user, A.a. is not considered, but A.b. is considered. B.a. is considered, especially for DERs that singly could not participate in DR, but which may be aggregated in order to satisfy condition B.b..

Another approach categorizes DR solutions based on different time frames in which they are executed. This approach distinguishes between DR markets and the technical requirements and profit-making opportunities related to participating in a specific market. One method for performing DR is to reschedule electricity consumption to reduce the consumption in hours when the spot market price is high and to increase the consumption when the spot market price is low. However, since domestic consumers typically pay a fixed price to a retailer, the retailer should have some direct or indirect means of controlling the consumer loads in real time in order to be able to perform this kind of demand response [8]. Another method for performing DR is to participate in ancillary markets, such as FCR-N, which would compensate participants for their readiness to adjust their consumption in real-time when there are frequency deviations; the compensation is paid regardless of whether the frequency deviations occur. In ancillary service markets, such as FCR-N, in order to participate in the reserve provision, it is required to bid during the day-ahead, therefore planning and forecasting actions are necessary before placing the bids. Thus, in order to profitably exploit DESs in ancillary service markets through DR, an aggregator needs to operate on three timeframes:

i **Day-ahead**: the aggregator needs both to forecast hourly prices on spot and ancillary markets as well as to estimate the energy consumption and storage capacity at the households in order to be able to bid intelligently on day-ahead markets and to establish a day-ahead plan for controlling DESs. This planning is typically conducted as an automated interaction between the aggregators and consumers [9].

ii **Intraday**: currently, intraday markets for ancillary services only exists as a proposal by researchers, since the actual markets require day-ahead bidding [8]. Thus, henceforth in this dissertation, the term intraday will be used to refer to an intraday planning activity that is carried out between the aggregator and its consumers, as a refinement to the day-ahead plan mentioned above for day-ahead time frames i. Refinements are needed, since errors may have occurred in the forecasts and estimates used as the basis for the day-ahead plan.

iii **Continuous DR**: real-time control of consumers' DERs is required to fulfill the day-ahead and intraday plans. In the case of a DR that exploits spot market price fluctuations, it will be necessary to ensure that the overall electricity consumption during a specific hour occurs according to the plan. However, in the case of ancillary markets, the participant is required to monitor the frequency and automatically react to frequency deviations if they occur. The role of an aggregator is to coordinate several consumer-owned DERs in order to increase or decrease in real-time the overall energy consumption increase or decrease that is required to react to over-frequency or under-frequency situations, as specified in the technical requirements of the chosen ancillary service market.

The type of DR market that will be chosen and the actions that are required on these different timeframes depend on the type of DERs. A category A. DER could be well suited to a mode of operation that charges the DER when the spot price is low and then used to cover the household energy consumption several hours later when the spot price is high. However, the time constant of the heating and cooling processes performed by category B. DERs is such that any attempt to shift energy usage by several hours will impact the comfort of the user. If the users are unwilling to accept these impacts in return for a compensation that is profitable for the aggregator [5, 10], it may still be possible to participate in ancillary services markets. However, this requires careful planning and real-time coordination of the DERs in several households in order to meet the technical requirements for the ancillary services without sacrificing the comfort of the users.

In order to participate in ancillary markets, aggregation is mandatory, for the following reasons:

I the minimum bid on ancillary markets is too high for individual consumers. For example, in Finland, the minimum bid on day-ahead market is 0.1 MW for FCR-N and 1 MW for FCR-D [11],

II individual consumers are lacking of technical know-how and economic power needed to validate both the DERs capability to provide reserves, as well as the required ICT infrastructure for participating in the FCR markets.

III a single DER, such as a refrigerator belonging to category B.a. cannot participate in frequency containment reserves without aggregation since it has a limited power that cannot be used to bid in markets with a minimum bid in the order of several kW or MW. Therefore, a large number of intelligently aggregated as well as coordinated DERs could participate.

For these three reasons (I-II-III), a major question arises concerning automation architecture, as most of the scientific literature has investigated centralized versus decentralized approaches:

1) One extreme approach would be a fully centralized solution, which would provide a centralized actuator with access to the sensor data of all DERs under its control, thus allowing it to control the DERs reliably in real-time in order to react to frequency deviations as required from participants in frequency containment reserves.

2) Another extreme approach would be fully decentralized. Such an approach would require that the participating DERs negotiate and jointly agree on a plan.

3) Finally, it is possible to split the control logic, so that some of it is performed in a centralized way by the aggregator and some of it is performed locally by intelligent DERs in the households.

The first and second approaches raise hard real-time communication requirements for large numbers of messages, which is problematic if using the public Internet. If the public Internet is not used, the cost of the communication infrastructure will undermine the viability of the entire approach, since the financial incentives for DR do not offer large profit margins [12]. Thus, the focus of this dissertation is on the third approach. However, aside from its real-time requirements, the third approach also presents additional requirements for the automation architecture in terms of the ease of adding one domestic user to the system or coping with a consumer's DER becoming suddenly unavailable for whatever reason.

1.2 Research goals

This Ph.D dissertation aims to achieve the following research goals:

RG1 Define requirements for using smart domestic loads to provide frequency containment reserves

- RG1.1 functional requirements (in terms of use cases)
- RG1.2 non-functional requirements arising from technical requirements of FCR-N

RG2 Propose and assess a hybrid (or partially decentralized) ICT architecture capable of coordinating consumer-owned DESs in the provision of FCR-N reserves.

RG3 Identify the key decision-making to be considered in order to exploit the developed system profitably in FCR markets. Then, focus on a crucial prediction task to support reducing the participation risks and uncertainties, namely the day-ahead prediction of the market prices.

1.3 Hypothesis

In this dissertation, the hypothesis investigated is that a hybrid ICT architecture can efficiently exploit DESs for participating in the provision of frequency containment reserves.

1.4 Contribution to the field

The main contributions of the dissertation are summarized hereafter:

- A novel hybrid ICT architecture has been proposed, which enables the coordinated participation of residential consumers and their DESs in the DR. The proposed architecture enables the execution of DR, which is executed for both DR phases, DR planning and frequency control provision.
- A coordination algorithm has been designed to enable consumer-owned DESs for the provision of FCR-N reserves. The coordination algorithm has been formulated as an auction-based task allocation algorithm, which helps to achieve simultaneously two fundamental objectives: avoid the need to send hard real-time messages over the public Internet, and flexibly handle DESs being plugged and unplugged from the DR system.
- A solution for performing day-ahead predictions of hourly FCR-N prices has been proposed, where the prediction performance of various machine learning methods have been compared, including artificial neural network (ANN). In addition, a detailed empirical assessment has been performed for the data selection and preprocessing as well as the hyper-parameter tuning of the ANN.

1.5 Summary of the publications

This dissertation consists of seven publications (two journals and five conference papers), which can be divided in two groups. The first five publications (I-V) comprise research on designing and assessing the DR system, which combines ICT architecture and coordination algorithms to enable the execution of DR during different time frames. The two remaining publications (VI-VII) aim at exploiting the developed system to profitably participate in the FCR markets by presenting the research done for the prediction of the FCR-N market prices.

Publication I presents a novel distributed multiobjective algorithm designed for an electricity aggregator, that schedules its aggregate energy consumption. The aggregated total consumption is in the form of distributed consumer-owned DESs, where the aim of the optimization is to minimize the spot market acquisition costs for the day-ahead while maximizing the flexibility of the consumption schedule. The developed optimization was then utilized as an application for the execution of DR planning in Publication II.

Publication II extended the work presented in Publication I by defining a novel hybrid ICT architecture that can enable the coordinated participation of distributed residential consumers into the DR, thus providing the capability of optimizing scheduling of the DESs involved, and the capability of operating the two planning phases of DR, namely day-ahead and intraday. This publication identifies the requirements and designs an ICT architecture for a DR system capable of executing optimization schemes performed during DR planning. In addition, the publication uses simulations to evaluate the developed architecture and its capability to optimize the DR.

After defining an ICT architecture for DR planning, Publication III extends the research to enable the ICT architecture to provide frequency control, by coordinating several consumer-owned DESs for the provision of FCR-N reserves. The publication focuses on the ICT architecture and the communication required for coordination between the aggregator and several consumer-owned DESs, which in the presented case study consisted of refrigerators. It is demonstrated that the designed ICT architecture is also capable of executing continuous frequency control.

Publications IV and V focus on the coordination of consumer-owned DESs by designing a novel auction-based task allocation algorithm for the provision of reserves on the FCR-N market. The aim of the two publications is to provide a comprehensive solution that combines coordination algorithms and ICT architecture, with the main objective of developing a task allocation algorithm for DESs participating in FCR-N reserve provision. In doing so, the task allocation is designed to achieve the two following sub-objectives: to avoid the need to send hard real-time messages over the public internet, and to flexibly handle DESs being plugged and unplugged from the system. This work has been presented in both publications, with Publication IV introducing the concept of a task allocation algorithm, and Publication V describing extensively the design process and several simulated scenarios that apply the task allocation algorithm. The task allocation algorithm is shown to handle the plugging and unplugging of the DESs, and when combined with message-oriented middleware, is capable of avoiding the need for hard real-time communication messages. In addition, it is demonstrated that the task allocation algorithm fulfills the participation requirements specified by the transmission system operator (TSO) for the FCR-N market.

The last two publications of this dissertation, Publications VI and VII, focus on supporting the decision-making strategies for participating in DR ancillary markets, which use the FCR-N market as a case study. Publication VI presents an architecture for managing intelligent bidding on the FCR-N market and proposes a technical solution that relies on data and several machine learning methods for prediction of FCR-N prices. The prediction performance of the employed methods have been compared and evaluated by means of experimental results. Finally, Publication VII proposes a solution for the prediction of FCR-N market prices, which employs an artificial neural network model. The publication analyzes the FCR-N prices, identifies relevant data for the predictions and presents a methodology that can be applied for predicting FCR-N prices. The prediction performance of the developed model has been evaluated in detail and compared with other state-of-the-art methods.

1.6 Structure of the dissertation

The remainder of this dissertation is structured as follows. Chapter 2 presents related work. Chapter 3 describes the proposed system by defining the requirements (Section 3.1), designing the DR system (Section 3.2) and enabling the participation of such a system in the FCR-N market (Section 3.3). Moreover, Chapter 4 presents and discusses simulation and experimental results. Finally, Chapter 5 concludes the dissertation and identifies further work.

2. Related work

2.1 Demand response

Traditionally, the power grid was structured to enable a small set of large producers to provide electricity for a large set of geographically distributed consumers [13, 14]. In this traditional top-down structure, the balance of the power grid was maintained by the producers, who were capable and flexible enough to follow changes in electricity consumption. In recent years, both the production and consumption side have undergone a profound modernization, which no longer allows the power grid to operate using the traditional top-down approach [15]. In fact, the increase in the penetration of distributed variable renewable generation has made the production of electricity less flexible [1, 2]. On the other hand, the introduction of electric vehicles is rapidly changing the consumption patterns of electricity [16, 17]. With all these radical changes, relying solely on the production-side for balancing the power grid can have serious consequences for the reliability of the grid itself [18]. Thus, modernization of the power grid requires the design and development of new strategies to ensure that the reliability of the grid is not endangered.

New strategies for enabling modernization of the future smart grid will require engaging the demand-side in efforts to balance the power grid, thus making the demand-side more flexible. The set of different strategies for enabling increased flexibility of the demand-side has been referred as demand side management (DSM) [19]. Specifically, DSM includes all the methods that can be applied to the demand-side in order to modify the consumer demand for electricity. A classification scheme for DSM has been proposed by Palensky et al. [19] based on the time scale and the impact that such measures have on the consumer process. Thus, DSM can be classified in terms of:

a. Energy Efficiency

b. Time of Use

c. Demand Response (DR)

d. Spinning Reserve

Energy Efficiency consists of actions that can permanently improve the efficiency of energy systems, such as: physical and apparatus changes in the energy systems, as well as behavioral changes in the consumers [20]. Time of Use consists of tariffs that are defined to penalize certain periods of time during the day, causing the consumers to shape their consumption and thus minimize their energy costs [21]. DR is defined as "a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized." [22]. Palensky et al. [19] further subcategorizes DR into market DR and physical DR. Market DR consists of price signals or incentives meant to induce consumption changes, while physical DR includes emergency signals and continuous regulation that aim at preventing grid failures. Spinning Reserve refers to large power reserves that are usually activated when severe imbalances occur in the grid [23]. Among these DSM methods, DR is the focus of this dissertation, which seeks to identify solutions for both market DR and physical DR.

2.1.1 Time frames

DR can be categorized based on three different time frames in which it is to be implemented [24]:

i. Day-ahead

ii. Intraday

iii. Continuous DR

Of the three DR time frames, this dissertation focuses on both DR planning, i.e. more precisely on the day-ahead (i.), and on the constant execution of DR, defined as continuous DR (iii.). Although several solutions have been proposed for implementing DR in different time frames, current research has focused only on either day-ahead planning or continuous DR, without considering how these two phases can be combined and integrated together. In fact, most of the research on the day-ahead time frame has focused on optimizing the scheduling of DERs participating in the DR [25], taking into consideration factors, such as the impact of variable renewable generation [26], the penetration of EVs [27,28], and the exploitation of consumer-owned DERs [12,29,30]. On the other hand, research on continuous DR has mainly focused on designing the control logic for enabling several DERs to participate in the continuous DR [31,32], while addressing various types of DERs, including thermo-dynamic loads [33], EVs [34], and energy storages [35]. However, such studies on day-ahead and continuous DR remain narrow in focus dealing only with one of the DR time frames, without considering how such time frames should be integrated and implemented.

2.1.2 The stakeholders

In recent years, the evolution of the power grid has introduced new opportunities for old and new stakeholders, who need to undertake new roles and new responsibilities, while at the same time having different objectives [36]. In the context of DR, various smart grid stakeholders can benefit from DR endeavors [37, 38]:

a) Suppliers

b) Transmission System Operators (TSO)

c) Distribution System Operators (DSO)

d) Retailers

e) Aggregators

f) Consumers

Suppliers can benefit from DR by reducing the capacity of their expensive power plants activated during few peak periods [39]. This would then provide TSOs and DSOs with an additional and alternative source of flexibility for efficiently maintaining the balance in the grid [40, 41]. Flexibility could be brought by retailers in order to provide new tailored services to their consumers. Furthermore, retailers could also provide aggregating services, though these services might also be offered by aggregators independent of retailers [42, 43]. Aggregators are new stakeholders in the smart grid, which aim to aggregate consumers and their respective loads in order to enable their participation into the DR [5], by acting as brokers between the consumers and other energy players. Aggregators provide new electricity services to the consumers and have the responsibility of managing the flexibility provided by the consumers as an aggregated asset that can be used during the occurrence of unbalance events in the grid [44]. Finally, consumers are moving from being passive to being actively involved in the balancing of the grid by participating in the DR [45], thus monetizing with the flexibility provided by their assets.

DR consumers
In the literature, DR is considered to have three different types of consumers [46]:

- industrial consumers,
- commercial consumers,
- residential consumers.

The active engagement with DR by these three types of consumers has developed in different ways. However, while DR is already a reality for industrial and commercial consumers [47, 48], expansion of DR to residential consumers requires overcoming several new challenges [49].

One key challenge hindering residential consumers from participating in the DR is the collaboration between aggregators and consumers [50]. In fact, residential consumers need to be aggregated in order to be able to provide enough capacity for a DR market [51]. Moreover, individual residential consumers might lack the motivation to make large investments in DR equipment, nor do they have the required technical knowledge necessary for participating in a DR market [45]. Thus, aggregators play a crucial role in engaging residential consumers into the DR [5], by mediating between consumers and DR markets, as well as providing the required ICT infrastructure for the coordination of a large number of distributed consumer-owned smart loads. The collaboration between these two smart grid stakeholders, aggregators and residential consumers, is investigated in this dissertation, with a particular focus not only on the coordination of a large number of distributed consumer-owned smart loads but also on the ICT infrastructure necessary for both planning and executing the DR.

2.2 Energy markets

Since the mid-1980s, several countries have started the process of modernization, liberalization, and privatization of the wholesale electricity markets [52]. This process brought several advantages including an increase in competition and market participants, while improving generation and distribution productivity, encouraging innovation of new power technologies and providing a better service to the end customers [53]. On a global scale, several approaches have been employed to design and develop the electricity markets [54]. In Europe, despite the declared aim of building an integrated competitive electricity market, the European energy markets still remain regionally fragmented [55]. Of these regional markets, this dissertation focuses on Nordic energy market.

The Nordic energy market is a common market for electricity which was established in the Nordic countries [56] (i.e., Denmark, Finland, Norway, and Sweden), and has recently been extended to other neighboring countries (i.e., Estonia, Latvia, Lithuania, UK, and Germany). The energy market is divided into electricity and ancillary service (or balancing) markets. The electricity markets are operated by the Nord Pool exchange [57], which trades power via two markets, the day-ahead and the intraday markets. On the other hand, the ancillary service markets are operated by the TSOs of each country; more specifically, in Finland, these markets are operated by Fingrid [58]. The ancillary service markets can be classified into three distinct levels of reserve, which can be used to maintain the balance between production and consumption: primary, secondary and tertiary ancillary service markets.

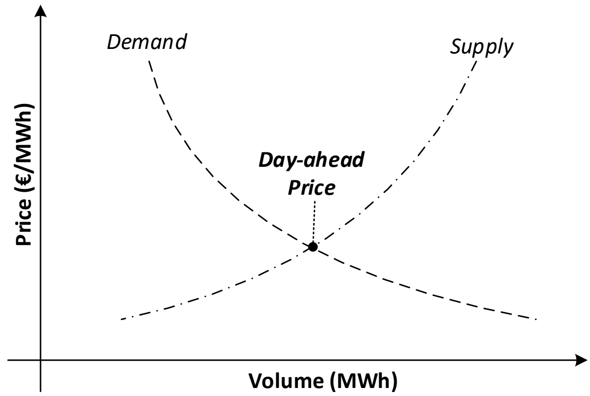

Figure 2.1. The day-ahead prices are calculated as the intersection between the demand curve and the supply curve

2.2.1 Nord pool spot markets

In the Nordic countries, the Nord Pool Spot operates two electricity markets:

- the Elspot Day-ahead market [59],
- the Nord Pool Intraday market [60].

The Elspot Day-ahead market is an auction market where most of the electricity is traded every day. The participants, power buyers, and sellers, that want to trade electricity need to send their bids to the Nord Pool Spot by noon (CET) of the previous day. The electricity is traded on an hourly timescale, i.e. the participants can make bids for each hour of the following day, specifying prices and volumes. For each hour, the Nord Pool Spot computes the day-ahead prices based on a double auction [61], i.e. both buyers and sellers have to bid. Thus, day-ahead prices are calculated as the intersection between the demand curve (i.e., generated by aggregating the bids from the buyers) and the supply curve (i.e., generated by aggregating the bids of the sellers) as shown in Figure 2.1.

Since the Elspot Day-ahead market requires the participants to plan one day in advance, the Nord Pool Spot provides the Nord Pool Intraday market in order to allow the participants to update their production and consumption plans. Hence, the Nord Pool Intraday market aims at helping to secure the balance in the power grid, which is becoming increasingly important due to the growing penetration of variable renewable generation, which requires close to real-time production/consumption updates. The Intraday market allows continuous trading until one hour before delivery. In the Intraday market, instead of a double auction, the prices are decided based on a first-come, first-served principle, i.e. the highest buy prices and the lowest sale prices have priority.

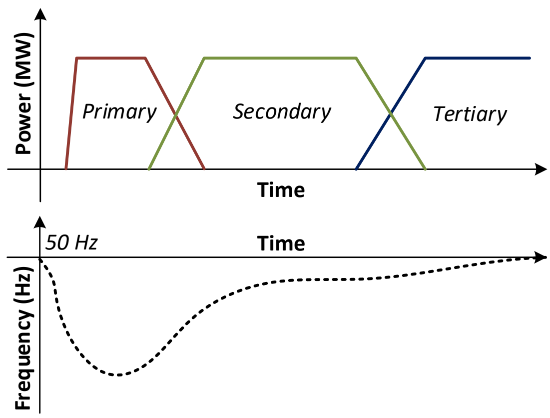

Figure 2.2. Classification of ancillary energy markets

2.2.2 Ancillary service markets

Relying solely on electricity markets is not sufficient to ensure a reliable power grid. Therefore, in addition to electricity markets, ancillary service markets are used as supporting mechanisms to guarantee continuous power balance in the grid [3, 4]. On a global scale, the importance of the ancillary service markets has grown rapidly in recent decades, mainly due to the liberalization of the energy markets and the increasing penetration of variable renewable generation [62]. This has led to a wide variety of solutions, both in terms of regulations and technical requirements, for developing ancillary service markets in different countries [63]. Thus, it is not possible to provide a uniform classification of ancillary service markets and their balancing mechanisms. Consequently, this dissertation focuses on the ancillary service markets in only the Nordic countries, and more precisely in Finland.

The ancillary services in the Nordic countries can be classified as primary, secondary and tertiary services. Figure 2.2 shows how the three ancillary services are utilized for frequency control, as proposed in [64]. As shown in the figure, the primary service aims at providing frequency control to enable frequency containment, while the secondary and tertiary services aim at restoring the frequency in the power grid. The primary ancillary services are used to contain the frequency deviations in the power grid and are composed of two services: FCR-N and FCR-D. The FCR-N provides frequency control for minor deviations in the power grid, while FCR-D aims at supplying fast-reacting reserves when large frequency deviations occur (e.g. a power plant failure). On the other hand, secondary and tertiary services are used to restore the frequency to the nominal value (i.e. 50 Hz in Europe) and are provided by the automated Frequency Restoration Reserve (aFRR) and the manual Frequency Restoration Reserve (mFRR), respectively. The aFRR acts as secondary frequency control reserves, which are activated automatically by the TSO. In contrast, the mFRR act as

Table 2.1. Participation requirements for the ancillary markets in Finland

Market	Type of Contract	Minimum Bid Size	Market closure
FCR-N	Yearly and hourly markets	0.1 MW	Hourly market day before at 18:30 (EET)
FCR-D	Yearly and hourly markets	1 MW	Hourly market day before at 18:30 (EET)
aFRR	Hourly market	5 MW	Day before at 17:00 (EET)
mFRR	Hourly market	5 MW	45 min before each hour

tertiary reserves that need to be manually activated by the TSO.

The FCR reserves can be provided either through a production response, e.g. a hydropower plant that maintains production flexibility to be used as FCR reserve, or through demand response, e.g. a change in consumption from the demand-side for providing flexibility to the FCR market. This dissertation focuses on the provision of FCR service through demand response. The FCR markets provide the possibility for both yearly and hourly trading. In order to participate in the hourly trading of the FCR markets, the participants need to submit their bids by 18:30 EET on the day-ahead containing the product (i.e. FCR-N or FCR-D), the capacity (MW), the price (€/MW) and the hour of the next day [65]. The minimum bids in terms of capacity are 0.1 MW for the FCR-N and 1 MW for the FCR-D, while the maximum bids are 5 MW and 10 MW respectively. The aFRR are traded only hourly the day before, with market closure at 17:00 EET and a minimum bid requirement of 5 MW [66]. In contrast, mFRR are traded for each hour until 45 minutes before the delivery. The requirements for participating in the ancillary service markets are summarized in Table 2.1.

Technical requirements

In order to participate in the ancillary service markets, the participants need to be able to meet the technical requirements specified by the TSO. Table 2.2 presents the key technical requirements for the FCR-N, FCR-D, aFRR, and mFRR, in terms of activation time constraints, activation frequencies as well as the number of times these ancillary services are activated. Concerning the FCR, the technical requirements are specified every year by the TSO in an agreement with the participants [67, 68]. For instance, the technical requirements for the FCR-N are as follows. The FCR-N reserve shall react linearly, i.e. the relationship between provided reserves (or flexibility) and frequency deviation is linear as specified in the technical requirements [68]. The FCR-N reserve reacts

Table 2.2. Technical participation requirements for the ancillary markets in Finland

Market	Activation Time	Activation Frequency	How often is activated
FCR-N	3 minutes	Fully after frequency step change of ± 0.1 Hz - max deadband ± 0.05 Hz	Several times a day
FCR-D	Within 5 s / 50 % and 30 s / 100 %	Activated when frequency < 49.9 Hz, fully activated at 49.5 Hz	Several times per day - per year
aFRR	Begin within 30 s of the signal's reception from TSO, fully activated in 2 minutes	-	Several times a day
mFRR	15 minutes	-	Several times per day - per year

within the specified frequency range of $\pm\Delta f_{max}$, where in Finland $\Delta f_{max} = 0.1$ Hz. In addition, a dead-band frequency $\pm\Delta f_{dead}$ is specified in order to prevent the reserves to react at small and natural fluctuations from the nominal frequency of 50 Hz. The value of Δf_{dead} is defined to be at most 0.05 Hz. In terms of activation time, the FCR-N reserves are required to be fully activated within three minutes from a frequency deviation of $\pm\Delta f_{max}$. Figure 2.3 presents how the FCR-N reserves are required to be activated based on frequency deviations in the grid, emphasizing the linear relationship between flexibility to be provided and frequency deviation.

2.3 Distributed energy resources

The integration of DERs into the smart grid represents one of the key challenges ensuring power supply reliability in the smart grid. DERs consist of electric power resources directly connected to the distribution network of the smart grid [69]. DERs can be subdivided into distributed generation (DG), energy storage resources and electric loads. DG are distributed sources of electric power with a limited capacity that are connected to the distribution network

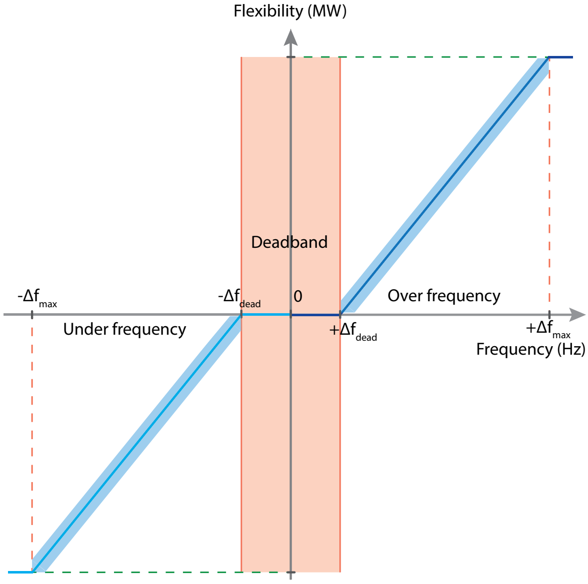

Figure 2.3. Technical requirements for the FCR-N that shows the required provision of reserves depending on the frequency deviation of the power grid from the nominal frequency value of 50 Hz

and directly exploited by the end consumers [70]. Examples of DG include wind turbines, solar photovoltaics, hydro-thermal power, and biomass. Since an increasing share of DG consists of distributed variable renewable generation, there is a need both for storing energy to overcome fluctuations in the energy supply and for exploiting the produced energy in the future. Hence, energy storage resources are required to increase the power supply reliability [71], thus mitigating the occurrence of unbalancing events.

2.3.1 Residential DERs

With the emergence of DERs and development of the smart grid, residential consumers have new opportunities for engaging in the DR. In order to assist residential consumers to participate in the DR, home energy management systems (HEMSs) aim at improving energy efficiency and comfort within residential buildings [72]. These objectives are achieved by automatically monitoring, optimizing, shifting and curtailing the residential energy demand on behalf of consumers. However, to achieve these objectives, HEMSs are required to have a flexible architecture that enables the coordination of a wide range of DERs found in residential buildings. In fact, HEMSs need to be capable of exploiting the characteristics of the DERs in order to provide the best control possible, with respect to the multi-objective nature of residential environments [73].

Despite the diversity of DERs present in residential environments, DERs can be modeled based on their contribution to the DR. To date, a uniform representation of DERs for DR does not yet exist. In fact, several studies propose different classifications of DERs [73–76], providing different approaches that aim at limiting the modeling complexity of the existing range of DERs. In this dissertation, DERs consists of electric loads which are represented based on the models proposed in [73], where DERs are modeled by classifying their DR behavior in response classes. Therefore, DERs can be classified based on the following response classes:

- *Uncontrollable*: loads that cannot be altered by HEMS, since they provide primary services for the well-being of the consumers. Examples of such loads include televisions, essential lighting, and computers. In addition, this response class can also include uncontrollable DG, such as PV and wind turbines.
- *Curtailable*: loads that can be curtailed by HEMS without affecting the consumers. An example of curtailable loads is a lighting system that can be dimmed.
- *Uninterruptible*: loads that HEMS can schedule but once started cannot be interrupted before ending their tasks. Examples include dishwasher and washing machines.
- *Interruptible*: loads that can be interrupted and resumed at later times with minor impacts on the end users. An example of such devices are EVs.
- *Regulating*: typically thermal loads that maintain an energy state at a defined state. Examples include air conditioning, space heating systems, boilers, and refrigerators.
- *Electric storage*: loads that can store energy for later use. Examples include home batteries and EVs capable of V2G and V2B [77].

In this dissertation, the DERs considered are *Regulating* loads (e.g., thermal energy storage resources) and *Electric storage* resources, which are identified as DESs.

2.4 Aggregating residential DERs

Engaging residential consumers in DR is a challenging task that presents several obstacles. For instance, participation in DR markets requires a minimum bid in the order of Mega Watts [11] (e.g., minimum size in Table 2.1), thus disabling the independent participation of residential consumers in the DR. Moreover, since each consumer provides a limited portion of power, the existing DR programs tend to benefit large operators rather than consumers, thus providing insufficient incentives for consumers [5]. Consequently, residential consumers are required to be aggregated by new entities, such as aggregators, that provide brokering services to the consumers thus promoting their participation in DR markets [43].

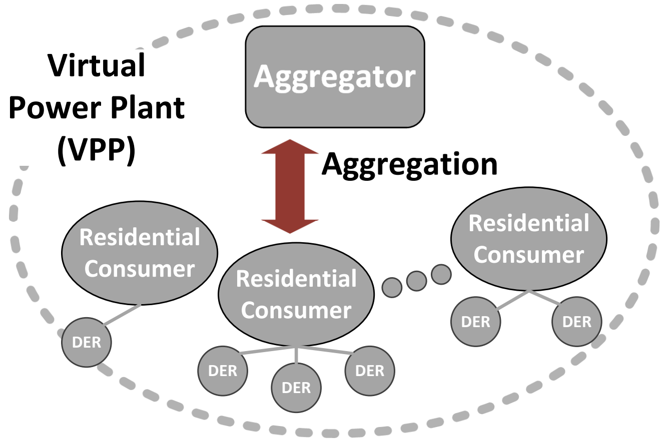

Figure 2.4. Virtual Power Plant (VPP) framework considered in this dissertation

Since the state of heterogeneous DERs changes dynamically, affecting the duration of their availability for DR actions, the aggregation places requirements on the coordination of large sets of residential DERs. Therefore, the coordination of residential DERs represents a distributed automation problem where the integration of both coordination algorithms and electrical components need to be designed interdependently with the ICT architecture which is capable of enhancing the performance of the smart grid [78]. ICT architectures can enable the exchange of information and data, which are essential for enhancing the management and the performance of smart grid operations (e.g., DR operations) [79], while providing economic benefits to the stakeholders involved [80].

The remainder of this section analyzes four key approaches for aggregating DERs and implementing DR for frequency control:

- Virtual Power Plant (VPP),
- Coordination algorithms for DR,
- ICT architectures for DR,
- Exploitation of data for DR operations.

2.4.1 Virtual Power Plant

The VPP framework has been widely used in the literature, leading to the adoption of various definitions, strategies, and components [81–83]. In this dissertation, a VPP aggregates the capacity of a heterogeneous set of DESs, as presented in Figure 2.4. The VPP framework is organized hierarchically. The aggregator stays at the root of the hierarchy and owns the entire VPP. In addition, residential consumers provide the VPP with a heterogeneous set of DESs. The set of DESs can be exploited during several operations of the VPP, such as participation in the FCR-N market, which requires the execution of operations at different time frames. Thus, the VPP supports the integration of the DESs by acting as a single entity in the energy markets. The VPP provides the required ICT technologies for the aggregation of the DESs and is capable of bi-directional communications among stakeholders as well as DESs. This enables the collection and exploitation of data for various VPP operations, including the DR, the execution of coordination algorithms for the DR, and the execution of market intelligence operations, thereby allowing the aggregator to profitably trade flexible capacities of the VPP on several markets.

2.4.2 Coordination algorithms for DR

In order to coordinate a large amount of residential DERs for DR, there is a need for designing algorithms that can effectively enable the active participation of residential consumers in the DR. Coordination algorithms have a key role both in the DR in general as well as in frequency control [84]. Since these coordination algorithms can be designed using various approaches, they can be classified according to the communication and coordination requirements that each algorithm requires. Based on this classification, two distinct classes of coordination algorithms can be obtained: centralized and decentralized [85, 86].

Centralized coordination algorithms use a central authority (e.g., an aggregator) to coordinate the consumers through control signals. Therefore, they require an underlying ICT architecture to enable bidirectional communication between the central authority and the DERs. Various centralized coordination algorithms have been developed that exploit an ICT architecture. In [87], a centralized coordination algorithm is designed and simulated in a small proof of concept system, which is then evaluated in terms of both the presence of renewable wind power and the impact of communication delays. Central coordination algorithms have been used to mitigate the imbalance between actual aggregated demand and the desired aggregated demand [88]. In [89], a centralized coordination algorithm is developed based on direct load control, where the central authority requires that the participants provide the current states of the DERs, which are then used to define the control signals to be dispatched.

On the other hand, in decentralized algorithms, no coordination with a central unit is needed, since decisions are made locally. Thus, decentralized algorithms require no ICT architecture to operate, relying instead on local measurements and data instead. Decentralized algorithms for frequency control have been used by several studies. Various decentralized algorithms have been designed and simulated in systems where power system requirements, as well as consumer comfort, are considered in order to investigate the impact of decentralized algorithms on the power system [31]. In [90] a decentralized algorithm is designed for allowing DERs to directly react to the frequency deviations based on a frequency-time characteristic that defines when the DERs need to provide flexibility. In addition, state machines have been used as decentralized coordination algorithms [32], where each DER is classified based on their usefulness in a residential environment, and then different reaction policies are assigned to each class.

Centralized and decentralized coordination algorithms present different advantages and disadvantages [84]. For instance, centralized coordination algorithms allow the central authority to gain a global overview of the system [91], allowing the aggregator to commit to different volumes of reserves for short time periods. This advantage becomes particularly relevant when the provided reserves need to be agreed upon beforehand, i.e., during the planning phases of day-ahead and intraday markets. In addition, the increased level of controllability in the centralized strategy can reduce financial risks, while enabling prioritization and cooperation. However, the large number of DERs to be coordinated could increase the complexity of the computational tasks as well as the exchange of information and data. In contrast, decentralized strategies require less information and data exchange as well as no need for global ICT architecture since the decisions are made locally. Further, another important feature of decentralized strategies is their capability of enabling the plug and play of new DERs [85].

Given the classification of coordination algorithms for DR, a third class can be derived from the two aforementioned classes: a hybrid (or partially decentralized) coordination algorithm. The hybrid coordination algorithm is the combination of centralized and decentralized strategies, which aim at enhancing coordination performance [92]. However, the hybrid approach has been investigated in only a few studies. For example, a hybrid coordination algorithm is introduced in [5], which focuses is on defining a three-layer hierarchical architecture and a DR mechanism that could provide benefit to the stakeholders involved (i.e. residential consumers, aggregators, and retailers) rather than focusing on how the coordination should take place in a hybrid coordination algorithm. Nevertheless, hybrid coordination algorithms have shown higher performance than decentralized strategies [93], while reducing computational load compared to centralized strategies.

DESs coordination through task allocation

One of the research objectives of this dissertation is to propose a hybrid coordination algorithm that coordinates a set of DESs for the provision of FCR-N reserves. The hybrid coordination algorithm is developed as a task allocation algorithm that employs an auction-based mechanism. Such task allocation problems have attracted wide attention in various engineering domains, including parallel computing [94], data centers [95] and robotics [96]. For example, swarm robotics [97], game-theory [98], and auction-based [99] methods have been applied to enable distributed and heterogeneous entities to cooperate in order to tackle complex tasks. Indeed, the coordination of heterogeneous DESs for the provision of FCR-N reserves represents a complex task, in which the aggregator is responsible for coordinating a large number of DESs. Therefore, the task allocation algorithm is formulated as a swarm intelligence model as defined by

Cornejo et al. [100], which employs an auction-based mechanism to allocate the tasks to the DESs [99]. In fact, auctions are multidisciplinary methods employed to solve complex task and resource management problems [101]. Auction-based mechanisms have been extensively used in multi-robot [102], wireless [103] and parallel computing [104] systems. However, auction mechanisms have not been applied for allocating tasks that would allow consumers owned DESs to participate in ancillary services in general and FCR-N in particular. Thus, the proposed hybrid coordination algorithm represents the first attempt to formulate a task allocation algorithm based on an auction mechanism that aims at enabling participation in FCR-N reserve provision.

2.4.3 ICT architectures for DR

ICT architectures can support the integration of both DERs and the coordination algorithm by providing communication capabilities. Thus, ICT architectures are foreseen to play a fundamental role in the development of the future smart grid [78, 105]. However, the large number of requirements that ICT architectures for DR need to satisfy [106] calls for the development of a wide range of technologies in order to enhance current ICT architectures [13].

Currently, development of ICT architectures for smart grids focuses on middleware architectures for integrating distributed and heterogeneous entities. Middleware architectures are expected to act as brokers between a vast number of heterogeneous entities, enabling communication and computation within a future power grid [107]. Middleware architectures consist of distributed software that can abstract underlying heterogeneous entities (e.g., DERs, DESs) with the objective of providing high-level functionalities that can be accessed by an overlying application layer [108]. Several middleware architectures exist that have the potential to be employed in a smart grid [109]. However, each architecture presents tradeoffs that need to be cautiously examined beforehand [110]. Among the current middleware architectures, service-oriented [111] and message-oriented (MOM) [110] middleware architectures could provide potential solutions due to the distributed nature of the problem.

In addition, cloud computing has emerged as a candidate driver technology for the future power grid [112]. Cloud computing helps in reducing costs while providing several benefits [113]. ICT architectures based on cloud computing could offer increased security, scalability and reliability for smart grids [114]. Furthermore, cloud computing can reduce the costs of information management [115], which is seen as a major issue in the smart grid due to the complexity implied by such a distributed system. However, employment of cloud computing for the aggregation of DERs is still at an early stage of development, with only a limited number of solutions having been proposed [114, 116].

2.4.4 Exploiting data for DR operations

With advancements in new ICT architectures for aggregating DERs and more intelligent DERs, an ever-growing amount of data is becoming available from the power grid, enabling the exploitation of the data for DR operations [79]. In fact, several data sets can be collected from a large assortment of sources [79], including markets, smart meters, and weather. These datasets can be used to support operations and decision processes in the smart grid [117]. It has been demonstrated that analyzing data can improve the execution and optimization of operations, such as planning, monitoring, and power grid protection [118]. In addition, data analysis can enhance the decision-making capabilities of stakeholders, such as electricity retailers [119], and aggregators [5]. These stakeholders can benefit from the data collected from available market and smart meters to minimize the uncertainties of the operations in which they are involved [120]. Retailers and aggregators can also exploit data in order to target different segments of consumers for different DR programs [121]. Indeed, big data has been shown to be central in understanding the energy consumption behavior of residential consumers [122]. Therefore, the exploitation of data is playing an increasingly important role in supporting various operations and decision-making strategies in the smart grid, including DR.

Exploiting data for predicting energy prices

Predicting energy prices is fundamental in supporting the decision-making strategy for participating in day-ahead energy markets. Therefore, the prediction of energy market prices has attracted considerable interest. Several modeling approaches have been developed for the analysis and prediction of energy prices [123, 124]. In [123], the modeling approaches are classified into five categories: game theoretic models, fundamental methods, reduced-form methods, statistical approaches, and computational intelligence (or machine learning). Of these approaches, the autoregressive integrated moving average (ARIMA) model is one of the most common and traditional statistical methods for time series prediction [125]. ARIMA models are commonly employed as benchmark for comparing the performance of the prediction [126, 127].

For the prediction of energy prices, more recent attention has focused on machine learning methods [123], [123], such as support vector regression (SVR) and artificial neural networks (ANNs), which exploit data to train the models and output the price predictions for the day-ahead. SVR has been introduced for regression analysis in [128]. Since then, SVR has been used in several domains to predict time series, including the prediction of day-ahead electricity prices [129] [130]. In [131], SVR prediction performance has been compared with ANN performance for the prediction of energy prices.

Since the prediction of energy prices requires to target a non-linear system, ANN are commonly used machine learning methods to perform these type of predictions. One possible ANN classification is based on their architecture [123], in which two major ANN categories can be identified: feed-forward neural networks and recurrent neural networks (RNN). In [126, 132, 133], feed-forward networks have been demonstrated to perform well for day-ahead prediction of spot market prices. On the other hand, RNN have been shown to better predict the spikes in energy prices [134]. ANN have already been used to predict ancillary market volumes for electricity market simulation [135] and for estimating the locational marginal pricing for optimizing the ancillary services security [136]. However, ANN have not been employed to predict ancillary market prices in order to analyze the day-ahead prediction performance and any possible advantages or disadvantages of such an approach.

3. Proposed system

This chapter first elaborates the requirements and then presents the architecture and the algorithms for addressing these requirements. The research goals RG1, RG2 and RG3 defined in Section 1.2 are addressed in Sections 3.1, 3.2 and 3.3, respectively.

3.1 Requirements

The design of the DR system defined in this dissertation needs to fulfill several requirements. The first indispensable requirement for the DR system is to be capable of performing the demand response. The DR needs to be achieved by aggregating DESs, in the form of regulating loads as well as electric storage resources, owned by residential consumers. Therefore, the DR system consists of a VPP composed of an aggregator and a set of consumers that are collaborating together in order to execute the DR and participate in a DR market, more specifically in the FCR-N market, as depicted in Figure 3.1. The DR system needs to provide a solution for the ICT architecture, the communication logic as well as the coordination algorithms in order to coordinate residential consumers for two use cases specified in Section 3.1.1. The two use cases identify functional requirements for enabling the DR system to execute DR in both planning and provision of DR. Finally, non-functional requirements are defined for the DR system in Section 3.1.2.

3.1.1 Functional requirements through use cases

The functional requirements are specified through two use cases that define the functionalities needed in the DR system. The two defined use cases consist of:

UCI DR planning,

UCII frequency control provision.

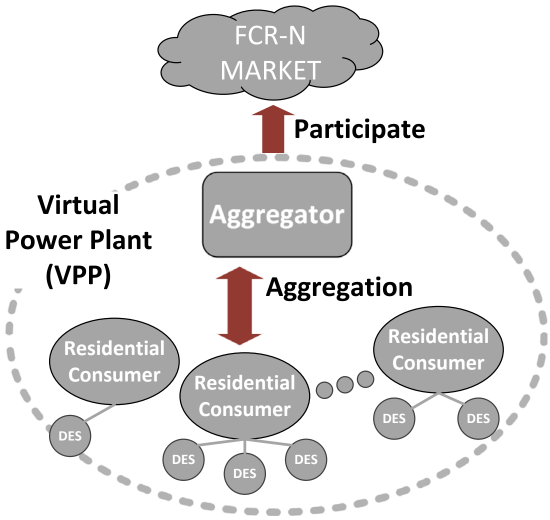

Figure 3.1. The DR system consists of a VPP, composed of an aggregator and a set of residential consumers owning DESs, and the FCR-N market

UCI: DR planning

UCI requires that the DR system is capable of performing day-ahead planning of DR in a partially distributed manner. The design of the DR system needs to consider a set of optimization algorithms that can be executed during the planning phases of the DR. Therefore, since *UCI* is required to enable execution of the DR planning phase, no real-time constraints are imposed on the DR system. However, in order to design the DR system, two key requirements need to be considered: the computational capabilities of the stakeholders involved (i.e., the aggregator and the consumers) as well as the ICT architecture to be utilized.

Determining whether the designed DR system is capable of planning the DR, requires the implementation of an application. For this purpose, the application utilizes the DR optimization algorithm defined in Publication I. This decentralized optimization algorithm is used to optimize DR in two different phases: the day-ahead and the intraday phases. The day-ahead phase is executed once every day, during which the aggregator has to coordinate the consumers to enable optimization of their energy storage consumption schedule for the following day. The intraday phase is performed every hour of the day and consists of rescheduling energy storage resources consumption, due to the need for minimizing imbalances between the energy acquired during the day-ahead phase and actual consumption.

UCII: frequency control provision

UCII requires the DR system to enable execution of frequency control, enabling residential consumers to provide power reserves to the FCR-N market while being coordinated by an aggregator. Since a solution for FCR exploiting numerous consumer-owned DESs is a distributed automation problem, this requires the joint design of ICT architecture, communication logic, and coordination algorithms. The aggregator is required to coordinate the consumers in order to provide the defined amount of flexibility to the TSO when the frequency of the power grid deviates from the nominal value (f_{nom}) of 50Hz. The VPP needs to provide power reserves for two separate tasks:

- the under-frequency task (τ_1): when there is a lack of production and the frequency goes below the nominal value,
- the over-frequency task (τ_2): when energy production is higher than consumption, and thus the frequency goes above the nominal value.

Furthermore, by planning the DR (*UCI*) and then bidding on the FCR-N market, the aggregator knows beforehand the amount of reserves ($flex_{\text{target}}$) to be provided at any given hour of the day.

Provision of frequency control has more stringent requirements for the DR system compared to those for *UCI*. In *UCII*, the DR system needs to fulfill certain electrotechnical requirements imposed by TSO for participation in the FCR-N market. The TSO requires that the provided reserve must be available and fully activated within three minutes after a frequency deviation (Δf_{max}) of +/- 0.1 Hz from f_{nom} of 50 Hz. In addition, the TSO defines a maximum dead-band deviation (Δf_{dead}) of +/- 0.02 Hz, which require no power reserves to react. The amount of provided reserve is the activated power after three minutes against the step change. However, it should be noted that this dissertation does not consider the minimum power reserve size of 0.1 MW (Table 2.1) required by the TSO for participation in the FCR-N market.

3.1.2 Non-functional requirements

Specification of the two use cases (*UCI* and *UCII*) in Section 3.1.1 implies a definition of non-functional requirements for the DR system. The distributed nature of the DR system requires the system to be scalable, i.e. starting from several hundreds up to few thousands residential consumers for one aggregator, enabling the provision of DR services to a wide range of consumers. Further, given the stringent communication requirements provided by *UCII*, the DR system must enable execution of the frequency control by providing near real-time communication capabilities. Due to the requirement of having the reserves active within three minutes, the communication should be able to work under these near real-time constraints. Therefore, a large amount of network traffic will occur over unreliable Internet connections. Hence, the DR system needs to be designed to avoid the need to send messages with hard real-time constraints over the public Internet. In addition, the DR system needs to be designed to achieve the plug and play of new DESs, which can be connected as well as disconnected from the DR system.

Consequently, although several other non-functional requirements can be identified for the DR system (i.e., security, reliability, semantic interoperability, etc.), this dissertation focuses on only the following non-functional requirements:

- *scalability*: the capability of the DR system to scale up to several thousand residential consumers
- *plug-and-play*: the capability of the DR system and its coordination algorithms to enable the plug-and-play of DESs for the FCR provision
- *near real-time*: the capability of the DR system to avoid the need for hard real-time communication messages in the DR system

3.2 DR system design

In this section, a hybrid architecture for a DR system is designed in order to fulfill RG2. As specified in the requirements (Section 3.1), the DR system is composed of three different types of stakeholders: an aggregator, a set of residential consumers, and a DR market, namely the FCR-N market. Figure 3.2 shows the DR system, which is comprised of the electric grid, the stakeholders, and their main interactions. The aggregator acts as the mediator between the residential consumers and the FCR-N market. By interfacing with the consumers that are participating in the DR, the aggregator has an obvious advantage of having a complete overview of the entire system. Therefore, the aggregator coordinates the residential consumers in the provision of reserves, and bids on their behalf to the FCR-N market. The coordination occurs for both use cases: the DR planning (*UCI*) and the continuous frequency control for the provision of FCR-N reserves (*UCII*).

The residential consumers $c \in C$ (where C is set of consumers in the DR system) are provided with a HEMS and a set of DESs capable of providing flexibility for the DR. The HEMS consist of a gateway device that is capable of interfacing with the various DESs in the home area network (HAN) as well as with the aggregator through the wide area network (WAN). In addition, the HEMS is capable of locally measuring the frequency ($f(t)$) of the electric grid by embedding a frequency meter [137], thus enabling the HEMS to locally control the DESs based on $f(t)$. The frequency measurement can be performed with a frequency meter device that satisfies the specifications of the TSO. For example, in Finland, the requirements provided by Fingrid for frequency measurement specify that the accuracy of the frequency measurement of the reserve unit shall be at least 10mHz [68]. The HEMS computational capabilities are limited in order to minimize the costs while providing DR services to residential consumers. A DES is identified as a resource ($r \in R$), where R is the set of DESs in the entire DR system. The DESs that can be used by the consumers for the FCR-N consist of regulating resources (e.g., fridges, freezers, water boilers) or electric storage

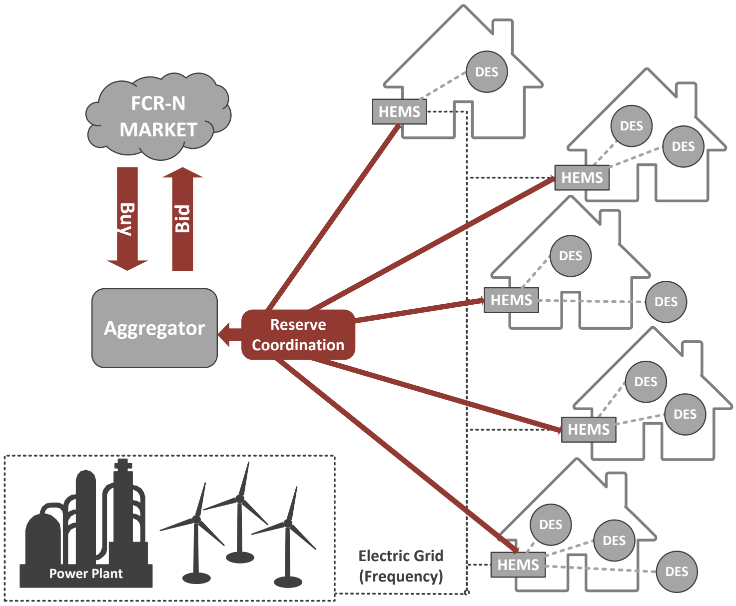

Figure 3.2. Overview of the DR system, where the electric grid, the stakeholders, and their main interactions are represented

resources (e.g., electric vehicles, home batteries). The number $|R|$ of DESs utilized for participating in the DR can vary over time. Furthermore, since this dissertation focuses on residential customers, even though the proposed solutions are generic and equally applicable to single-phase and three-phase DESs, the considered DESs are all single-phase.

3.2.1 ICT architecture

To enable the aggregation of DESs in the DR system, an ICT architecture needs to be designed. Therefore, Figure 3.3 presents the designed hybrid ICT architecture, in which the aggregator communicates with the consumers through a cloud-based system. The cloud-based system implements three types of applications: the Aggregator, the DR Consumer, and the DR Services. The Aggregator application performs the functionalities required from the aggregator. Furthermore, each consumer has one instance of the DR Consumer application. The DR Consumer application enables the residential consumers to interact with the aggregator and provides computational intensive services for the residential consumers, such as forecasting of energy consumption as well as decision-making services for every single consumer. The DR Consumer application directly communicates with the HEMS via WAN and performs DR cooperating with the aggregator. In addition, both DR Consumer and Aggregator applications can access the services provided by the DR Services application. The DR Services application provides a set of services, such as optimization services for DR or services for scheduling DESs.

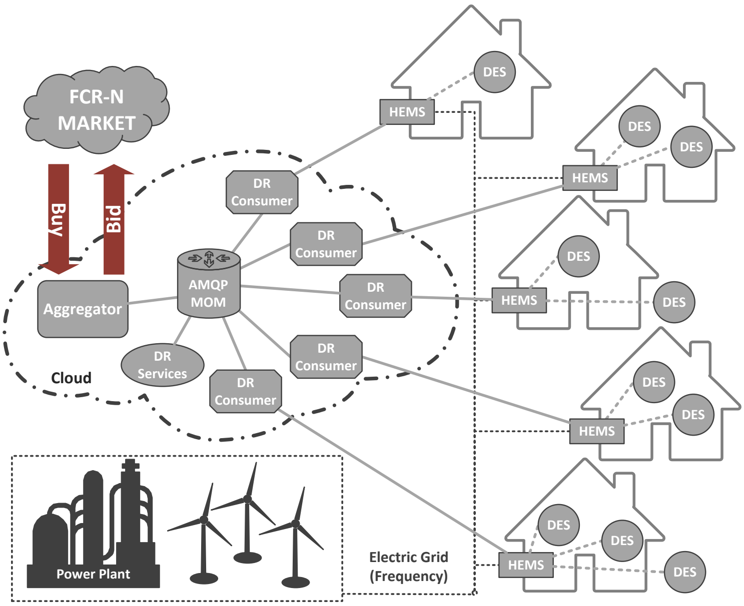

Figure 3.3. Designed ICT architecture for the DR system.

Intra-cloud communication between applications plays an important role in the ICT architecture. An asynchronous message-oriented middleware (MOM) is adopted for intra-cloud communication [110]. The MOM is based on the Advanced Message Queue Protocol (AMQP) [138]. AMQP provides asynchronous message-oriented queuing communication and is capable of advanced routing messaging. Among others, AMQP supports both publish-subscribe and request-response communication. The AMQP MOM provides several features which are of fundamental importance to fulfill the communication requirements of the DR system. In fact, the AMQP MOM supports the scalability of the communication as well as enables interoperability among the various applications. Furthermore, the AMQP MOM ensures that the various applications are decoupled and offers a reliable, secure communication protocol.

3.2.2 UCI: DR planning

UCI requires the DR system to be capable of planning the DR in a distributed manner. In the following, DR optimization algorithm is utilized to define the required communication logic for the planning of the DR. DR planning is divided into two phases: the day-ahead and the intraday phases. The day-ahead phase aims at optimizing the scheduling of the DESs belonging to the residential consumers, while the intraday phase minimizes the imbalances between the consumption scheduled during the day-ahead phase and the actual consumption. For *UCI*, the DESs of residential consumers are modeled as DESs, which can only charge and thus do not have the capability of discharging into the grid.

Nevertheless, the DR optimization algorithm (DROS) is available as a service in the DR Services, and can be accessed by both Aggregator and DR Consumers applications. For the given DROS, the aggregator is assumed to charge the spot price for the consumed energy to the residential consumers, while compensating for their participation in the FCR-N market.

DR optimization

The employed DROS aims at scheduling generic DESs of residential consumers. While scheduling the DESs, the DROS intends to minimize the cost of acquiring electricity for the residential consumers from the day-ahead spot market while including some flexibility to be provided in the FCR-N market. A multiobjective cost function is utilized by the aggregator for determining the day-ahead balance between the electricity acquisition costs and flexibility to be provided in the FCR-N market. The aggregator considers the estimated hourly aggregated consumption as well as flexibilities for a consumption increase or decrease in the consumers' DESs, while also taking into account the hourly targeted flexibility schedules. Then, by arbitrarily choosing a heuristic weight (w) value, the aggregator determines how much the flexibility is valued in the multiobjective cost function. In addition, multiobjective optimization is constrained by the energy consumption and the DESs of the consumers, in terms of initial charge, maximum charge, and the maximum charging rate of the generic DES. *It should be noted that since the formulation of such optimization is not considered as a contribution of this dissertation, the formal mathematical formulation is not presented. More details on the formulation are specified in Publication I.*

Communication logic

The communication logic between the stakeholders of the DR system is coupled with the implemented algorithm. This is necessary since the information exchanged are related to the optimization objectives. For the designed application, the communication logic has been defined based on the requirements of the optimization algorithm, which is divided into two phases: day-ahead and intraday. In addition, the communication logic supports structural interoperability, as required in the non-functional requirements (Section 3.1.2), by defining the format of the data exchange that takes place between the applications. However, the usage of a different optimization algorithm would imply changes in the communication logic while maintaining the ICT architecture unchanged.

Figure 3.4 presents a sequence diagram of the communication logic during day-ahead optimization. The aggregator initiates the iterative day-ahead algorithm by communicating in sequence with DR Consumer applications with a point-to-point message (*DR Request*). Then, each DR Consumer retrieves information from the HEMS regarding the DES status with a *H-S Request*. In the subsequent step, the DR Consumer requests to the DROS to optimize the day-ahead schedule by sending a *DR Optimize Request*. Once the optimization is executed, the DR Consumer responds back to the aggregator with a *DR*

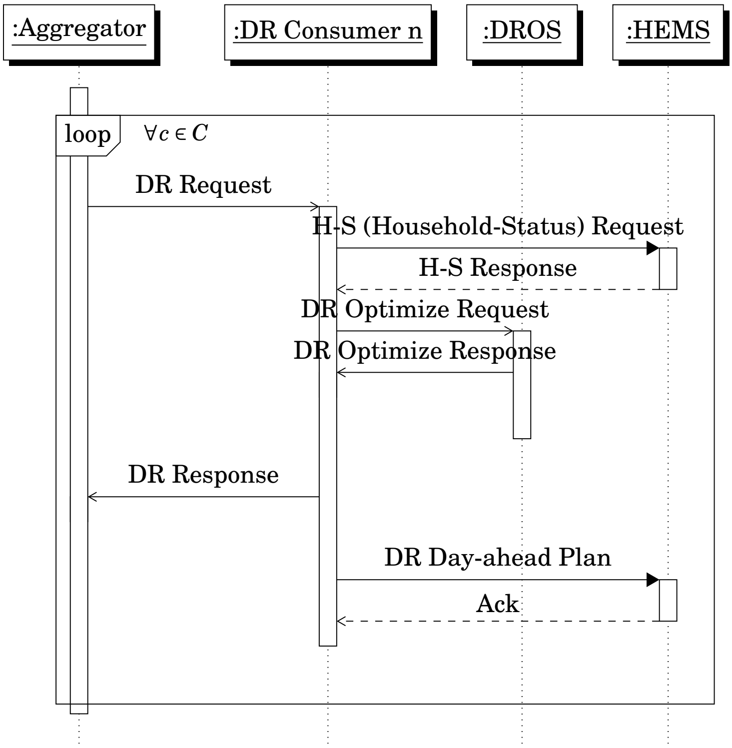

Figure 3.4. Sequence diagram detailing the information flow between the stakeholders during the day-ahead optimization

Response message containing the results of the optimization. Finally, the DR Consumer informs the HEMS about the planned charging schedule and the forecast consumption (*DR Day-ahead Plan*).

The sequence diagram depitcting the intraday optimization is shown in Figure 3.5. The aggregator publishes to the DR Consumer applications an *Intra-day Request*, which initiates the intraday DR for the next hour. In this case, the DR Consumer applications are executing the intraday DR task in parallel. Having received the *Intra-day Request*, the DR Consumer applications retrieve the needed information from the HEMS with a *H-S Request*. Then, the DR Consumer applications send a *Reschedule Request* to the DROS in order to reschedule their storage charging for the following hour. In the following step, the DR Consumer applications communicate the updated charging schedule to the aggregator with an *Intra-day Response*. Once the DR Consumer applications have sent the updates, the aggregator calculates the hourly aggregated imbalance, between the day-ahead forecast and the new estimated consumption, and then determines how to minimize the imbalance by changing the consumers' schedules. A *Minimize Imbalance* message is then published to the DR Consumer applications which contain orders on how to minimize the imbalance.

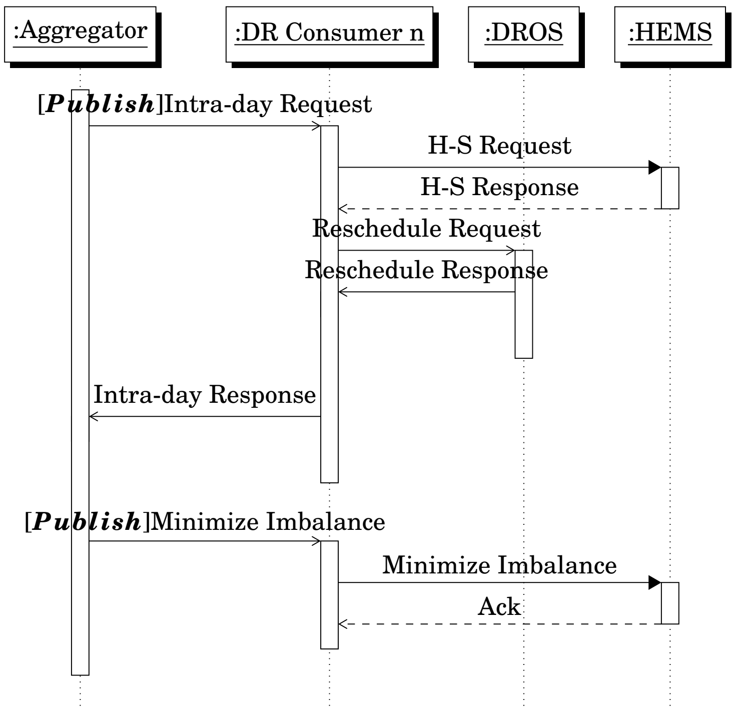

Figure 3.5. Sequence diagram for the intraday optimization

3.2.3 UCII: frequency control provision

The second use case (*UCII*) requires execution of frequency control, in order to allow residential consumers to provide power reserves to the FCR-N market while being coordinated by an aggregator. Therefore, in order to enable the DR system to perform continuous frequency control, coordination algorithms are jointly designed with the ICT architecture. In the following, a hybrid architecture, composed of a coordination algorithm and an ICT architecture, is designed with the final aim of developing a task allocation algorithm that employs an auction-based mechanism to enable an aggregator to coordinate a set of DESs to provide reserves for the FCR market. In addition, the task allocation algorithm is designed to achieve the following objectives:

- *near real-time*: to avoid the need for sending any messages with hard real-time constraints over the public internet, and
- *plug-and-play*: to flexibly allow new resources to be plugged into the system as well as existing resources to be disconnected.

The frequency control provision of the DR system as specified in *UCII* is designed as a hybrid architecture, where the coordination, control, and communication logic are designed in order to divide responsibilities between the aggregator and consumers, thus enabling the DR system to achieve the aforementioned objectives (i.e., *near real-time* and *plug-and-play*). Therefore, the design of the frequency control provision starts with a formulation of the problem, followed by the definition of the operational states for the DESs of the DR system. This is followed by introducing the frequency task allocation algorithm, the control logic of the DESs and the DES participation algorithm. Finally, the communication logic is introduced for the provision of frequency control. In *UCII*, the DESs have been modeled as regulating loads, more specifically as refrigerators. Nevertheless, the presented solution can be generalized to other DESs, such as regulating loads and electric storage resources.

Problem formulation

For the continuous provision of frequency control, two tasks have been identified in *UCII*: the under-frequency $\tau_1 \in T$ and the over-frequency $\tau_2 \in T$, where T is the set of tasks that the DR system needs to execute ($|T| = 2$). Furthermore, given $t \in \mathbb{R}_{\geq 0}$, representing the discrete time in seconds, it is possible to define the following functions:

- $flex_{\text{target}}(\tau, t)$ consists of the target power demand for a task τ at the given time t. This function represents the amount of committed reserves that the DR system needs to provide.
- $flex(r, \tau, t)$ specifies the flexibility, in terms of power, that a DES $r \in R$ of a consumer $c \in C$ can supply to the task $\tau \in T$, at a given time t.
- $flex_{\text{total}}(\tau, t)$ refers to the total flexibility provided by the DESs R of the DR system for a task τ:

$$flex_{\text{total}}(\tau, t) = \sum_{r \in R} flex(r, \tau, t) \tag{3.1}$$

To participate in the FCR-N market, the aggregator needs to coordinate the set R of DESs in order to satisfy the requirements imposed by the TSO as specified in 3.1.1.*UCII*. In exchange, the TSO compensates the aggregator for offering a the reserves for the FCR-N market, thereby enabling the aggregator to share benefits with users. FCR-N is an hourly market with high price variations, and the aggregator is required to bid on the day-ahead. If users have specific expectations for their financial compensation, the bid can be set high enough to ensure that the aggregator can profitably meet these expectations.

The consumers are required to react to deviations $\Delta f(t)$ from the nominal frequency f_{nom}. However, instantaneous reaction to any abrupt changes in the frequency or errors in its measurement could lead to unwanted oscillations in the control and in the realized frequency of the grid. Therefore, a frequency filtered value is computed with a first-order filter of the locally measured grid frequency signal:

$$\overline{f}(t+1) = e^{-\frac{1}{\beta}}\,\overline{f}(t) + (1 - e^{-\frac{1}{\beta}}) f(t) \tag{3.2}$$

where β represents a time constant. The time constant is chosen with $\beta = \frac{-\gamma}{log(1-p)}$, such that the control satisfies the requirements for the TSO of reaching,

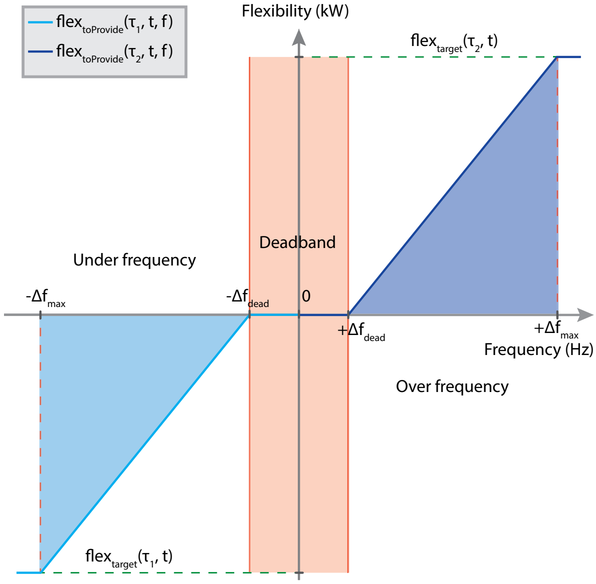

Figure 3.6. The objective function $flex_{\text{toProvide}}(\tau,t,f)$ and the target reserve function $flex_{\text{target}}(\tau,t)$ for both the under-frequency and the over-frequency tasks

e.g., $p = 99\%$ of the required activation time γ, the value of which was chosen to be 120 seconds to fulfill the requirement for activating the reserves within three minutes ($\gamma < 180$) [11].

Based on the filtered frequency, a desired control target can be defined for the DR system:

$$DR_{\text{desired}}(t) = \begin{cases} (3.4) & |\Delta f_{\text{dead}}| < \left|\Delta \overline{f}(t)\right| < |\Delta f_{\max}| \\ 0 & \left|\Delta \overline{f}(t)\right| < |\Delta f_{\text{dead}}| \\ (3.5) & \left|\Delta \overline{f}(t)\right| > |\Delta f_{\max}| \end{cases} \tag{3.3}$$

where function (3.4) is defined as:

$$sign(\Delta \overline{f}(t))\left(\left|\Delta \overline{f}(t)\right| - \Delta f_{\text{dead}}\right)\frac{flex_{\text{target}}(\tau,t)}{(\Delta f_{\max} - \Delta f_{\text{dead}})} \tag{3.4}$$

and function (3.5) is:

$$sign(\Delta \overline{f}(t))\, flex_{\text{target}}(\tau,t) \tag{3.5}$$

The amount of reserve that the DR system needs to provide is required to scale linearly with the frequency deviation Δf from f_{nom}. Therefore, the aggregator has an objective function $flex_{\text{toProvide}}(\tau,t,f)$, which represents the flexibility required for a task τ at given time t giving the frequency value f. Figure 3.6 shows how the function is defined for both cases: the under-frequency $flex_{\text{toProvide}}(\tau_1,t,f)$, and the over-frequency $flex_{\text{toProvide}}(\tau_2,t,f)$ containment.

The aggregator needs to allocate the required flexibility for both τ_1 and τ_2 at any given time t. For this reason, the total flexibility that the DR system can provide for a task τ will always have to exceed the target power demand for τ at any given time t. Therefore, if the following condition subsists for every t:

$$flex_{\text{target}}(\tau,t) - flex_{\text{total}}(\tau,t) < 0 \tag{3.6}$$

then the task allocation problem is satisfiable. This equation requires the aggregator to estimate ahead the hourly $flex_{\text{target}}(\tau,t)$ that the DR system will be able to supply to the FCR-N market, enabling the DR system to provide the reserve for the entire hour, and thus fulfilling the participation requirements. Since estimation of the $flex_{\text{target}}(\tau,t)$ is not within the scope of this dissertation, it is assumed that the aggregator will solve task allocation problems in which the equation (3.6) is always satisfied.

DES operational states
The set R of the DR system consists of DESs which are controllable by the HEMS of the residential consumers, enabling the provision of reserves to the grid. Based on the task allocation algorithm, at any given time t, a DES can be either allocated to one task τ or none. Therefore, a task allocation function ta is defined, which assigns for the time t either one or zero tasks for each DES r:

$$ta(r,t) : R \times \mathbb{R}_{\geq 0} \to T \cup \{\varnothing\} \tag{3.7}$$

Since resources can simultaneously participate in several tasks, such as τ_1 and τ_2, the idle function is defined in terms of specific tasks as follows:

$$R_{\text{idle}}\left(\tau_j, t\right) = \{r \in R : ta(r,t) = \varnothing \vee ta(r,t) = \tau_i (i \neq j)\} \tag{3.8}$$

Each DES that belongs to $R_{\text{Idle}}(\tau,t)$ is in the *Idle* state. On the other hand, DESs that are allocated to τ belong to the *Allocated* state, and the set of these DESs $R_{\text{allocated}}(\tau,t)$ can be specified as:

$$R_{\text{allocated}}(\tau,t) = \{r \in R : ta(r,t) = \tau\} \tag{3.9}$$

Figure 3.7 presents the *Idle* and the *Allocated* states as composite states for the DESs, in which the control logic is defined as a state machine.

Each DES of the DR system can belong to the *Idle* composite state for two distinct reasons. Firstly, because of the inability of the DES to provide the flexibility to the task τ. Thus, the DESs are disconnected from the DR system for FCR-N. In this case, the DES belongs to the *Disconnected* state:

$$\begin{aligned} &R_{\text{disconnected}}(\tau,t) = R_{\text{idle}}(\tau,t) \cap \\ &\{r \in R : flex(r,\tau,t) = 0\} \end{aligned} \tag{3.10}$$

Secondly, the *Available* state is defined for the DESs that can provide flexibility to τ but have not been allocated to the task. Therefore, the *Available* state is specified as:

$$R_{\text{available}}(\tau,t) = R_{\text{idle}}(\tau,t) \cap \{r \in R : flex(r,\tau,t) > 0\} \tag{3.11}$$

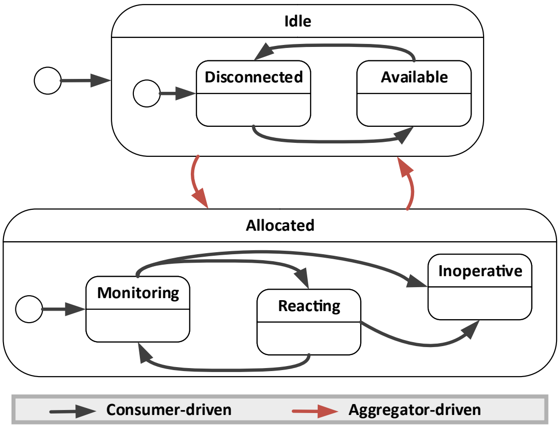

Figure 3.7. The operational states of the DESs. The *Idle* composite state represents the DESs that are either *Disconnected* from the DR system or *Available* to participate in FCR. The *Allocated* composite state represents all the DESs that have been allocated to provide the reserve, which are either *Monitoring* the frequency without reacting, *Reacting* to the frequency deviations, or *Inoperative*, and thus waiting to be replaced and reallocated by the aggregator.

Depending on the capability of a DES to provide flexibility to τ, a residential consumer can change the state of the DES between the two states: *Disconnected* and *Available*. This action will be performed by the consumer through the DES Participation algorithm. If a DES is moved to the *Available* state, the consumer sends a bid to the aggregator containing the flexibility value (i.e. $flex(r,\tau,t) > 0$) and the estimated time for which the DES will be *Available*, defined as $t_{\text{available}}(r,\tau)$. Whereupon, the DES is considered as being plugged into the DR system for providing flexibility to τ. On the other hand, when the DES changes to the *Disconnected* state, it is unplugged, and thus not considered for τ. In this case, the consumer needs to notify the aggregator, thus canceling the previous bid of the DES r for task τ, indicating that $flex(r,\tau,t) = 0$.

The composite state *Allocated* is composed of the DESs that have been allocated by the aggregator to perform the task $\tau \in T$. The DESs in this composite state can be one of three different states: the *Monitoring* state ($R_{\text{monitoring}}$), the *Reacting* state (R_{reacting}), and the *Inoperative* state ($R_{\text{inoperative}}$). The set of DESs in the *Monitoring* state consists of the DESs $r \in R$ that can provide flexibility to the power grid. These DESs are currently not reacting to the frequency deviations, since their allocated frequency deviation $\Delta f_{\text{alloc}}(r)$ is not exceeded by filtered deviation $\Delta\overline{f}(t)$:

$$R_{\text{monitoring}}(\tau,t) = R_{\text{allocated}}(\tau,t) \cap \left\{ r \in R : flex(r,\tau,t) > 0 \wedge \Delta\overline{f}(t) < \Delta f_{\text{alloc}}(r) \right\} \tag{3.12}$$

The DESs that are currently reacting to a frequency deviation are in the *Reacting* state, which is defined as:

$$R_{\text{reacting}}(\tau,t) = R_{\text{allocated}}(\tau,t) \cap \\ \left\{r \in R : flex(r,\tau,t) > 0 \wedge \Delta\overline{f}(t) \geq \Delta f_{\text{alloc}}(r)\right\} \tag{3.13}$$

The final state is called *Inoperative*. The *Inoperative* state consists of each DES that can no longer provide any flexibility to the power grid. These DESs are waiting to be reallocated to the *Idle* state by the aggregator, which should then replace their share in the flexibility provided by other DESs that are in the *Available* state. Hence, the set $R_{\text{inoperative}}$ of DESs that belongs to the *Inoperative* state can be defined as follows:

$$R_{\text{inoperative}}(\tau,t) = R_{\text{allocated}}(\tau,t) \cap \\ \{r \in R : flex(r,\tau,t) = 0\} \tag{3.14}$$

Frequency task allocation algorithm

By executing the frequency task allocation algorithm, the aggregator aims at allocating the required flexibility to each of the given tasks. The objective of the algorithm is to allocate the flexibility of the DESs in such a way that the reserve provided by the DR system remains as close as possible to the objective function $flex_{\text{toProvide}}(\tau,t,f)$. The frequency task allocation algorithm is composed of three main procedures: the *frequency task allocation*, the *continuous allocation*, and the *corrective control*.

1. *Frequency task allocation procedure*

The *frequency task allocation procedure* represents a total reallocation of the flexibility provided to a task τ. The procedure is executed once every 15 minutes, and can be formulated as a multi-task (τ_1 and τ_2), multi-resource ($r \in R$) and multi-unit auction, where one unit corresponds to one Watt and one DES can provide multiple units. Further, $flex_{\text{target}}(\tau,t)$ represents the total amount of units for one task τ. The consumers, in order to make a DES *Available*, send a bid to the aggregator which expresses the flexibility that the DES can provide ($flex(r,\tau,t)$) and the expected time of availability ($t_{\text{available}}(r,\tau)$) of the DES for the task τ. Once received a bid, the aggregator calculates a bid function $b^r(\tau)$ as follows:

$$b^r(\tau) = flex(r,\tau,t) \cdot t_{\text{available}}(r,\tau) \tag{3.15}$$

In addition, the aggregator defines the function $y(\tau,r)$, which specifies whether a resource is allocated or not to the task τ:

$$y(\tau,r) = \begin{cases} 1 & \text{if } r\, allocated\ to\ \tau \\ 0 & \text{if } r\, not\ allocated\ to\ \tau \end{cases} \tag{3.16}$$

Thus, the frequency task allocation procedure can be formulated as an auction-based problem in which the amount of resources allocated to the task τ is minimized in respect to the bid functions $b^r(\tau)$ as:

$$\min_{y(\tau,r)} \sum_{r\in R_{\text{available}}} \sum_{\tau\in T} b^r(\tau) y(\tau,r) \tag{3.17}$$

s.t.

$$\sum_{\tau\in T} \sum_{r\in R_{\text{available}}} flex(r,\tau,t)\cdot y(\tau,r) - flex_{\text{target}}(\tau,t) \geq 0 \tag{3.18}$$

$$\sum_{\tau\in T} y(\tau,r) \leq 1, \forall r \in R \tag{3.19}$$

$$y(\tau,r) = 0,1, \forall \tau \in T, \forall r \in R \tag{3.20}$$

where (3.18) expresses the objective to provide the target flexibility ($flex_{\text{target}}(\tau,t)$) required when the deviation from f_{nom} is the maximum specified by the FCR-N (i.e. Δf_{max}); while (3.19) specifies the condition in which each DES can be allocated to a single task τ at a time.

Having selected the best DESs from the $R_{\text{available}}$, the aggregator needs to define the frequency deviation Δf_{alloc} at which each DES needs to react, thus providing its flexibility. Hence, the selected DESs are randomly ordered, allowing the random allocation of the Δf_{alloc} to each DES, thus avoiding the most frequent exploitation of few better resources when the frequency deviations are smaller. Then, the frequency deviation $\Delta f_{\text{alloc}}(r)$ is calculated by the frequency allocation function $fa(r,\tau,t)$. For each resource r allocated to τ by $y(\tau,r)$, the function $fa(r,\tau,t)$ derives the respective frequency deviations ($\Delta f_{\text{alloc}}(r)$) in order to provide a linear behavior as the objective function $flex_{\text{toProvide}}(\tau,t,f)$. Figure 3.8 shows in detail how the frequency deviations $\Delta\text{alloc}(r)$ are allocated by the frequency task allocation procedure. Once every $\Delta f_{\text{alloc}}(r)$ is calculated for each selected resource r, the aggregator proceeds to allocate the DESs by sending a task allocation message, which specifies the allocated task τ and $\Delta f_{\text{alloc}}(r)$. Consequently, this operation moves the DES from the *Idle* state to the *Allocated* state.

The *frequency task allocation procedure* enables the readjustment of the flexibility provided by the DR system in order to adhere to the objective function $flex_{\text{toProvide}}(\tau,t,f)$, as shown in Figure 3.6. Moreover, the *frequency task allocation procedure*, in conjunction with the following procedure named *continuous allocation procedure*, enables the plug-and-play of DESs.

2. *Continuous allocation procedure*

While the frequency task allocation procedure is executed at pre-defined time intervals, the continuous allocation procedure runs continuously to replace inoperative DESs. The continuous allocation procedure replaces the DESs that are in the *Inoperative* state with new DESs $r \in R_{\text{available}}$. The algorithm monitors whether there are DESs in the $R_{\text{inoperative}}$ set, and when it finds any, it starts deallocating each of the DESs $r_{\text{dealloc}} \in R_{\text{inoperative}}$. Then, the

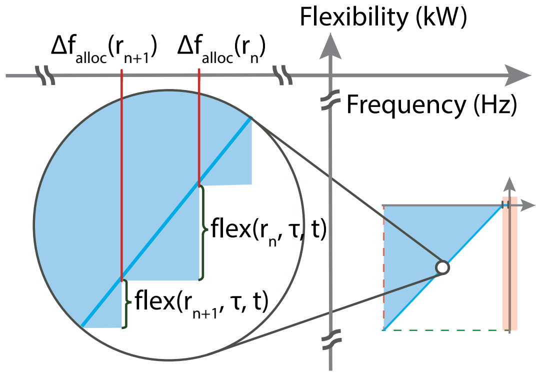

Figure 3.8. Allocation of the DESs performed by the *frequency task allocation procedure*. The flexibility $flex(r_{\text{next}}, \tau_1, t)$ of the *Available* DESs are collected in sequence and each resource is allocated a reaction policy that specifies the respective frequency deviation $\Delta f_{\text{alloc}}(r_{\text{next}})$.

aggregator retrieves DESs $r \in R_{\text{available}}$ in order to replace the flexibility that was previously guaranteed by r_{dealloc}. The replacement of an *Inoperative* DES (r_{dealloc}) is performed in a similar manner to that of *frequency task allocation procedure* (i.e. (3.15) - (3.20)), which only considers the single task where the r_{dealloc} was allocated, and denoted as $\tau_i \in T$ (i.e. τ_1 or τ_2). The only change in the formulation is in (3.18), which is modified in order to replace only the flexibility of the r_{dealloc}, and defined as:

$$\sum_{r \in R_{\text{available}}} flex(r, \tau_i, t) \cdot y(\tau_i, r) - flex(r_{\text{dealloc}}, \tau_i, t) \geq 0 \qquad (3.21)$$

3. *Corrective control procedure*

The requirements for an intelligent load that provides ancillary services on the FCR-N market are specified as relative changes to a baseline consumption that is assumed to be constant. Since the DESs considered in this dissertation do not have a constant baseline consumption, it is problematic to validate that the system fulfills this specification. Hence, the purpose of the corrective control is to coordinate a subset of DESs in such a way as to achieve this constant baseline consumption. Thus, the flexible resources from a subset of the consumers are reserved for the purpose of this corrective control instead of being used for reacting to frequency deviations. The consumption of these consumers is increased if the total consumption of all the consumers in the system is less than the baseline; similarly, the consumption of these consumers participating in the corrective control is decreased if the total consumption of all consumers exceeds the baseline. The corrective control is run by the aggregator at regular intervals; which was chosen to be once every 30 seconds.

DES control logic

The control logic of the DES is composed of two separate logic: frequency control and comfort-driven control. The two control logic are specified in the following.

Together, the two control logic enable execution of frequency control, while also maintaining the DES within the comfort limits specified by residential consumers. The proposed solution enables the DESs to participate in the frequency control only when within the consumers' comfort limits. In other words, execution of frequency control while providing minor discomforts to the consumers is not part in the investigations of this dissertation.

1. *DES frequency control*

As shown in Figure 3.7, the aggregator, by allocating and deallocating the DESs, is driving each change of state between the two composite states (*Allocated* and *Idle*) of the DESs, while the internal transitions within each composite state are locally controlled by the consumers' HEMS. The clear division of responsibilities between the aggregator and consumers allows the DR system to avoid the need for hard real-time messages. In fact, once the aggregator preemptively allocates the task τ with the respective frequency deviation $\Delta f_{\text{alloc}}(r)$ to a DES, the DES moves in the *Allocated* composite state. Then, within the *Allocated* state, the consumers need to control the DES autonomously in order to react locally to the frequency changes by following a specified control logic.

Algorithm 1 DESs Control Logic for Frequency Control

function DESControlLogic
    while $ta(r,t) = \tau_1$ **do**
        while $flex(r,\tau_1,t) > 0$ **do**
            if $\Delta\overline{f}(t) \geq \Delta f_{\text{alloc}}(r) \wedge$
              $stateOf(r) = Monitoring$ **then**
                $stateOf(r) = Reacting$;
            else if $\Delta\overline{f}(t) < \Delta f_{\text{alloc}}(r) \wedge$
              $stateOf(r) = Reacting$ **then**
                $stateOf(r) = Monitoring$;
        $stateOf(r) = Inoperative$;

A control logic example for task τ_1 of a DES r is presented in Algorithm 1. The algorithm defines how a HEMS should control a DES that has been allocated by the aggregator to provide FCR-N. As long as the DES is allocated to τ_1, and it can provide flexibility to the DR system, the HEMS maintains the DES either in the *Monitoring* or *Reacting* states. Indeed, when the filtered frequency deviation $\Delta\overline{f}(t)$ is greater than the allocated frequency deviation $\Delta f_{\text{alloc}}(r)$, then the HEMS places the DES into the *Reacting* state, and by controlling the DES it provides the promised flexibility $flex(r,\tau_1,t)$. Conversely, if $\Delta\overline{f}(t)$ is less than Δf_{alloc}, the DES will be placed in the *Monitoring* state. Moreover, if the DES is not deallocated by the aggregator before it can no longer provide flexibility, the HEMS drives the DES into the *Inoperative* state, and communicates this with a status update message to the aggregator, which will replace the resource as soon as possible.

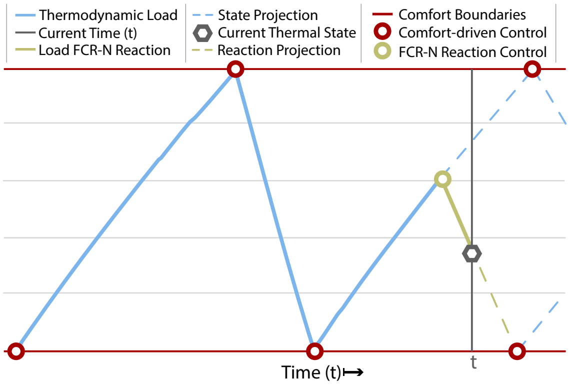

Figure 3.9. Example of the control applied to a regulating DES in order to provide FCR-N reserves while maintaining the comfort constraints.

2. <u>*DES comfort-driven control*</u>

In addition to the control logic utilized by the HEMS to provide flexibility for FCR-N, a comfort-driven control is implemented for the DESs. This control is intended to maintain the appliance within the comfort limits, which according to the type of DESs can be either embedded in the appliances or defined by the users. Since user comfort is prioritized over the participation in the FCR containment, the HEMS gives priority to the latter control over the DES control logic defined in Algorithm 1.

Figure 3.9 presents the state dynamics of a regulating DES, that combines the control logic for providing FCR-N reserves and the comfort-driven control. The comfort-driven control is executed every time the DES reaches its comfort boundaries, and has priority over the provision of reserves. When the boundaries are reached while the DES is reacting to the frequency deviations, the flexibility of the thermal DES becomes equal to zero ($flex(r,\tau,t) = 0$), driving the DES into the *Inoperative* state, and the DES is then replaced by the *continuous allocation procedure*.

DES participation algorithm

The DES participation algorithm aims at deciding whether or not a DES takes part in the frequency control. This algorithm is implemented in the DR Consumer application of the DR system. The participation algorithm drives each DES of the consumer eligible for frequency control in one state of the composite state *Idle*. In doing so, the algorithm decides whether to plug in or disconnect each DES by changing their state to either *Available* or *Disconnected*.

Based on the types of participating DESs or on the level of abstraction of each DES, the participation algorithm can use different logics. In this dissertation, the participation algorithm, by knowing the status of the DESs, estimates two time-based parameters called Participation Time (PT) and Reaction Time (RT). These two parameters are then used to decide whether the consumer has the capability of providing reserves. For example, in a regulating load, the controlled variable has to stay between defined upper (T_{MAX}) and lower (T_{MIN}) bound limits. Given the current thermal status (T_{CTS}) of the controlled variable, it is possible to project the status to the respective boundaries in order to calculate the two parameters. Assuming that Figure 3.9 represents the thermodynamic status of a refrigerator as presented in [139], the following equations show how PT and RT can be calculated for such a case:

$$PT = -\frac{1}{\tau} ln(\frac{T_{MAX} - T_{AMB} + \eta\frac{ptcl}{A}}{T_{CTS} - T_{AMB} + \eta\frac{ptcl}{A}}) \tag{3.22}$$

$$RT = -\frac{1}{\tau} ln(\frac{T_{MIN} - T_{AMB} + \eta\frac{ptcl}{A}}{T_{CTS} - T_{AMB} + \eta\frac{ptcl}{A}}) \tag{3.23}$$

where τ is a time constant, T_{AMB} represents the external ambient temperature, η is a coefficient of performance, $ptcl$ consists of the rated power (W) for the appliance, and A represents the thermal conductance ($W/^{\circ}C$). In addition to refrigerators, this example can be applied to various types of regulating loads, including air conditioning, space heating, and boilers.

Communication logic

The communication logic of the DR system can be divided into two phases: the status update phase and the task allocation phase. The two communication phases are asynchronous between each other. The status update phase is used by the consumers to provide the last updates to the aggregator and is executed every time a DES state changes or within a defined time limit. In contrast, the task allocation phase is used during execution of the frequency task allocation algorithm by the aggregator in order to allocate the DESs of the consumers with new tasks.

1. *Status update phase*

The status update phase consists of all the necessary communication steps needed by the consumers to notify the aggregator about their possible participation in the DR for frequency control. Figure 3.10 shows the sequence diagram of the status update phase. The update phase starts with each DES that sends status update messages to the respective HEMS. The HEMS operates as a network gateway by interfacing with various DESs using different protocols within the HAN. After processing the data of the DESs, the HEMS sends a message containing the information of the DESs that can be used for frequency control to the DR Consumer. Then, the DR Consumer retrieves the provided data for each DES and establishes whether or not the DES can participate in the frequency control (i.e. executing the DES participation algorithm), either to the under-frequency (τ_1), the over-frequency (τ_2) or both controls. In the last step, the DR Consumer updates the aggregator, with a *Frequency Control S-U* message, about its capability to participate in the frequency control, thus deciding to plug in or disconnect DESs.

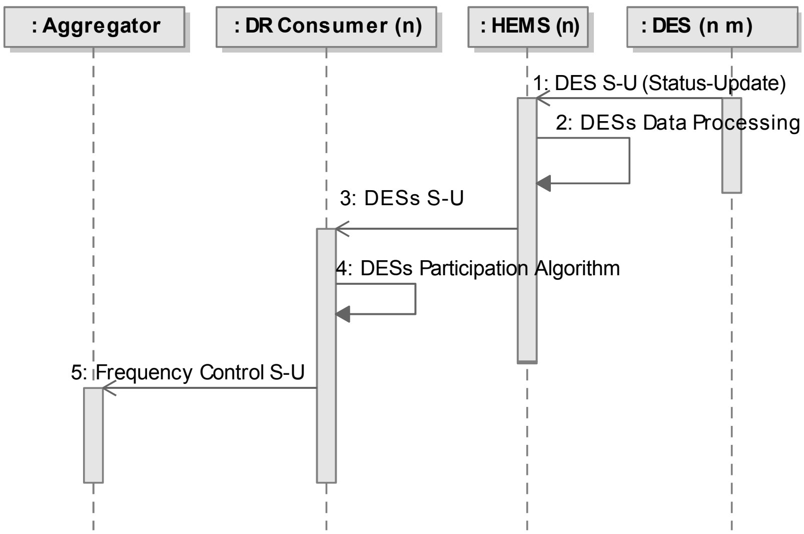

Figure 3.10. Sequence diagram showing the status update phase of the communication logic for frequency control provision

2. *Task allocation phase*

The second phase of the communication logic is called the task allocation phase. During this phase, the aggregator allocates the tasks to the consumers, enabling their participation in frequency control. Figure 3.11 presents the sequence diagram of the communication logic for the task allocation phase. After executing the frequency task allocation algorithm, the aggregator sends to the DR Consumers applications a *Task Allocation Message*, which contain the instructions needed to react to the frequency control. If the consumer has to use multiple DESs, the DR Consumer disaggregates the instructions of the aggregator and allocates the tasks to each separate DES. Then, the DR Consumer sends a *DES Task* message to the HEMS which contains the tasks and control instructions scheduled for the DESs. The HEMS, when instructed to apply frequency control, measures the frequency of the electric grid and applies the control logic to the DESs following the provided instructions and the control logic defined in Section 3.2.3. When the frequency exceeds the given limits, the HEMS sends a *DES Control logic* message to the DESs involved, which are then participating in frequency control.

3.3 Market participation

The flexible capacity provided by the DESs of the DR system can be exploited in several ways. Some of these involve the use of the DESs to reduce electricity bills, and comparing the profitability of these approaches can be straightforward especially if experiments are made in the same region using a fixed electricity

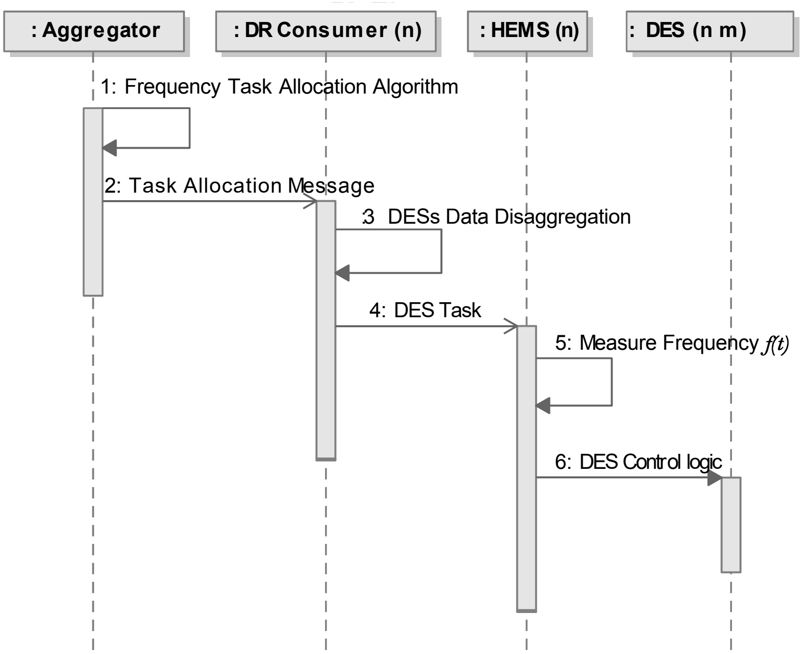

Figure 3.11. Sequence diagram that shows the communication logic of the task allocation phase for frequency control provision

price. Besides, the flexible capacity of the DESs can also be traded on various markets, in which case the consumer owning the DES is required to enter into some business relationship with a party that is willing to pay for the possibility of using the DES. Consumers can make an agreement with an aggregator that will participate in the market on their behalf. Therefore, this dissertation investigates the exploitation of the flexibility provided by the DR system for the participation in FCR markets.

This section introduces the participation of a generic VPP into FCR markets, as defined in RG3. At first, an architecture is proposed which involves a VPP that is able to handle the intelligent bidding on the TSO market using the FCR price estimates as well as the consumption estimates derived from the smart meter data of numerous small consumers. Then, a detailed technical solution, employing open data and machine learning, is used to empower the consumers by providing FCR-N price forecasts enabling market participants to bid intelligently. The solution consists of an analysis of the FCR-N prices followed by the methodology used for predicting the day-ahead prices of the hourly FCR-N market.

3.3.1 VPP market participation

The participation of a VPP in a DR market, such as the FCR markets, involves several stakeholders, which are required to consider multiple risks and uncertainties. Figure 3.12 presents the scenario where a VPP, composed of an

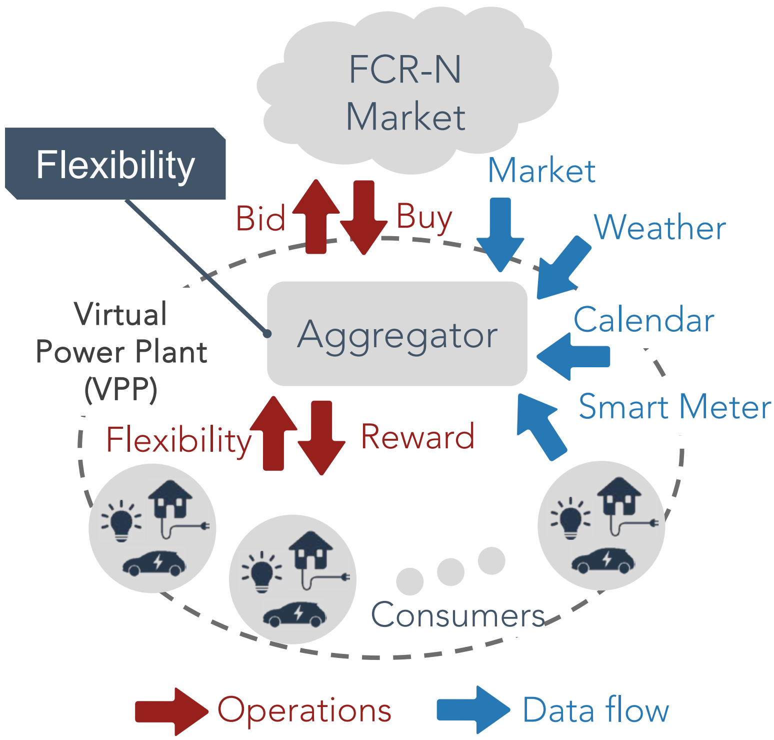

Figure 3.12. The required operations and the data flows needed for the participation of a VPP to the FCR-N market

aggregator and a set of consumers, participates in the FCR-N market. Both, the required operations and the main data flows are represented in the figure. The aggregator acts as a broker between the consumers and the market. The consumers, in exchange for a fair compensation, provide a certain amount of hourly flexibility to the aggregator. Consequently, the aggregator holds a flexibility asset and uses this asset to bid in the market, with the final aim of participating in the provision of reserves. However, it is necessary to execute and optimize during the day-ahead the operations of planning the hourly flexibility provided and bidding to the FCR-N market.

To optimize the bidding strategy, the aggregator has to consider several uncertainties. The aggregator needs to predict the prices of the FCR market for the next day. Furthermore, the aggregator has to establish the sensitivity of the consumers to different compensations, as well as to estimate, in cooperation with the consumers, the hourly amount of flexibility that the VPP will be able to provide. Thus, the aggregator can employ big data and machine learning methods to enhance its ability to make decisions and reduce the uncertainties. In fact, the aggregator can acquire and utilize historical data, such as market data, smart meters data, consumers data, and several other factors affecting the presented scenario (i.e. data flows in Figure 3.12).

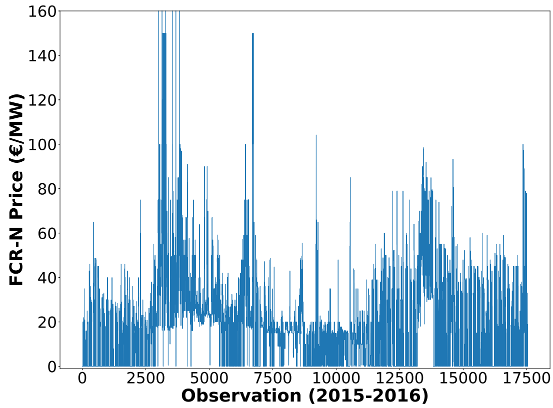

Figure 3.13. Two years data collected of the FCR-N market prices, limited to a maximum value of 160 €/MW

The remainder of this Chapter focuses on the prediction of FCR-N prices as a use case. The following sections start by highlighting the main characteristics and behaviors of the FCR-N prices. Then, a methodology is presented for the FCR-N price prediction. The further work outlined in Chapter 5 complements this work on price prediction with estimates of what level of flexibility consumers are expected to provide at specific prices. However, this prediction in itself is a complex problem as the volume of flexibility provided by consumers as a function of the financial compensation is highly nonlinear [140]. At the time of writing, there is a lack of available open smart meter data on this type of consumer behavior, since demand response has traditionally been limited to large industrial loads. Recent piloting of frequency containment reserves has focused on small and medium-sized enterprises, with domestic customer pilot projects possibly emerging in the near future [66].

3.3.2 FCR-N price analysis

In order to analyze FCR-N prices, two-year data was collected, for the year 2015 and 2016, from the open data service provided by Fingrid [141]. Figure 3.13 shows the 17544 observations of FCR-N prices; the maximum price on the vertical axis is limited to 160 €/MW for the sake of clarity, due to the small number of occurrences above this threshold. Figure 3.14 presents the violin plot [142] of the FCR-N prices for each month of 2016, which is the year targeted for the predictions. The figure shows the median and the distribution of the FCR-N price data. In addition, Figure 3.15 displays the mean and the variance of the FCR-N prices for each month of 2016. Both Figures 3.14 and 3.15 demonstrate that the FCR-N price data are a non-stationary distribution, where the data distribution, the monthly mean and variance change considerably between consecutive months.

Statistics of the FCR-N prices are presented in Table 3.1. The skewness value of the data is large, demonstrating that the time series has a non-symmetric

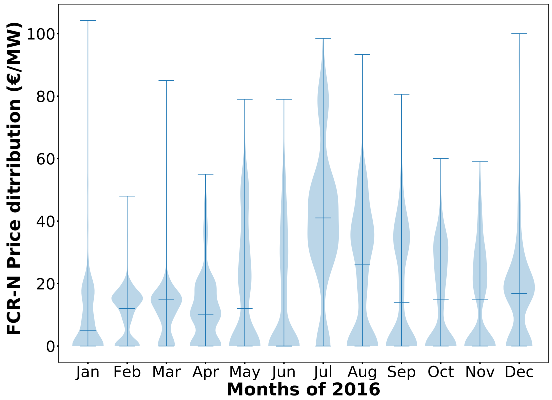

Figure 3.14. FCR-N prices distribution by month for the year 2016, with representation of the median value

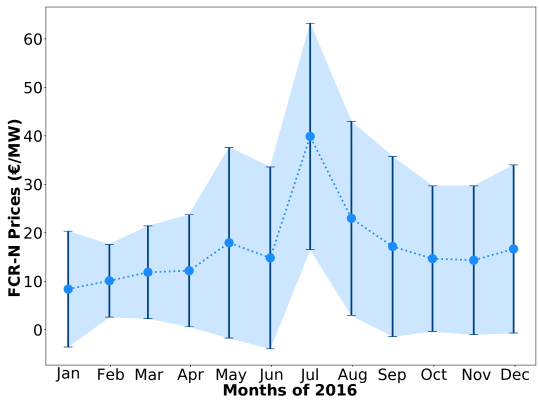

Figure 3.15. Average and variance for the FCR-N prices during the months of 2016

distribution. Moreover, by comparing the distribution of the FCR-N prices (Figure 3.14) with the distribution of the Elspot market prices presented in Figure 3.16, it can be observed that the FCR-N prices behave differently, with the data being less distributed around the median and more towards the minimum and maximum value. A further difference from the spot market prices is that the FCR-N prices are zero for around 30% of the time (Figure 3.14). Thus, any insights gained from predicting spot market prices cannot be assumed to apply to this market.

Furthermore, several studies on spot market prices prediction employ seasonal adjustment methods to remove the spot market seasonal component [133, 143,

Table 3.1. Statistics of FCR-N price data for 2015 and 2016

Mean	19.560	Min	0.0
Median	17.725	Max	500.0
Skewness	89.335	0-value	29.10%

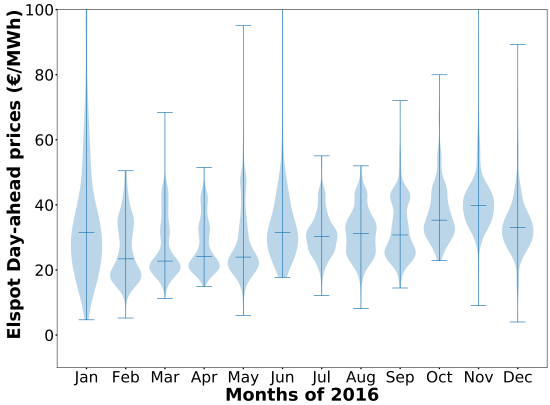

Figure 3.16. Elspot market prices distribution by month for the year 2016, with representation of the median value

144]. In fact, spot market prices present a strong seasonal behavior [123, 143]. On the other hand, FCR-N market presents a significantly weaker seasonality, with the price patterns changing considerably in a short period of time, as also shown in Figure 3.14 and Figure 3.15. Therefore, unlike spot market prices, seasonal adjustment methods cannot be employed in the methodology for prediction of the FCR-N market prices.

3.3.3 Predicting FCR-N prices

This section presents the methodology utilized for predicting FCR-N market prices. The first step consists of collecting the data sources to be used for predicting the prices, followed by the study of the autocorrelation of the FCR-N prices. Then, prediction models are formulated as regression analysis problems, which introduces machine learning regression methods, including the formulation for the employed ANN. In addition, a normalization preprocessing step for the input data is described followed by the validation method employed for the prediction models as well as the performance measures utilized to evaluate the prediction performance. Finally, the ANN model is empirically configured through the tuning of its hyper-parameters.

Data collection

A crucial aspect in the prediction of time series is the identification of meaningful variables to be used as input for the forecasting model [145]. Since energy markets have recently faced major changes in the fast-evolving power grid [146] and the targeted year of prediction was 2016, two-year data are collected, for 2015 and 2016. In fact, adding earlier years to the collected data would add noise to the prediction models, worsening the prediction performance. Therefore, as for the FCR-N prices, two-year data were collected for the selected variables from vaious data sources, such as Fingrid [141], Energia.fi [147], Nord Pool [148] and the Finnish Meteorological Institute [149].

Table 3.2. Collected data for the prediction of the FCR-N market prices

Category Name	#	Data Source
FCR market data	5	Fingrid [141]
Electricity Import/Export	12	Fingrid [141]
Electricity Load	2	Fingrid [141]
Electricity Generation	12	Fingrid [141] and Energia.fi [147]
Day-ahead Elspot Prices	1	Nord Pool [148]
Oil Prices	1	
Weather	26	Finnish Meteorological Institute [149]
Calendar	5	
Total	64	

Table 3.2 provides an overview of the categories of the data collected with these variables and data sources. The first category consists of variables associated with the FCR market, which include the FCR-N prices to be predicted. The second category is related to the import and export of electricity in Finland from and to neighboring countries. Variables were collected for electricity generation in Finland. Examples of electricity generation variables include total generation, nuclear generation, the wind generation. The total electricity load is also considered as a variable as well as the Elspot prices for the Nord Pool day-ahead market and the oil prices. Another set of variables consists of weather variables that can affect the production and consumption of electricity. Temperature, wind speed, solar radiations, and humidity data were collected from several locations in Finland. In addition, calendar variables have been used to take into account seasons, holidays, weekdays and weekends.

Autocorrelation and variable lag

The autocorrelation of the FCR-N prices has been investigated for the data from 2016. Figure 3.17 shows the average autocorrelation of the FCR-N prices. It can be observed that the FCR-N prices present a daily correlation (24 hours lag) as well as a subordinate weekly correlation (168 hours lag). Due to this daily correlation, a lag of 24 hours is added to the variables, from which no predictions are accessible for future times. Thus, the lag was added to all the variables except those belonging to the Weather and Calendar categories.

Prediction model formulation through regression analysis

Regression analysis is a form of predictive modeling technique which investigates the relationship between a dependent variable (Y), and one or more independent variables (X). More specifically, regression analysis helps one understand how the typical value of the dependent variable (or 'criterion variable') changes when varying any of the independent variables, while the other independent variables

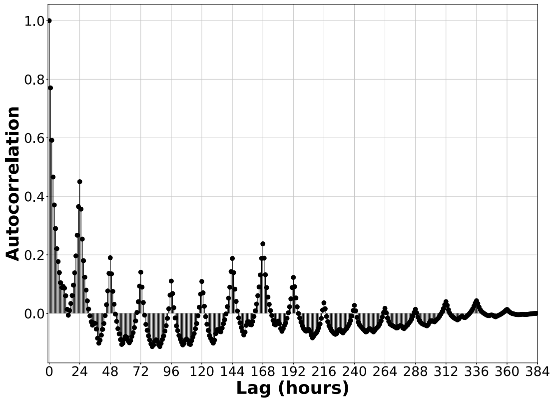

Figure 3.17. Average autocorrelation of the FCR-N prices observed

are held fixed.

The objective is to provide a solution for predicting of the 24 distinct prices for each hour of the day-ahead FCR-N market prices. Thus, the prediction horizon for the presented solution consists of 24 distinct prices. Of the various machine learning strategies for time series forecasting [150], the Multi-Input Multi-Output (MIMO) strategy is selected [151], since MIMO will return a vectorial forecast for the future 24 hours by modeling the time series in a multiple-input multiple-output regression model. Using the MIMO strategy, it is possible to define a prediction model, such that given as input n features, denoted by the matrix X, it learns a function $f(X)$ that generates as output the prediction of the following $ts = 24$ time steps, denoted by the vector $\hat{Y}$.

In the MIMO strategy with ts outputs, each training sample is a matrix X and the prediction for each training sample is a vector $\hat{Y}$ with ts elements. Thus, the training sample X must have ts values for each variable. For one training sample at time t, the input matrix X and the output prediction vector $\hat{Y}$ are defined as:

$$X = \begin{bmatrix} x_1^{t-ts+1} & \dots & \dots & x_1^t \\ x_2^{t-ts+1} & \ddots & \ddots & x_2^t \\ \dots & \ddots & \ddots & \dots \\ x_n^{t-ts+1} & \dots & \dots & x_n^t \end{bmatrix} \quad ; \quad \hat{Y} = \begin{bmatrix} \hat{y}^{t+1} \\ \hat{y}^{t+2} \\ \dots \\ \hat{y}^{t+ts} \end{bmatrix} \tag{3.24}$$

where t represents the time in hours, while x_1^t represents the variable 1 at time t and $m = n * ts$ refers to the total number of elements in the matrix X.

Several techniques for carrying out regression analysis have been developed. In this dissertation, the focus for the predictions is twofold. Several state-of-the-art machine learning regression methods, alternative to deep learning methods such as ANNs are employed. Next, an ANN is designed and empirically configured to perform market price predictions, with the final aim of comparing the prediction performance, using the ARIMA model as benchmark.

1. <u>*Machine learning regression methods*</u>

Linear regression establishes a relationship between the dependent and independent variables using a best fit straight line (also known as a regression line) [152]. Linear regression only looks at linear relationships between dependent and independent variables. That is, it assumes that there is a straight-line relationship between them, which is often incorrect. Moreover, Linear regression is very sensitive to outliers, which can adversely affect the regression line and eventually the forecasted values.

The Decision tree uses a tree as a predictive model which maps observations about an item to yield conclusions about the item's target value [153]. Decision trees that can take the target variable as continuous values are known as regression trees [154]. Decision trees in general have an advantage over other learners in that they are highly interpretable. Furthermore, they require relatively little effort from users for data preprocessing and are not sensitive to outliers since the splitting happens based on a subset of samples within the split ranges and not on absolute values. Finally, decision trees require no assumptions of linearity in the data. However, decision trees can be extremely sensitive to small perturbations in the data: a slight change can result in a drastically different tree. Furthermore, a decision tree can easily overfit. This can be negated by validation methods and pruning [155].

Support vector machines (SVM) constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, and were originally proposed for classification tasks [156]. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. A version of SVM for regression is SVR [128]. Similar to the classification approach, the motivation is to seek and optimize the generalization margin given for a regression.

The gradient boosting decision tree (GBDT) is one of the most widely used learning algorithms in machine learning today [157]. It constructs an additive regression model, utilizing decision trees as the weak learner. Specifically, it builds decision trees one at a time, where each new tree helps to correct errors made by previously trained tree. The advantages of GBDT include adaptability, interpretability, scalability (it can handle very high dimensional spaces as well as a large number of training examples) and accuracy. In addition, GBDT is able to model feature interactions and inherently perform feature selection.

2. *Formulation of an artificial neural network*

An ANN is a computing system that mimics the function of the human brain and nerves, organized in such a way that the structure simulates a network. As shown in Figure 3.18, an ANN can be composed of a certain amount of layers, that can be divided into three categories: the input layer, the hidden layers, and the output layer. The input layer consists of input nodes where the X matrix will be represented. The hidden layers consist of any layer in between the input and the output layer, while the output layer consists of the output

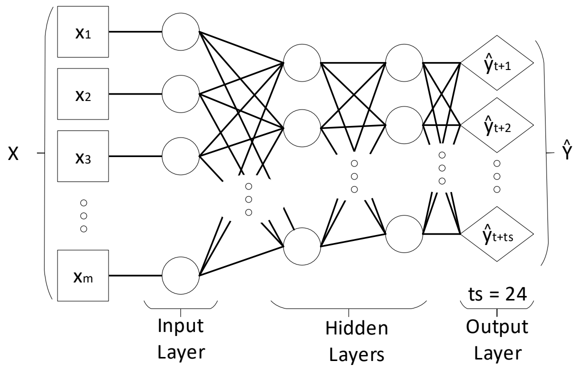

Figure 3.18. Structure of an ANN model

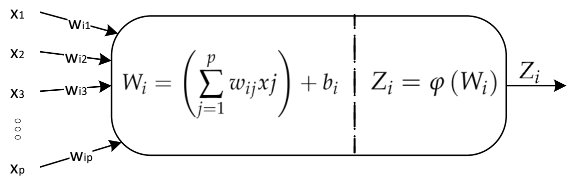

Figure 3.19. Structure of an ANN neuron

variable to be predicted, i.e. $\hat{Y}$. The key elements of an ANN are the neurons, which are depicted in Figure 3.19. Each neuron receives as input the $|p|$ output values ($i = 1, 2, ..., p$) from each neuron of the previous layer with their respective weights w_{ij} and calculates a linear function as follows:

$$W_i = \left(\sum_{j=1}^{p} w_{ij}xj\right) + b_i \tag{3.25}$$

where p is the number of neurons of the previous layer, and b_i consist of a bias term. Then, in order to introduce nonlinearity into the ANN, and thereby allowing the ANN to better learn $f(X)$, each neuron applies a nonlinear function to W_i, also called activation function $\varphi()$, as follows:

$$Z_i = \varphi(W_i) \tag{3.26}$$

Data normalization

Each variable in the input matrix X needs to be normalized, in order to be standardized to the same range of values. The normalization method is chosen in order to rescale the features as a standard normal distribution. The normalization method utilized is called unit variance [158]. Thus, the employed unit variance method distributed the variables in the range [-1,1], which is specified as follows:

$$\widetilde{x} = \frac{x - \mu}{3\sigma} \tag{3.27}$$

where μ is the mean of the distribution, and σ the standard deviation.

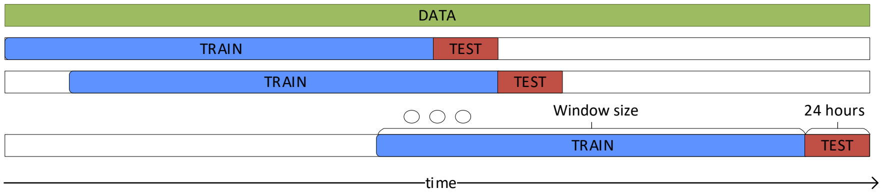

Figure 3.20. Employed walk forward validation method

Model validation

A forward validation method is employed to validate the predictions of the regression models [159]. Figure 3.20 shows the employed walk forward validation method, where an in-sample training data set is utilized to train the prediction model, while an out-sample testing data set is reserved for evaluating the prediction performance. The size of the sliding in-sample training data set will be determined by means of an experiment in Section 4.2.2. In addition, since the objective is to predict the day-ahead, the size of the testing data set size is set to 24 hours of out-sample data. In time series prediction, contiguous subsets of data (in time) are segmented in two folds (Figure 3.20) [160]. The first fold is used for training the model and precedes the second fraction in order of time, while the second fold is used for testing. Thus, the performance is then evaluated by averaging the testing error over the various data sets generated using the walk forward validation method.

Prediction performance evaluation

Prediction performance coefficients are selected in order to enable performance comparison of the different regression models. Therefore, of the various measures of prediction accuracy presented in the literature [123], the mean squared error (MSE) is utilized. The MSE is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.28}$$

where y_i is the price data, while $\hat{y}_i$ is the predicted price. The decision to employ the MSE coefficient is mainly related to one key feature of the FCR-N prices, which present several instances of zero-value (Table 3.1). In fact, due to the large amount of zero-value in the FCR-N price data, several state-of-the-art performance measures would produce a division by zero or an undefined division of zero by zero [161].

Empirical configuration of an ANN

One of the first design decision is the selection of the best performing ANN architecture, which includes identifying the activation functions, the number of hidden layers, and the number of neurons for each layer. Currently, ANN architectures are selected by means of an empirical process [162], in which various architectures are tested, handcrafted and adjusted. General guidelines for designing an ANN architecture are well-known among practitioners, as described in [163]. Following those guidelines, several architectures have been tested for prediction of the FCR prices. Among these, the results of the two best-performing architectures are presented in this dissertation, with the final aim of selecting the one that provides the best performance. The two architectures compared are presented in Figure 3.21 and Figure 3.22. The difference between the two architectures is that the architecture in Figure 3.21 is composed of 2 hidden layers, containing $n = 64$ and 24 neurons respectively. The architecture in Figure 3.22 has 3 hidden layers, with $n = 64$, $n/2 = 32$ and 24 neurons respectively. In the following, the architecture of Figure 3.21 will be referred as the 3-layer architecture, since the depth of the architecture is $depth = 3$, while the architecture in Figure 3.22 will be called the 4-layer architecture, since $depth = 4$.

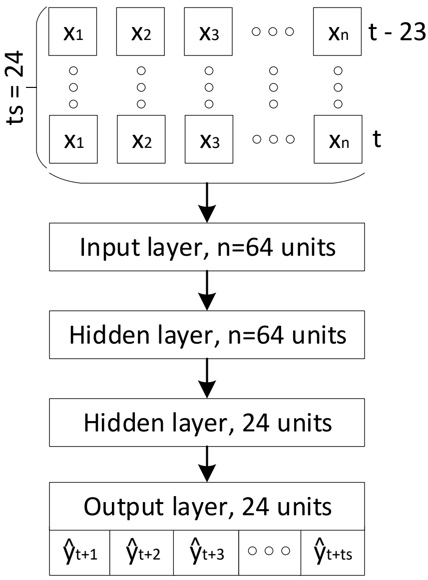

Figure 3.21. Architecture of the 3-layer ANN

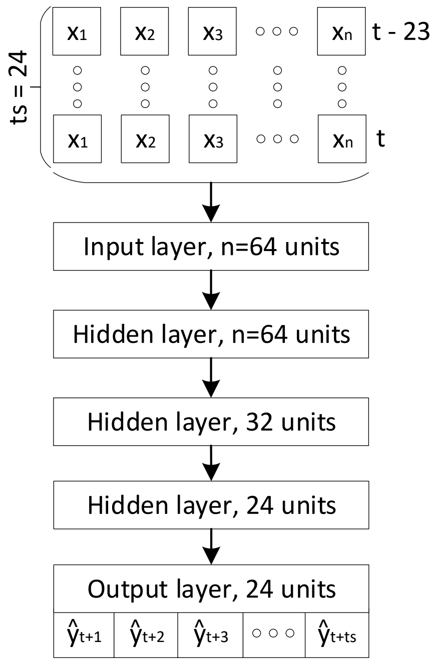

Figure 3.22. Architecture of the 4-layer ANN

To compare the performance of the two ANN architectures, namely the 3-layer and the 4-layer, a set of gradient descent optimization algorithms has been employed. The set includes the Stochastic Gradient Descent (SGD) [164], the RMSProp [165], the Adam [166] and the Nadam [167]. The performance of the two architectures for the different gradient descent optimization algorithms are presented in Figure 3.23 for the 3-layer architecture and Figure 3.24 for the 4-layer. The two figures show that the 3-layer architecture has better performance than the 4-layer, while the difference in performance for the four gradient descent algorithms is less significant. The best performance is obtained by training the 3-layer architecture with 750 epochs. Thus, in the following,

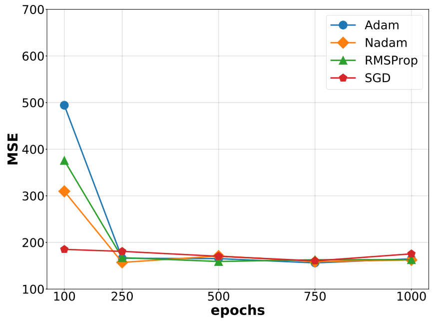

Figure 3.23. MSE performance of 3-layer ANN model with different gradient descent algorithms and epochs

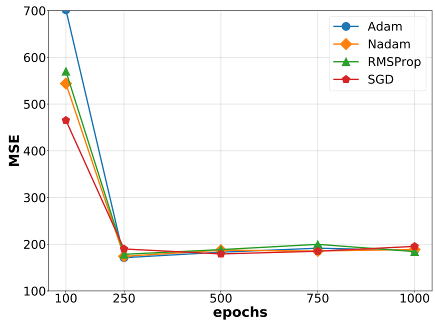

Figure 3.24. MSE performance of 4-layer ANN model with different gradient descent algorithms and epochs

the 3-layer architecture is chosen for the FCR-N price predictions, where the Adam algorithm is utilized to optimize the gradient with 750 epochs, since Adam provided the best MSE performance among the examined gradient descent algorithms.

One of the primary tasks when designing an ANN architecture is identification of the best-performing activation functions. This identification is accomplished through an empirical process. Figure 3.25 compares the performance of the 3-layer architecture using different activation functions (φ) for the hidden layers [168], namely *tanh*, *softmax*, *relu* and *sigmoid*. For this experiment, the *relu* function was used for the output layer, because the *relu* is defined as $relu(x) = max(0, x)$ and the FCR-N prices are non negative numbers. The box plot in Figure 3.25 shows the MSE prediction performance for a sample of thirty days uniformly distributed in the year 2016. This result shows that the best activation function for the hidden layers in terms of MSE performance is the *sigmoid* function. Thus, the $\varphi = sigmoid$ is used as activation function for the hidden layers, while for the output layer the $\varphi = relu$ is used as the activation function.

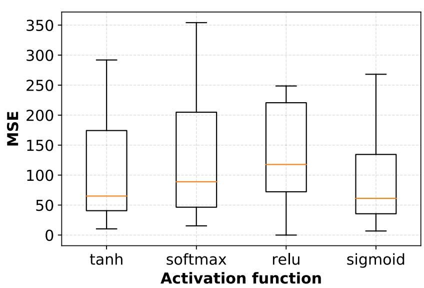

Figure 3.25. MSE performance distribution of the 3-layer ANN model with different activation functions (i.e. tanh, softmax, relu, sigmoid)

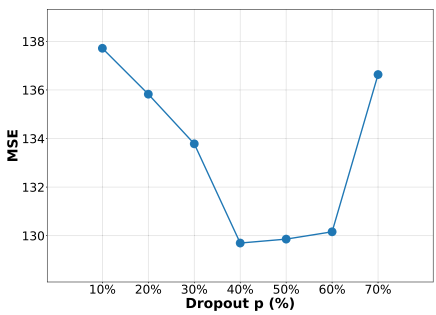

Figure 3.26. MSE performance of the 3-layer ANN model with different dropout probability values p

In order to prevent the ANN model from overfitting, the dropout regularization is utilized for the FCR-N price predictions [169]. The dropout is a regularization technique that temporarily drops neurons from the ANN model during the training phase in a random order based on a probability p. For the selected 3-layer ANN model, a validation set of sixty days uniformly distributed in the year 2016 is utilized to identify the best dropout probability value p (expressed as a percentage %) for the FCR-N price predictions. The results of the experiment are presented in Figure 3.26, which shows the average MSE performance for each of the tested dropout probability values p. The results indicate that the best p values are in the range of $[40, 60]$ %, with $p = 40\%$ being the best-performing value. Thus, a dropout probability value of $p = 40\%$ is chosen for the 3-layer ANN model.

4. Results

This chapter presents the results obtained through simulations and experimentations. Section 4.1 presents the implementation details and simulation results for the designed DR system related to RG2. In addition, in Section 4.2 presents the implementation details and the experimental results for RG3, focusing on the prediction of the FCR-N market prices.

4.1 DR system

4.1.1 Implementation details

The DR system has been implemented as a prototype system composed of several applications, developed in Java. The first application operates as the aggregator, and aims at coordinating the residential consumers for participating in frequency reserves provision during both use cases, *UCI* and *UCII* respectively. The Aggregator application contains the frequency task allocation algorithm and coordinates the DR in both use cases. The second application implements a scalable number of residential consumers, for which a cloud-based application (DR consumer) is developed together with a model of a HEMS and a set of DESs for each consumer. The HEMS operates as a gateway between the DESs and the cloud-based system of the DR system. The third application in the cloud-based system consists of the DROS, which is provided as a service to the other applications. The DROS service is implemented in MATLAB, which uses YALMIP for formulating the optimization algorithms, while the solutions are performed with Gurobi optimizer. Finally, a fourth application is used to simulate the frequency dynamics $f(t)$ of the electric grid.

Communication within the applications in the cloud-based system is performed through RabbitMQ [170], a MOM that implements the AMQP [138]. The communication logic was designed in order to exploit several advantages of AMQP, including advanced routing of messaging as well as both publish-subscribe and point-to-point request-response communication.

Time-varying communication delays have been included in the simulations of the DR system. The delays are considered as end-to-end, from the aggregator to the DESs, passing through the HEMSs of the residential consumers. Along the end-to-end path, the total delay δ_{total} is considered as the sum of the communication delay of the cloud-based system δ_{cloud} [171] and the delay in the consumers' HAN δ_{han} [172], as follows:

$$\delta_{\text{total}} = \delta_{\text{cloud}} + \delta_{\text{han}} \tag{4.1}$$

in which δ_{cloud} and δ_{han} are both defined as:

$$\delta_{\text{cloud}} = \delta_{\text{han}} = \delta_{\text{min}} + rand(0, \delta_{\text{max}}) \tag{4.2}$$

where δ_{min} is the minimum delay, δ_{max} is the maximum delay and $rand(0, \delta_{\text{max}})$ generates a random number within the interval $[0, \delta_{\text{max}}]$. In order to inject both the delays in the DR system, the communication between the DESs and the HEMSs has been modeled in such a way to allow δ_{han} to be added, while for the cloud-based system the delay is injected in the AMQP communication through a plug-in called RabbitMQ Delayed Message Plugin [173].

For the two use cases, *UCI* and *UCII*, different DESs are modeled and real data is adopted from several sources. In *UCI*, a population of 2000 DESs is modeled as storage resources, where the consumers' daily consumption are calculated using a normal distribution with 2 kWh as the mean. The energy storage resources are then constrained by a maximal charging rate ($P_{n,max}$), which is normally distributed within 5 kWh and 10 kWh, and a maximal energy storage charge ($C_{n,max}$), which is distributed between 10 kW and 20 kW. Furthermore, in the simulation results for *UCI*, the data used from the energy prices are taken from the Elspot day-ahead market [59], while frequency reserve volumes data are obtained from Fingrid [58].

On the other hand, for *UCII*, the modeled population of DESs consists of refrigerators, which have been implemented according to [139]. The refrigerators are initialized with random values, and their dynamics is simulated for twelve hours with the comfort-driven control, before being utilized for the DR system simulations. In addition, the refrigerators are modeled with a minimum resting period, which is uniformly distributed between the range of 2 and 4 minutes. In *UCII*, a population of 5000 DESs is utilized for the simulations. For this population, the required $flex_{\text{target}}(\tau_1, t)$ is arbitrarily chosen to be 50 kW for both tasks of the aggregator, the under-frequency τ_1 and the over-frequency τ_2. Since the controlled power is relatively small, it is assumed that the controlled power does not alter the frequency dynamics of the DR system. The frequency dynamics $f(t)$ is modeled with real frequency measurement data, which are taken from the historical frequency measurement data of the Nordic power system provided by Fingrid [141]. In addition, the specified dead-band deviation Δf_{dead} is 0.02 Hz, while the maximum deviation Δf_{max} is considered to be 0.1 Hz, as required by FCR-N.

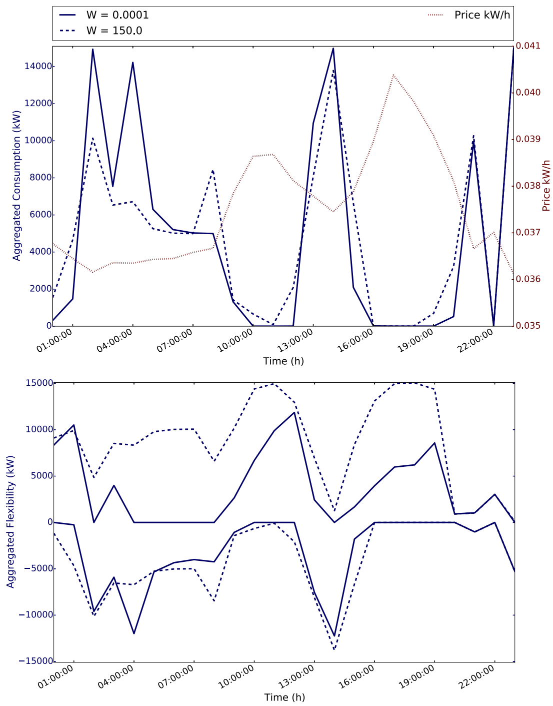

Figure 4.1. Optimization results for 2000 consumers when w = [0.001,150]

4.1.2 UCI: simulation results

Performance of proposed solution

For *UCI*, simulations are performed in order to evaluate the optimization capabilities of the DR system. The simulated scenario consists of one day-ahead distributed optimization for 2000 residential consumers. Figure 4.1 shows the simulation results obtained by varying the heuristic weight w of the designed DR optimization. The top diagram in Figure 4.1 illustrates how the aggregated charging schedule changes during the day based on the spot price and the heuristic weight w, while the second diagram presents the corresponding available flexibility for the simulated day. As can be seen, the aggregated charging schedule varies with the heuristic weight w. When w is increased, the distributed optimization algorithm shapes the charging schedule of the consumers, and by doing so provides additional flexibility to the aggregator.

In addition, the simulations are executed to evaluate the scalability of the DR system and analyze the computational requirements. Using the previous simulation set up, the DR system prototype was tested with a growing number of consumers in the set [250, 500, 1000, 2000]. Independently from the computational capabilities of the simulation test bench, tests have shown that both optimization phases require computational capabilities which are linearly dependent on the number of consumers participating in the DR. In addition, the

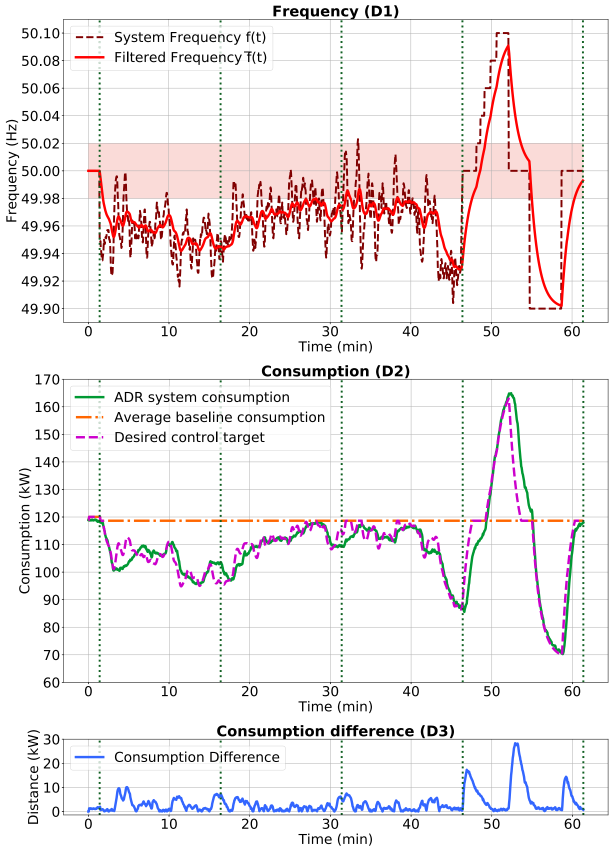

Figure 4.2. (D1) The frequency $f(t)$ injected to the DR system using real frequency data from Fingrid [141] and custom frequency patterns, and the filtered frequency $\overline{f}(t)$. (D2) The realized consumption of the DR system compared with the desired(t). (D3) The difference between the realized consumption of the DR system and the $DR_{\text{desired}}(t)$. The vertical dotted lines represent the time at which the frequency task allocation procedure was executed by the aggregator

computational requirements for the intraday optimization rely on the number of running instances of the DROS, since consumers can reschedule the intraday charging in parallel. Therefore, adding instances of DROS would reduce the computational time while increasing the computational resources needed.

4.1.3 UCII: simulation results

The first simulation for *UCII* analyzes the performance of the DR system during the execution of frequency control. The simulation aims at comparing the actual reaction control of the system with the $DR_{\text{desired}}(t)$ specified in Eq. (3.3), and at identifying possible pitfalls for the DR system. Thus, a one-hour simulation is executed, which in the first 45 minutes injected real data into the system from Fingrid [141], while customized frequency data were utilized for the remaining time (Figure 4.2.D1). In addition, the total end-to-end delay δ_{total} was distributed between a minimum of one to a maximum of three-seconds.

Thus, the results obtained from the simulation are presented in Figure 4.2.D2, which represents the DR system consumption. Based on the reactions during the last 15 minutes of the simulation, it is possible to observe that during the constant frequency deviations of $\Delta f_{\max}$ for a long time period (starting at the minute 54) the reactions of the DESs are well aligned with the desired control target $DR_{\text{desired}}(t)$. However, with a shorter frequency deviation based on incremental steps, as in the over-frequency deviation (starting at the minute 48) of the simulation, while the reaction remains aligned with $DR_{\text{desired}}(t)$, during the *counter-reaction* (i.e. when the frequency deviation restores within Δf_{dead}) the actual reaction of the system has a delay, resulting in a large difference between the desired control target $DR_{\text{desired}}(t)$ and the realized consumption of the DR system (Figure 4.2.D3). Similar behavior can be observed during the first 45 minutes of the simulation using real frequency data, in which delays occur during the counter-reaction phase. Since the delays were only observed in the counter-reaction phase, the result shows that the delays are caused by the resting period of the DESs, rather than from possible communication delays in the ICT system or the task allocation algorithm. Thus, the resting period for the DESs is the cause of the observed peaks in the consumption difference between the desired control target $DR_{\text{desired}}(t)$ and the realized consumption of the DR system (Figure 4.2.D3).

Another important aspect, presented in Figure 4.2.D1, is the comparison between the real frequency data $f(t)$, and the relative filtered frequency $\Delta\overline{f}(t)$. As can be seen, the frequency of the Nordic power system is affected by frequent fluctuations. This characteristic motivates the choice of filtering the frequency in order to avoid oscillations in the realized frequency of the grid, caused by erroneous reactions of the consumers in the DR. In addition, Figure 4.2.D2 shows how the aggregator, within the hour of simulation, tries to apply the corrective control to the DR system in order to maintain the total consumption of the system (when the frequency is within the dead-band) to a certain value established at the beginning of the hour. In fact, all the decentralized reactions to the frequency are then shaping the total consumption relatively to the established consumption value.

Figure 4.3 shows the amount of DESs in the DR system that has been in the *Allocated* composite state during the first simulation, for both tasks, τ_1 and τ_2. In addition, the diagram shows the amount of DESs utilized by the corrective control during the simulated hour. It is possible to observe that the DESs allocated for task τ_1 were actively participating in the frequency control, thus providing reserves to the grid. The diagram shows how the DESs were changing between the three states of the *Allocated* composite state, based on the filtered frequency $\Delta\overline{f}(t)$. Important to note are the small accumulations of *Inoperative* DESs during the under-frequency reaction, which typically occur during a counter-reaction phase. This phenomenon is caused by the resting period of the refrigerators, which does not permit the DESs to react instantaneously at two consecutive frequency drops, hence requiring the DESs to be rescheduled.

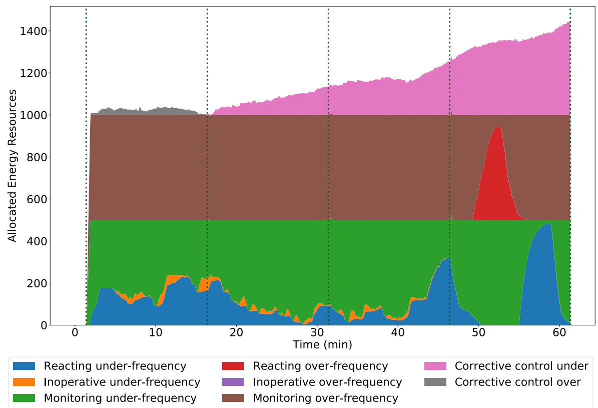

Figure 4.3. The DESs allocated to the *Allocated* composite state over time for the under-frequency and the over-frequency cases, and the amount of DESs used by the corrective control in one hour simulation

Therefore, a combination of different DESs, with (e.g., refrigerators) and without (e.g., HVAC) a resting period, would mitigate the accumulation of *Inoperative* DESs during the counter-reaction phase. Moreover, the diagram also shows the amount of DESs controlled by the corrective control. During the simulated hour, the amount of DESs utilized by the corrective control is growing, due to the large participation in the frequency control for the under-frequency task, causing the demand of the DR system to be shifted.

The impact of the communication delays on the DR system is verified through a simulation. For this simulation, the frequency measurements, injected into the DR system, were taken from the Continental Europe [137], demonstrating that the developed system can be operational in other regions with different frequency characteristics (Figure 4.4.D1). The performance of the DR system with different communication delays are shown in Figure 4.4 (D2, D3, D4). As can be seen, the DR system provides similar performance regardless of the distribution for the total communication delay δ_{total}, which was randomly distributed in intervals of [1,3], [10,30], and [30,90] seconds. This demonstrated that the DR system is robust to communication delays, and does not require real-time communication for participation in the FCR-N.

In the worst case scenario of Figure 4.4, delays were distributed in the range [30,90]. These values were determined experimentally, since a higher value was found to result in significant performance degradation. Thus, the significance of these results is to demonstrate that the DR system is robust against delays that are longer than what can be expected in the public internet. The Continuous Allocation Procedure is executed every 3s. In this procedure, *Inoperative* resources are deallocated and replaced. As illustrated in Figure 3.7, the aggregator immediately moves a resource away from the *Inoperative* state, thus keeping the percentage of *Inoperative* resources minor as long as the communication delays are within certain limits. Because *Inoperative* resources represent a minor fraction of the total resources, delays in their replacement will similarly

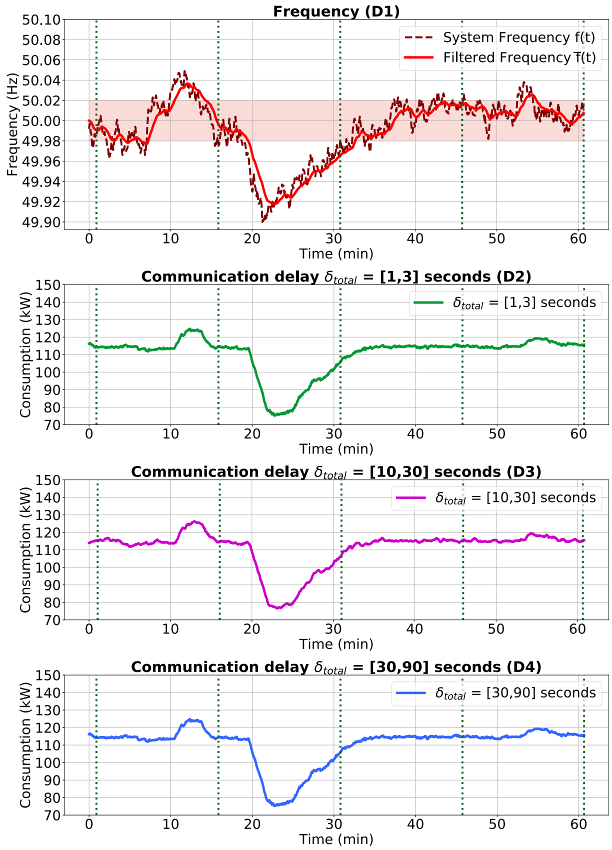

Figure 4.4. (D1) The frequency $f(t)$ injected to the DR system using real frequency data from the Continental Europe [137]. (D2) The realized consumption of the DR system with a δ_{total} within the range [1,3] seconds. (D3) The realized consumption of the DR system with a δ_{total} within the range [10,30] seconds. (D4) The realized consumption of the DR system with a δ_{total} in the range [30,90] seconds

have only a minor impact on overall performance, as demonstrated in Figure 4.4. Quantitative values for 'minor' and 'within certain limits' have been determined experimentally. As stated above, the communication delays were distributed in the range [30,90] in the worst case scenario for which the system has been simulated. In this case, the 'minor' fraction of *Inoperative* resources is presented in Figure 4.5.

Comparison with the State of the Art

The following results compare the task allocation algorithm with the decentralized solution for frequency control presented in [90], in which the DESs are reacting in a totally decentralized DR system, with no communication required, and the consumers are reacting directly to the frequency deviations based on a frequency-time characteristic which defines when the energy resource should provide the flexibility. Whilst this solution requires no cooperation, one limitation is the static definition of the frequency-time characteristic that the DERs

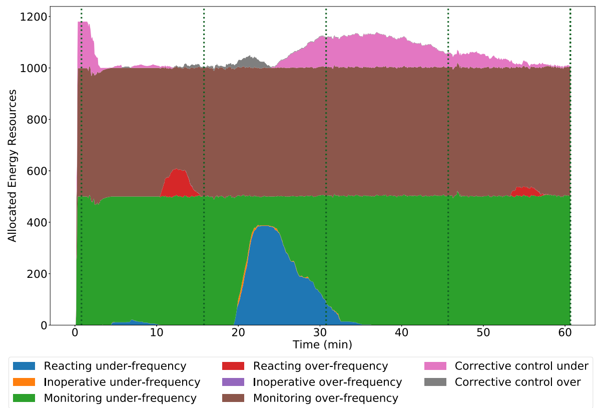

Figure 4.5. The DESs allocated to the *Allocated* composite state in the worst case scenario (D4) of Figure 4.4, where the δ_{total} was in the range [30,90] seconds

need to follow, without enabling the plug-and-play or the disconnection of the DERs. Thus, there is no automatic control that compensates for a resource that is unexpectedly disconnected from the DR system. In fact, such automatic control is needed to ensure that the DR system is able to provide the targeted power $flex_{\text{target}}(\tau,t)$, which was sold by the aggregator to the ancillary market.

A second disadvantage is the incapability of the totally decentralized solution to have control over the amount of reserve effectively provided to the grid. Figure 4.6.D2 shows the consumption profiles for the one-hour simulation of the task allocation algorithm and the decentralized solution. By comparing the first period (15 minutes) of simulation with the last 2 periods (30 minutes), despite having similar frequency deviations in the DR system, it can be seen that in the first period the two systems have similar responses, whilst in the last two periods the two solutions provide different responses in terms of total consumption. This anomaly is due to the fact that after a short time, the static allocation starts to lose its capability to provide the reserves, and the total consumption of the static solution rapidly increases, even if the DESs are still reacting to the frequency deviations. On the other hand, the task allocation algorithm allocates the DESs and applies the corrective control based on a total consumption value for the DR system (i.e., 120 kW for the executed simulation) established at the beginning of every hour. This solution enables control of the provided reserves during each hour, by dynamically allocating resources and utilizing a hybrid coordination algorithm: decentralized, by allocating the tasks, combined with centralized, by applying the corrective control.

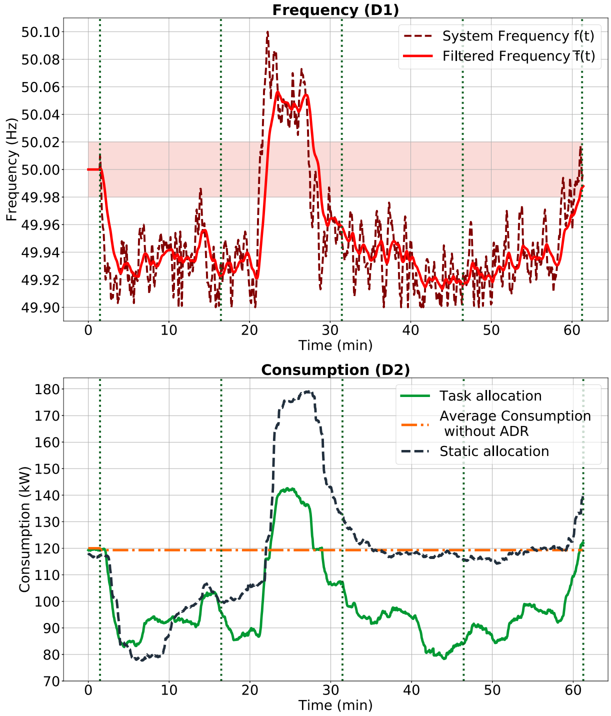

Figure 4.6. (D1) The frequency $f(t)$ injected to the DR system using real frequency data from Fingrid [141], and the filtered frequency $\overline{f}(t)$. (D2) The comparison of the provided reserve of the DR system based on the task allocation with the static allocation of DESs presented in [90]

4.2 FCR-N price prediction

4.2.1 Implementation details

Prototype software has been implemented for prediction of the FCR-N market prices for the day-ahead. The first phase consisted of collecting two-years data from several data source presented in Table 3.2 by accessing the provided open APIs. After collecting the data, the models for predicting the FCR-N prices have been developed using Python through the exploitation of several libraries including Keras, Scikit-learn, Pandas, Matplotlib and Numpy. Since the experiments on the developed methods consist of an empirical process, a high performance computing cluster named Triton, provided by the Aalto Science-IT project, is utilized to perform the experiments.

4.2.2 Experimental results

The following experiments aim at defining the size of the training window for the ANN model, followed by an extensive analysis of the prediction performance of the ANN model. Finally, the prediction performance of the ANN model is

Figure 4.7. MSE performance of the 3-layer ANN model with different training window sizes fpr {30, 90, 180, 270, 360, 450 } days

compared with several machine learning regression methods as well as the benchmark method ARIMA.

Experimental results for the ANN model
The selected ANN model for the experiments consists of a 3-layer model, as described in Figure 3.21, where the gradient optimizer utilized is the Adam with 750 epochs. In addition, for the hidden layers, the selected activation function utilized is the *sigmoid*, while the *relu* function is selected for the output layer. Finally, a dropout value p of 40% is utilized in order to prevent the ANN model to overfit.

The first experiment on the ANN model aims at defining the size of the training window. Figure 4.7 shows the MSE for the 3-layer model for a sample of thirty days uniformly distributed. From the figure, it can be noted that the size of the training window tends to start stabilizing the prediction performance after 180 days. Thus, since no fundamental improvements or degradations of the performance are registered with training window sizes larger than 360 days, the training window size chosen for the following experiments is 360 days, which is a good trade-off between being too small and thus start degrading the prediction performance, and being too large, thus slowing the training of the ANN model. Moreover, further enlarging the training data set add perturbation the prediction model, thereby weakening the prediction performance. Hence, to summarize, the training window size consists of one-year data, while the testing window size corresponds to 24 hours ahead unless otherwise stated.

For the ANN model, the prediction performance of the FCR-N prices is analyzed for the entire year 2016. For each day in 2016, an ANN model is trained for predicting the day-ahead FCR-N prices. The following experiment aims at analyzing the prediction performance for each month of the year 2016. Therefore, the prediction performance for each month of 2016 is presented in Figure 4.8

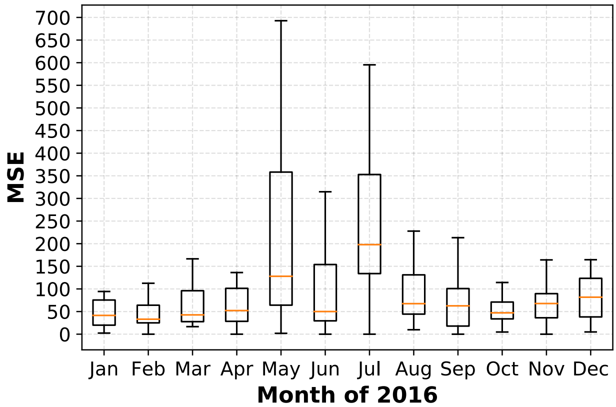

Figure 4.8. MSE performance of the 3-layer ANN model for the entire year of 2016 aggregated by month

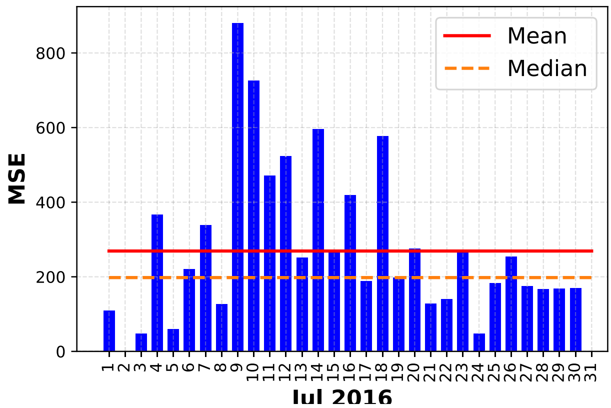

Figure 4.9. MSE performance of the 3-layer ANN model for the month of July 2016

in the form of a box plot, where the median value is denoted with by a line within the boxes. As can be observed, the worst performance in the predictions is observed during the months of May and July. This performance result reflects the analysis presented in Section 3.3.2. In addition, the months of May and July present a distribution of the price data which differentiates considerably from their respective previous months (Figure 3.14), thus preventing the ANN model from efficiently learning the fast-occurring changes in the market.

However, it can be noted that the median values in Figure 4.8 are found in the lower part of the respective boxes, demonstrating that prediction performance is affected by a small number of outlier days. In fact, this can be observed by looking at the prediction performance in more detail. As examples, the performance for the month of July and August are analyzed, i.e., the month with the highest variance (July) and its next in order of time (August). Thus, the prediction performance for each day of July and August are presented in Figure 4.9 and Figure 4.10 respectively, which also represent the monthly mean and

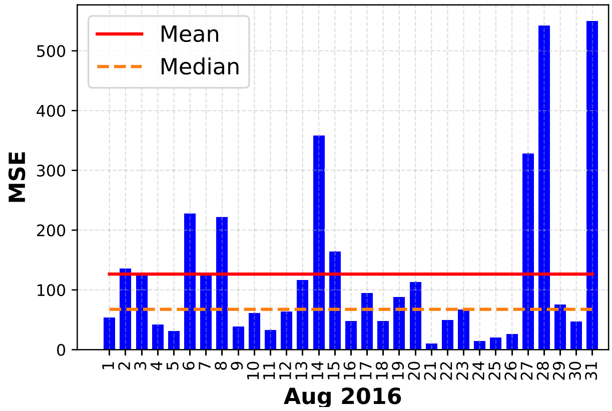

Figure 4.10. MSE performance of the 3-layer ANN model for the month of August 2016

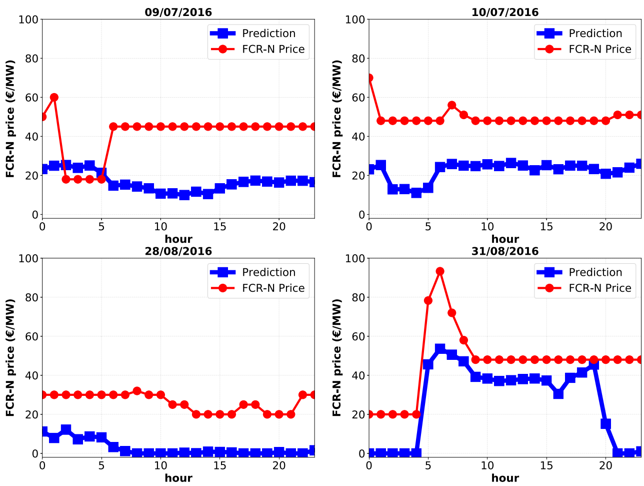

Figure 4.11. Examples of four outlier days in terms of FCR-N price behaviors in the period July - August 2016

median for the MSE of each day. The figures show that the difference between the mean and the median of the performance is due to a small set of outlier days. The main four outlier days in July and August are presented in Figure 4.11. All the outlier days present very unusual price patterns, which were not registered in past observations, making them exceptionally difficult to predict.

On the other hand, Figure 4.12 shows the prediction of the FCR-N prices for four days in the time span of two weeks between July and August 2016. As can be noted, the FCR-N prices can quite rapidly vary their pattern in a short time period, making FCR-N price prediction more challenging than spot prices, which present an evident seasonality between contiguous days. Moreover, the first row in Figure 4.12 presents two days with an outlier behavior (i.e., price patterns specific to the analyzed period of time and not commonly observed in other periods) which are adequately predicted by the ANN model. While the second row of Figure 4.12 shows two price patterns with their respective predictions,

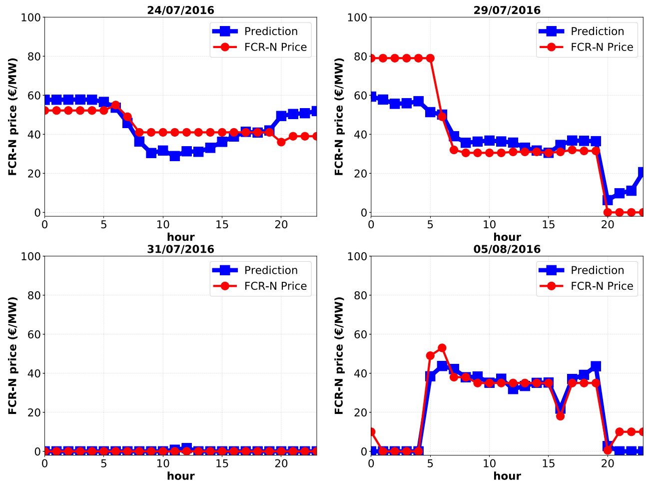

Figure 4.12. Examples of four days in the period July - August 2016, which have been accurately predicted by the ANN model, where in the first row there are two outlier price patterns while in the second row two of the most recurring price patterns for the FCR-N market

that regularly recur along the entire period of time analyzed (i.e. 2015 - 2106), during which the ANN model succeeds in providing accurate predictions.

Part of the methodology involves the decision on how often the computationally intensive retraining of the ANN needs to be performed. Thus, the second experiment aims at analyzing how the performance of the ANN model degrades when the ANN model is utilized for predicting several days in the future without a retraining of the model. Figure 4.13 presents the prediction performance (in terms of MSE) of the ANN model up to seven days in the future for the year 2016, in which the median of the daily performance is represented with a line while the daily mean performance is represented as a triangle. The prediction performance degrades linearly with respect to the number of days in the future to be predicted, proceeding from an MSE of 115.8 for the first day to 139.6 for the seventh day after training the ANN model. At the same time, the distance between the median and the mean as well as the variance in the prediction performance increase, indicating that a short retraining period for the ANN model is desirable for reducing the prediction errors in outlier price patterns.

Prediction performance comparison

The following experimental results evaluate and compare the performance of the developed ANN model with selected machine learning regression methods (i.e., Linear regression, Regression tree, SVR, and GBDT) using the ARIMA method as the benchmark. For this experiment, FCR-N prices have been predicted for the entire year of 2016. For the ANN model, a model for predictions has been trained for every day of 2016 and for each implemented machine learning regression method, where the size of the training window is composed of one-year sequential data, while the size of the testing window consists of the 24 hours in the

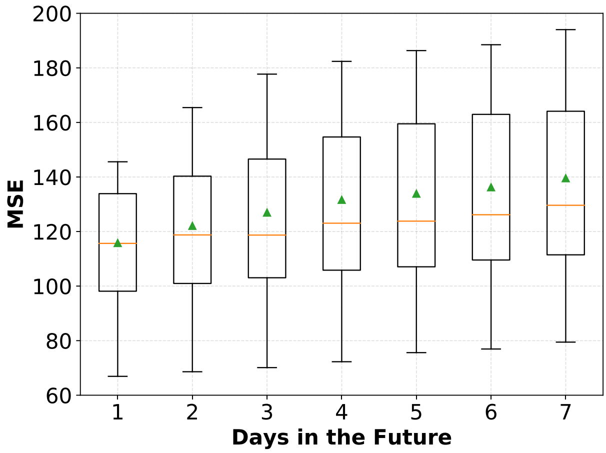

Figure 4.13. MSE performance of the 3-layer ANN model in the entire year 2016 for the prediction of several days in the future

following day. A similar configuration is applied to ARIMA where the training window for the autoregressive FCR-N prices is one year, the predictions are made for 24 hours ahead and the ARIMA parameters (p,d,q) (i.e., autoregressive, differencing, and moving average parameters) are $ARIMA(p=1,d=1,q=1)$, respectively.

Figure 4.14 compares the MSE performance of the ANN model with the four implemented machine learning methods and the ARIMA model. As shown, during the initial months of the year, i.e. when the prices are distributed around the median and have a low variance (Section 3.3.2), the models have similar performance, even if the ANN and GBDT models always outperforms the other models, though showing similar prediction performance. However, once the prices experience an increase in variance and a dispersion from the median value (i.e., between May and August), the ARIMA fails to adapt to the fast changes in the FCR-N prices, while the ANN and GBDT models still provide predictions with superior accuracy compared to the other models. Further, the ARIMA predictions for the last months of 2016 (i.e., September to December), during which the FCR-N prices have similar behavior, are largely affected by the previous period (i.e., May to August), showing that the ARIMA fails to adapt to the new changes of the prices. In contrast, the ANN and GBDT models are capable of adapting even in the third period of the experimented year and of significantly outperforming the ARIMA benchmark, without being perturbed by the prices from the preceding period (i.e. May to August).

The ANN model provided better performance than three of the four machine learning models (i.e., Linear Regression, Regression tree, SVR), showing the ANN model to be more robust to the perturbations introduced by previous prices. Furthermore, ANN is found to largely outperform the ARIMA benchmark model. The ANN model resulted in being more capable of adapting to new price patterns while maintaining the memory of the patterns occurring regularly and being

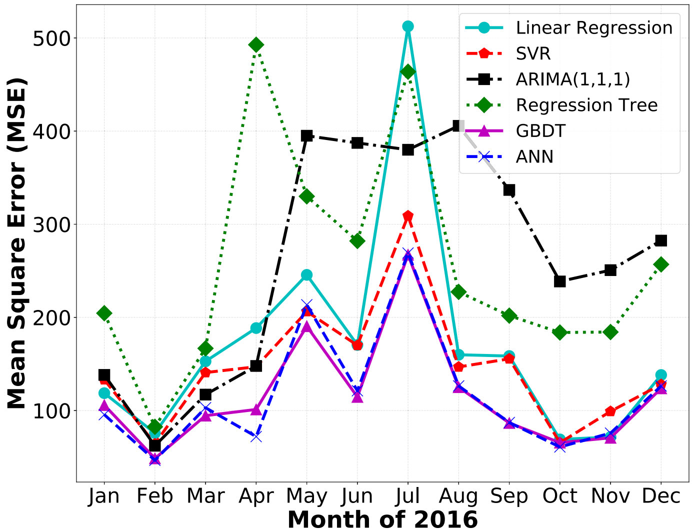

Figure 4.14. Performance comparison between ANN, ARIMA(1,1,1), and four other machine learning regression methods (Linear regression, Regression tree, SVR, and GBDT)

more robust to fast changes occurring in the FCR-N market prices. However, the experimental results showed similar prediction performance for the ANN and the GBDT models. This might be due to the fact that, even though several input variables were utilized for predicting the market prices, the number of variables is still limited, thus diminishing the possibility of the ANN to provide a major improvement in the performance. This limitation pertains to the prediction of energy market prices, where a tradeoff exists between the number of input variables employed as well as the size of the training window and the consequent prediction performance. In fact, the amount of variables correlated to the markets is limited and large training windows tend to perturb the accuracy of prediction models [126]. In addition, GBDT was observed to have good prediction performance because boosting methods are particularly robust to outliers [174].

5. Conclusions and further work

Demand response could be a valuable mechanism for maintaining the production/consumption balance in the power grid, by actively engaging residential consumers in balancing operations. However, the integration of residential consumers in the DR requires aggregation of DERs in order to enable the participation in DR energy markets. Therefore, this dissertation investigated how DESs can be aggregated to participate in the DR, and more specifically in the frequency containment reserve. In particular, the dissertation focused on three main research goals: defining the requirements for enabling consumer-owned DESs to participate in the FCR (RG1), designing and assessing a DR system that combines a hybrid ICT architecture and coordination algorithms to enable the execution of DR during different time frames (RG2) and exploiting the developed system to profitably participate in the FCR markets (RG3).

In order to design a DR system that combines ICT architecture and coordination algorithms, functional requirements, in the form of two use cases (*UCI* and *UCII*) and non-functional requirements were identified in Section 3.1. The identified requirements supported the design of a hybrid architecture for a DR system, in which the ICT architecture was designed to enable the execution of the DR for both DR planning (*UCI*) and frequency control provision (*UCII*). The DR planning consisted of two phases (day-ahead and intraday), which employed a DR optimization to minimize consumption imbalances. On the other hand, for frequency control provision, an auction-based task allocation algorithm was developed to coordinate the aggregated set of DESs for supplying the FCR-N reserve. The design of the task allocation algorithm focused on two key objectives: avoiding the need for real-time messages, and enabling the DESs to be flexibly plugged and disconnected from the DR system. The main results supported the hypothesis presented in Section 1.3, which stated that a hybrid architecture can effectively exploit DERs for FCR. The simulation results showed that the designed DR system provides FCR-N reserves by adhering to the participation requirements of the FCR-N market while being robust over communication delays.

The third research goal required to identify the decision-making to be considered for exploiting the designed DR system to profitably participate in the

FCR-N market. Since the scope of this goal was broad, this dissertation focused on providing a solution for predicting the FCR-N market prices for the day-ahead. Due to substantial differences between the ancillary FCR-N market and the spot market prices, a solution was proposed to predict FCR-N prices. This solution exploits openly available data together with regression analysis models, including the empirical formulation of an ANN model. The results showed that the presented solution for predicting the FCR-N prices is affected by a small set of outlier days, which could be mitigated by daily retraining of the ANN prediction model. Furthermore, comparing the prediction performance with several regression methods demonstrated that the ANN model shows better performance with four of the five state-of-the-art methods, and performance similar to that of the GBDT model, showing how the characteristics of the market and the large but still limited number of input variables prevented the ANN model from producing significantly better prediction performance.

Concerning the DR system proposed, further work might focus on generalizing the DESs utilized. In fact, in the implemented prototype DR system, while the DESs were modeled as either energy storage resources (*UCI*) or refrigerators (*UCII*), further work could investigate the participation of the DR system using a greater heterogeneity of DESs, thus providing a generalization of the current work. In addition, considering RG3, in which the final objective was to exploit profitably the developed system on FCR markets, further work could involve prediction of the hourly amount of flexibility for the day-ahead that a set of consumers could be expected to provide, and predicting the sensitivity of the consumers to provide flexibility in terms of different financial compensations. The final aim of this work could lead to employing the listed predictions for enabling the execution and optimization of VPP operations such as DR market participation, thus providing a toolset that could support the decision-making process by reducing the risks involved.

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