FP7-PEOPLE-2013-ITN 607774

ADVanced communicAtions and iNformaTion processing in smArt Grid systems

WP1 D2.1
Smart Home Networks

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Status-Version:	Final-1.0
Date:	26/06/2017
EC Distribution:	Consortium
Project Number:	607774
Project Title:	ADVanced communicAtions and iNformaTion processing in smArt Grid systems

Title of Deliverable:	Smart Home Networks
Date of delivery to the EC:	26/06/2017

Workpackage responsible for the Deliverable	WP1
Editor(s):	Aleksandar Mastilovic
Contributor(s):	Aleksandar Mastilovic, Pierre J.C. Vogler-Finck
Reviewer(s):	
Approved by:	All Partners

Abstract	The research results of Working Package 1 (WP1) team are focused on enabling technologies for Smart Home applications. In particular, the WP focuses on: 1) wireless machine-to-machine (M2M) communication technologies, and 2) smart modelling and optimization technologies for home heating systems. In the domain of communication technologies, the work is focused on the evolution of public wireless cellular systems 4G-LTE/5G towards supporting massive and critical M2M. M2M will enable automatized and human-free interaction among the devices, enabling smart systems to automatically provide optimal performance. Smart Homes are combination of the sensors placed in home-based devices which measure predefined parameters, acquire data and send them to storage/processing capacities for further analysis. Depending on the results of analysis, Smart Home can create an automatized action, as home lighting control, heating control, etc. Specifically, as one case study of Smart Home system, optimization of home heating systems from the perspective of thermal load monitoring and control for power system energy savings and demand response functionalities is considered. The goal of the home heating system optimization was to create energy-saving and cost-decreasing system with the same or better quality of the service for the customers. This is obtained by heat load prediction/forecasting techniques based on historical data from which predictive control models are developed that revealed significant potential for improving the operational efficiency of heating systems.
Keyword List:	Smart Grid, Smart Homes, Communications, Power Modelling, Home Heating Systems, 5G, Uncoordinated Radio Channel Random Access, Collisions, M2M

Document Revision History

Version	Date	Description	Author
First Draft	12/05/2017	Initial version, First read	Pierre J.C. Vogler-Finck Aleksandar Mastilovic
Second Draft	02/06/2016	Updated version	Pierre J.C. Vogler-Finck Aleksandar Mastilovic
Pre-Release Draft	22/06/2016	Joint version	Aleksandar Mastilovic
Final Version	26/06/2016	Final Edits	John S Thompson Dejan Vukobratovic Aleksandar Mastilovic

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1 WP1 - Introduction

Work package 1 is responsible for solutions for enabling smart grid HANs, taking in consideration all wireless communication protocols such as ZigBee, 6LoWPAN or WiFi and mobile cellular systems as 3G/4G, but also looking for new approaches and techniques which could be implemented in 5G future solutions. All presented solutions are focused to enable data acquisition and ensure reliable communications suitable for data gathering and processing, decentralized data storage and aggregation, fast data mining, analysis and representation for the purpose of communication from distributed HAN environment to/from smart meters and in-house display panels or software-based interfaces in smartphones, but also any other applications related to smart home applications.

The first part of Work Package 1 research is focused on future random access solutions for 5G, where different setup compared to current cellular systems is expected due to massive number of sporadically active devices, ultra-dense network infrastructure deployment, directional communications using beamforming in higher frequency bands, etc. The results present the performance comparison of coded slotted ALOHA-based random access, with and without presence of the synchronization. Special focus is to proof that the performance of asynchronous communications is enough for some class of applications in case that the synchronization couldn't be performed for all associated devices, what we expect for a enormous number of sensors in mM2M. The conclusion of this research proofs that the system ensures sufficiently high performance to support non-critical application in smart home environment, as control of heating/cooling systems, smart metering and etc.

Second part of Work Package 1 Report is focused on one of possible applications in smart home environment, called Smart heating system. Optimization of the energy use in the heating systems is important for few aspects: decreasing costs, saving environment, improving life quality in the homes etc. Smart heating system is based on some number of sensors for measurement indoor temperature but also outdoor temperature when it uses new approach to compensate varying of outdoor temperature on the indoor temperature with minimum energy spending and minimal variation of the indoor temperature in the time. This application is fully supported with previous 5G modern cellular communication system, which is ready to accept and serve enormous number of different sensors, including temperature and other sensors for measuring air quality and air parameters at all. The approach of design for smart heating system is oriented to distributed applications what enables D2D communication between sensors and actuators ("heating machine") with ability to collect data, analyses them and makes optimal decision with predefined targets and constraints.

Both part of the research work from Work Package 1 make full solution for one of possible smart home applications, but also define the model for common interdisciplinary approach involving novel results in communications field and power and civil engineering.

2 Uncoordinated Random Access Control: Enabling Massive and Critical M2M Communications

2.1 Introduction

The problem of connecting very large number of devices to dense small cell wireless cellular networks is gaining momentum as billions of devices are estimated to be connected to the Internet as part of Internet of Things (**IoT**, or *Internet of Everything*, referred to Cisco Inc.) and their smart services. In mobile cellular networks, this will be done through Machine Type Communication (MTC) services whose standardization is initiated within the fourth generation (4G) 3GPP Long-Term Evolution (LTE) technology and will continue to evolve into the upcoming fifth generation (5G) cellular network standards [1]. The vast majority of MTC users will be devices whose activity is irregular and unpredictable and that occasionally transmit small volumes of data. As the available infrastructure becomes increasingly dense due to proliferation of small cells, the 5G radio access networks are faced with increased density both in terms of user and base station deployments. In such a scenario, we are interested in the design of simple and efficient random access solutions able to support the expected surge of MTC traffic in the future.

We consider the challenge for enabling Massive and Critical M2M communications at MAC layer of existing 4G (LTE) and future 5G cellular systems and their abilities to handle and resolve collisions in the system caused by enormous number of machine-type devices and smaller number of human-centric devices. In this research, we consider random access using Slotted/Synchronous (SA) and Non-Slotted/Asynchronous ALOHA (ASA) with Successive Interference Cancellation (SIC) in the multi-base station (MBS) system. We suppose a model for establishing a cooperation between base stations by using Cloud Radio Access Network (C-RAN) in the system core, but also geographically-depended cooperation with neighbouring Base Station using direct communication channel for intra Base Stations Communications.

In the global cooperation mode, the C-RAN interconnects all base stations in the system allowing for joint processing of signals received at different base stations.

2.1.1 Technical Overview

ALOHA is a well known protocol for Random (Multiple) Access (RA) to shared medium. In contrast to RA, there are techniques for Demand Assigned Multiple Access (DAMA), where (centralized) system infrastructure assigns system resources such as time slots, frequency resources, orthogonal codes, to the clients (human-centric users or machines). DAMA techniques are suitable for some systems and traffic models, e.g., if the number of users is not too large and traffic behaviour is predictable. On the other hand, in scenarios such as machine-type communications, where devices occasionally transmit small amount of data and are usually unpredictably triggered by events, the RA solutions are more favourable.

ALOHA protocol is designed by a research group of University of Hawaii (USA), under the leadership of Prof. Norman Abramson in September 1968. Initially, ALOHA was designed as a very simple system called *Pure ALOHA* [2]. Later upgrades that improved throughput are well-known as *Slotted ALOHA* (SA) [3] or *Framed Slotted ALOHA* (FSA) [4]. Finally, recent years brought increased interest in ALOHA protocol enhanced by Successive Interference

Cancellation (SIC) and number of research proposals dramatically increased the throughput of classical ALOHA, such as *Contention Resolution Diversity Slotted ALOHA* (CRDSA) [5], *Irregular Repetition Slotted ALOHA* [6], *Frameless Slotted ALOHA* [7], *Coded Slotted ALOHA*, etc.

2.2 Description of Techniques and System with Scientific Methodology

Coordinated access to medium, which is very common nowdays, is difficult and/or very inefficient in the systems with huge number of devices. It renews the interest for random multiple access techniques, e.g. ALOHA and its variations.
Novel solutions for cellular networks will target support for machine-type communications that are described with few important characteristics:

- very large number of users/devices;
- sporadic and unpredictable user/devices activity;
- small amount of data per user/device;

Slotted ALOHA (SA) random access solutions with Successive Interference Cancellation (SIC) decoding have received significant attention lately due to their ability to dramatically increase the throughput of traditional SA. SA with SIC for single base station systems has been proposed in [5]. Using the analogy with sparse-graph codes and iterative erasure decoding, SA with SIC is further optimized to reach close-to-optimal throughputs [6]. Motivated by increased density of cellular networks due to the introduction of small cells, SA algorithms is recently considered with SIC operating cooperatively in multi base station (SA-MBS) systems [8]. In SA-MBS, users can be heard and decoded by any of the surrounding base stations as, from the system perspective, it is not important which of the small base stations collected the user. Thus, apart from temporal diversity exploited by SA with SIC in single base station systems, SA-MBS may additionally exploit spatial diversity combined with cooperative SIC-based decoding [9][10].
For the systems, where it is too difficult to ensure synchronization on slot-level because of various reasons (wide geographical dispersion of associated devices, very dispersive and unpredictable delays of data packets, etc.), the good approach is to avoid synchronization at all, or at least admit only the less demanding frame-level synchronization.
Placement model and User transmission model are common for all various ALOHA-based scenarios of Random Access.

2.2.1 Placement Model

We assume that both BSs and UEs are placed according to Poisson point processes (PPP) over a surface $\mathcal{A}$ of an area $\|\mathcal{A}\|$. The PPP for BSs has intensity λ_{BS}, while for UEs it has intensity λ_{UE}. The two PPP are mutually independent. The numbers of BSs and UEs, denoted as N_{BS} and N_{UE}, are hence random variables with Poisson distributions $\mathcal{P}(\overline{N}_{BS})$ and $\mathcal{P}(\overline{N}_{UE})$, with mean values $\overline{N}_{BS} = \lambda_{BS} \cdot \|\mathcal{A}\|$ and $\overline{N}_{UE} = \lambda_{UE} \cdot \|\mathcal{A}\|$, respectively. We denote users by U_i, $i = 1, 2, ...$, and BSs by B_j, $j = 1, 2, ...$ Unless otherwise stated, we will focus on a unit-square area $\mathcal{A}$ ($\|\mathcal{A}\| = 1$), in which case the expected number of BSs and UEs reduces to $\overline{N}_{BS} = \lambda_{BS}$ and $\overline{N}_{UE} = \lambda_{UE}$, respectively.

2.2.2 Random Access Model

Slotted ALOHA (SA-MBS) [8] and *Asynchronous ALOHA* (ASA-MBS) random access models are considered in the *Multi Base Station* scenario.
Slotted ALOHA random access model is based on the discrete time domain divided into time slots (TS). User transmissions are synchronized and aligned with TS boundaries, which are perfectly synchronized across all BSs. In any time slot, a UE transmits an equal-length data packet independently of other UEs with probability p, which we call the activity factor. Due to high BS density, the UE packet transmission may be detected at several neighbouring BSs. We assume BSs are interconnected via a backhaul network and any BS may collect any UE's data packet (i.e., we assume no a priori UE to BS associations). We consider the UE's packet to be collected as long as any BS successfully decoded it.
The average normalized load is defined by $G = p\frac{\overline{N}_{UE}}{\overline{N}_{BS}} = p\frac{\lambda_{UE}}{\lambda_{BS}}$. For the sake of analysis, without loss of generality, it is sufficient to consider the SA-MBS system behaviour at any single fixed TS. In the following, we will assume activity factor $p = 1$. This is sufficient, as any other $p < 1$ will only thin the PPP describing UE placement to intensity $p\lambda_{UE}$.
We also consider **Asynchronous ALOHA** random access model in the *Multi Base Station* (ASA-MBS) scenario. Regarding to that, the time domain is continuous and there is no predefined or preferred moments UEs to send data. This model understands existing theoretical *Time Frame* with length T_F, what is time limit for the targeted performance observation. Theoretically, this model could be reduced to *(Pure) ALOHA* in asymptotic scenario, when $T_F \to \infty$. We suppose that each UE transmits an equal-length data packets with the length τ, with same number of the data packet replicas. Number of packet replicas in the time frame, is reffred to as *User Packet Degree* d. In general model, each UE U_i selects its own packet degree d_i with corresponding probability p_d from Λ: $\sum_{i=1}^{d_{max}} p_i \cdot x^i$
This means that UE transmits with different packet degree in every new time frame, in general, and its chosen packet degree is the random variable defined with PDF $\Lambda(x)$.
In special case, if UE keeps the same packet degree in every time frame it transmits with degree d, that means that $p_d = 1$ and $p_j = 0$ for $j \neq d$.
Each user will send data in the time frame with probability p, which we call *Activity Factor*. Unless otherwise noticed, we assume that the activity factor, for each UE in the system, is equal to 1, which means that each UE transmit the data in the time frame.

2.2.3 User Transmission Model

In contrast to our previous work on SA-MBS [8], we assume that UEs use *directional antennas*, e.g., by exploiting beamforming techniques, to direct their transmission beams [12]. We assume a simple randomized beamforming model in which UEs choose the main lobe direction α uniformly at random from the interval $[0, 2\pi)$, as shown in Figure 1 [13], where the reference direction is set to the positive orientation of x-axis. The simple beamforming model avoids inefficiency due to beam-alignment procedures, while relying on assumption that the density of infrastructure λ_{BS} (e.g., small cells) is very large. The main lobe angular width θ is equal for

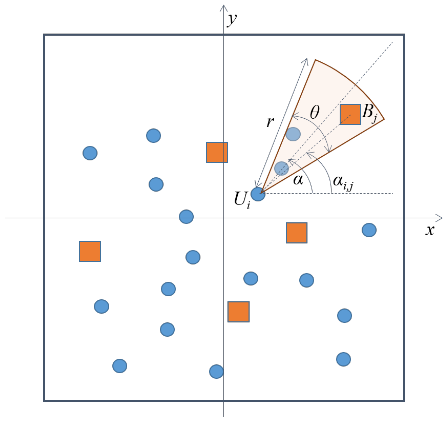

Figure 1: The user directional transmission model

all UEs. The UE signal range r is a constant, assumed equal for all UEs. In other words, we assume homogeneous model where each UE transmits using the same power. We simplify the signal propagation model by considering only path loss (shadowing and fading are neglected).

2.3 Example Results or Findings

In our research work, which results we present here, we were interested in the total achievable system throughput for two decoding scenarios:

- Non-Cooperative SA-MBS scenario, in which traditional SA operates at each BS independently.
- Cooperative SA-MBS, in which centralized SIC-based decoding is applied over all received user signals.

For both scenarios, we assume perfect synchronization of arriving packets and their alignment with time slots on base stations and absent of beamforming alignment delay, propagation delay and other processing delay effects. We provide upper system throughput limits and compare them against the simulation results.
One part of the following research results are presented in the paper "Cooperative Slotted ALOHA for Massive M2M Random Access Using Directional Antennas", which is presented on IEEE ICC 2017 conference in May 2017, in Paris (France), at the moment of writing of this report.
Other parts of research results are focused on ASA-MBS scenario.

2.3.1 Base Stations Decoding Model

Non-Cooperative SA-MBS Decoding: in this case, we assume all BSs apply classical Slotted ALOHA decoding algorithm independently of each other. In other words, in any time slot, a BS will collect a UE's packet if and only if that UE is the only one that covers the BS ("singleton"). In contrast, if BS detects empty TS (no UE cover the BS) or TS is occupied by two or more UE transmissions, the TS, at that BS, is wasted. Non-cooperative SA-MBS

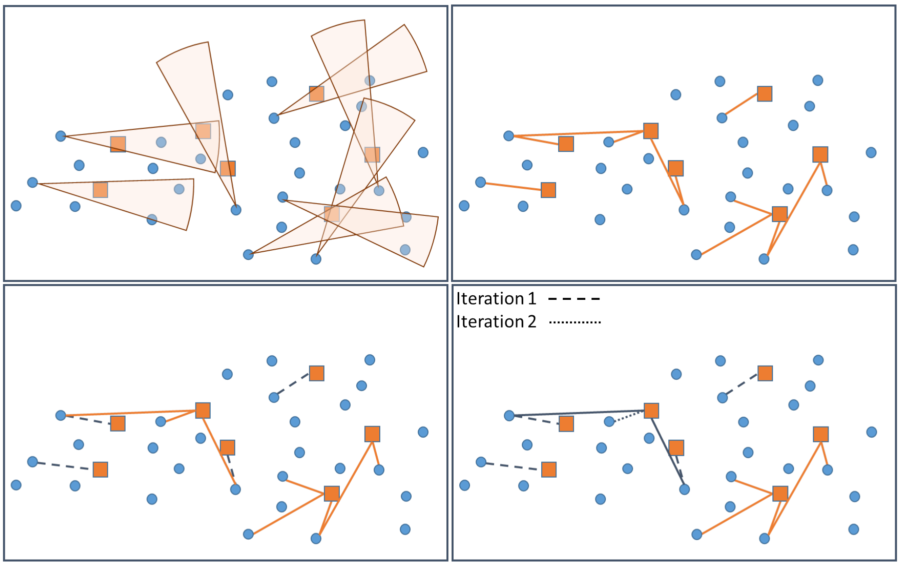

Figure 2: Upper-left subfigure: Randomly directed UE transmissions in a given time slot; Upper-right subfigure: Resulting network connectivity graph; Lower-left subfigure: Non-cooperative SA-MBS decoding example - only UEs connected via dashed edges will be collected; Lower-right subfigure: Cooperative SIC-based SA-MBS decoding example - the first iteration is identical to non-cooperative decoding; the SIC phase removes solid lines; the second iteration decodes UEs connected via dotted lines (note that the set of four UEs in the lower-right corner cannot be decoded as it forms a *stopping set* [15]).

decoding proceeds on a "slot-by-slot" basis, where TSs are independent among each other. In terms of the network connectivity graph, the algorithm allows simple interpretation: only BSs with degree equal to one are able to collect a corresponding UE.

Cooperative SA-MBS Decoding: in this scenario, we assume all signals collected at BSs are forwarded to the central processing location. Motivation for this assumption comes from the so-called Cloud-RAN (C-RAN) architecture, where BSs serve only as RF front-ends while the baseband processing is done centrally. For simplicity, we assume all UE signals are synchronized to the TS boundaries at all BSs (i.e., the distance differences can be neglected due to high density of both UEs and BSs), and that BSs know and share with the centralized processing location the channel state information of the UEs in their vicinity. Centralized cooperative decoding algorithm applies SA with Successive Interference Cancellation (SIC) [5]. In short, if UE's transmission is decoded as a singleton at any BS, its signal can be subtracted from collisions at all other BSs where a given UE signal is found in collision with other UE signals. In terms of graphical interpretation, the signal recovery using cooperative SA-MBS algorithm on the network connectivity graph is equivalent to the iterative erasure decoding of LDPC codes [6][8] (Figure 2, lower-right subfigure).

We compared non-cooperative and cooperative SA-MBS scenario. The key parameter is the system throughput, which is simulated for few values of the normalized load. From this simulation, we conclude that cooperation between BSs can significantly overperformed non-cooperative mode only for higher values of normalized load. Anyway, this result is important because it is expected that massive M2M applications create higher level of the load and this

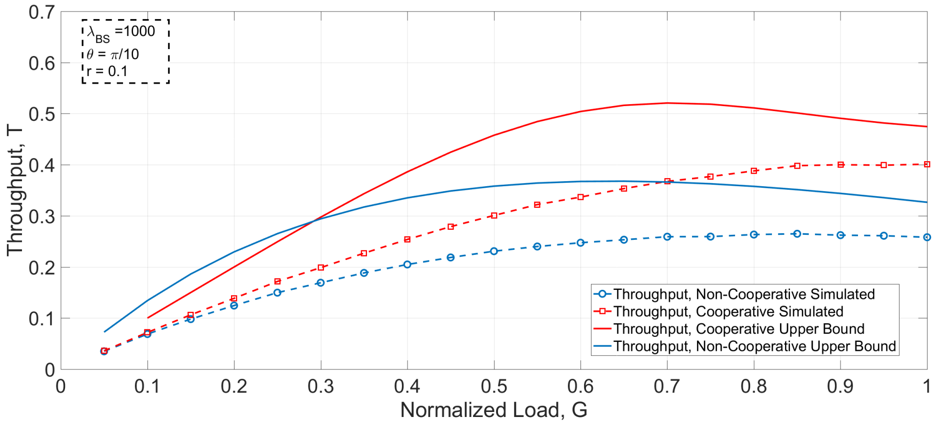

Figure 3: Average system throughput $T = T(G)$ for cooperative and non-cooperative SA-MBS decoding (simulation results and upper bound).

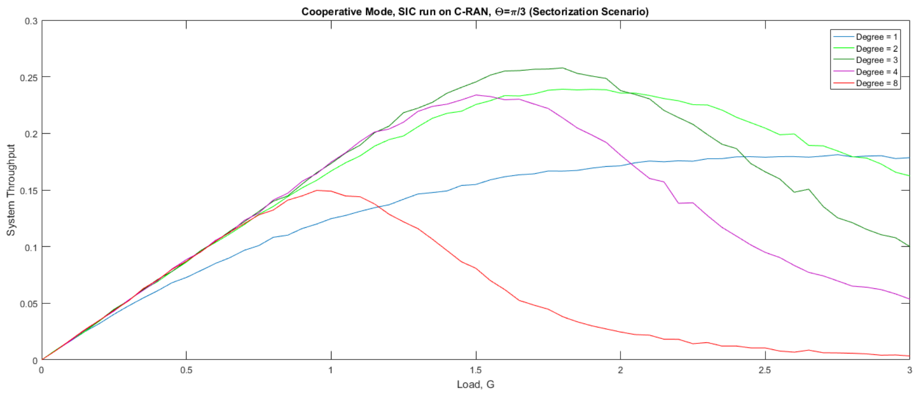

Figure 4: Average system throughput $T = T(G)$ for cooperative ASA-MBS decoding with SIC on C-RAN mode, Sectorization scenario with signal width $\pi/3$ and various user packet degrees (simulation results).

result justifies this approach, what is shown in Figure 3.
We proof that the simulation results are in the expected range using "AND-OR Tree" analysis to calculate analytically the most optimistic scenario for non-cooperative and cooperative mode. These upper-bound on the system throughput are not strict. More strict bound could be estimated changing some pre-assumption, what will be presented in the future work.
Cooperative ASA-MBS Decoding: in this scenario, we assume all signals collected at BSs are forwarded to the central processing location already known as C-RAN. We assume all UE signals are not synchronized and randomly choose the transmission time within the time interval called *Frame*. BSs know and share with the centralized processing location the channel state information of the UEs in their vicinity. Centralized cooperative decoding algorithm applies ASA-MSB with SIC running on the C-RAN. The key parameter is the system throughput and we compare it for varying different input parameters of UEs:

- user degree d (number of data packet replicas)

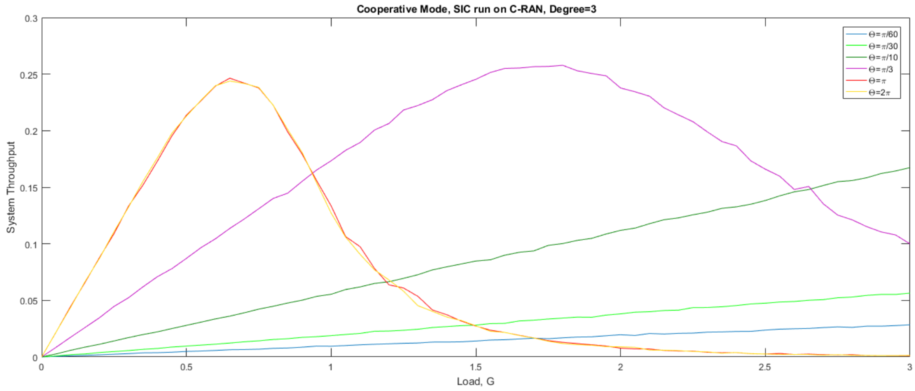

Figure 5: Average system throughput $T = T(G)$ for cooperative ASA-MBS decoding with SIC on C-RAN mode, with optimal user degree $\Delta = 3$ and various user signal width (simulation results).

- range R
- signal width θ

Last UE's parameter called *angle orientation* α is randomly chosen for each UE and fixed. We execute the simulation fixing all UE parameters, except one parameter. In the figures 4 and 5, we present the results of the system throughput as a function of the normalized load, for varied values of the user degree d and signal width θ. These model helps to conclude that optimal degree is between values 2 and 3. We also conclude that the maximum throughput could be reached for bigger values of the signal width, in the range of sectorization model e.g. $\theta = \pi/3$.

2.4 Future Work

In our future work, we consider:

- design and compare two approaches: **synchronous** vs. **asynchronous** Slotted ALOHA, where we observe packet-level asynchronism due to propagation delays resulting in misalignment of packets at the receiver (base stations),
- theoretical throughput lower and upper bounds, as a function of different system parameters (beamforming angle, radius of coverage, uplink power),
- non-cooperative and cooperative approach in MBS system, and for both, synchronous and asynchronous models
- optimization of uplink power allocation across system users to achieve optimal system throughput, minimizing interference and collisions.
- implementation advanced ALOHA algorithms, as CRDSA, CRSDA+, IRSA, for both synchronous and asynchronous approach without time slots, with implementation of novel approaches for collision avoidance and resolution.

2.5 Conclusions

We investigated SA-MBS scenario considering users that employ directional antennas. The total system throughput is investigated for two decoding algorithms: the non-cooperative SA-MBS decoding where BSs independently apply traditional SA, and the cooperative SA-MBS decoding where signals received at BSs are centrally decoded using SIC-based decoding. Both scenarios are analyzed by evaluating the total system throughput using both simulation experiments and analytical throughput upper bounds. The obtained results demonstrate that the cooperative SA-MBS decoding can significantly outperform non-cooperative SA-MBS decoding. In addition, the obtained bounds could be used to provide guidelines on the selection of directional antenna parameters that, under a given system setting, maximize the total system throughput. As a future work, we will extend the scenario where UEs employ directional antennas by additionally considering time-diversity, i.e., by exploiting Framed Slotted Aloha (FSA) and performing SIC-based decoding both spatially (across different BSs) and temporally (across different TSs).

We investigated ASA-MBS scenario considering users that employ directional antennas. In this phase of the research work, we consider only cooperative scenario with central point cooperation in C-RAN with SIC implemented within. For the future work in ASA-MSB model, we will analyze using simulation models and formalizing the results with analytic mathematical tools for non-cooperative scenario and geographically-depended cooperative mode, which means cooperation between BSs which are neighbours or within some predefined range from each other and they can communicate directly using different communication channel from BS-UE communication channel.

The final result of this research work is to define optimal model for maximizing the system throughput for MAC layer to enable massive M2M application in 5G system. We suggest ALOHA-based solution to ensure maximal throughput. We conclude that the directional antenna model for UEs improves the total performanse of the system and decrease intensity of collisions in the system. We estimate, as possible direction for future work, that it is possible to decrease the collision intensity/probability if we consider transmission power separately for each UE in the system (varying their range R and/or the signal width θ). We can optimize the UEs power vector using optimization methods and algorithms if we conclude in our future work that the definition of the target function is not too difficulty to find.

3 Modelling and Control of Heating Operation

3.1 Introduction

Buildings consume more than than 30% of mankinds final energy, including half of the global electricity demand. In developed countries, more than half of this energy used in buildings is for space and water heating [17]. It is therefore clear that improvements in efficiency of heating are important levers in climate change mitigation.
Mathematical modelling is a widely accepted and powerful tool to improve efficiency of energy systems operation. Progresses in sensing, computing and communication in the recent decades have allowed the collection of a vast amount of data which can be turned into additional knowledge to support decision making in operations. Statistical modelling methods are particularly suited to extract this precious knowledge from this mass of data, which is where the focus of this research is made. Applications of mathematical modelling to forecast of heat demand and control of heating systems at the building level are investigated in this research.
This section consists in four subsections briefly introducing the results of the research. In a first part, heat load forecast of large district heating consumers is examined. A second part introduces potential benefits from *model predictive control* (MPC) technologies for energy efficiency and thermal comfort in homes. A third part introduces findings on trade-offs between different strategies for MPC in building heating. In a last part, it is emphasised that the lack of an automatic robust dynamical model identification tool for buildings is a barrier to widespread deployment of model predictive control.

3.2 Adaptive load forecast reduces uncertainty in district heating operation

Some energy systems have operating boundaries defined by the behaviour of their most sensitive consumers. The case of the Danish island Funen was investigated in the research, as the district heating operator controls its supply temperature to ensure that greenhouses receive sufficient heat to cover their needs. As some of these greenhouses have a peak load of several megawatts, these can constitute a large share of the system load.
In such a system, a forecast of these sensitive loads can be highly valuable to improve the efficiency of the system operation. In particular, it is expected that it will allow operating reliably with a lower margin on the supply temperature, which will result in significant reduction of the heat losses in the district heating system.
These large loads are equipped with meter providing readings of the heat load with a 15 min to 1 h time resolution, which can be accessed remotely by the district heating operator. The district heating operator also has access to local historical measurement from its own weather station (ambient temperature, solar radiation, wind speed and direction, humidity, atmospheric pressure), as well as third party weather forecast. Sufficient data for statistical modelling is then available to build a predictor that can be used in operations.
A simple *recursive least square* approach [18] was investigated in the research to build a 48 h ahead forecast of the heat load. Data from 5 greenhouses of varying characteristics over a period of 8 months was used, together with weather forecasts from a third party. Detailed methodology and results are presented in the work [19] (under review at the time of writing).

The study found that greenhouses' heat load exhibits a high variability throughout the year, which makes an adaptive approach such as the recursive least squares particularly suited to this case. Moreover, an *automated explanatory variable selection* was proposed, allowing to build a tailored model for each greenhouse with little to no man-hours. Relevant explanatory variables were found to differ between greenhouses, showing different periodicities and dependencies to the weather conditions.
This forecast provided a root mean square error within 8 to 20 % of the peak load, with a performance varying among greenhouses. This technique provided a significant improvement compared to a nave tomorrow equals today forecast (where the daily load profile is assumed to remain unchanged). This performance drew the interest of the system operator towards implementing it in practise, where the simplicity of the approach should be a facilitating factor.

3.3 MPC improves efficiency in heating

Model predictive control (also known as *receding horizon control*) is a technique consisting in ensuring optimal operation according to a given criterion (e.g. cost) by predicting the future behaviour of a system using a numerical model and forecasts of system inputs and disturbances. In the case of building heating, the heating schedule can be optimised according to forecasts of future conditions such as ambient temperature, solar radiation, cost of power and $\mathrm{CO_2}$ intensity of power.
Different criteria can be optimised, depending on the focus of the designer. Typical examples found in the literature and applications are minimisation of: final energy consumption, power cost, $\mathrm{CO_2}$ emissions, non-renewable power, or thermal discomfort [20, 21].
While classic thermostatic control mostly is a corrective control (also known as feedback control), predictive control adopts a preventive approach (known as *feed forward control*). This is due to the ability of predictive control to explicitly take into account external information (e.g. weather forecast, power price, $\mathrm{CO_2}$ intensity), which cannot be made with classic thermostats (unless using the latest generations of communicating thermostats).
This preventive ability plays a particularly important role in avoid overheating due to solar gains by reducing heating before solar radiation starts improving the temperature beyond a comfortable level, resulting in both better thermal comfort and reduction of energy use [22]. In the case of heating systems with a large lag (e.g. concrete floor heating), the resulting improvements in comfort can be substantial [23].
A simple investigation was conveyed in Danish winter conditions, highlighting that in the case of a low energy house with floor heating, an ideal predictive controller would noticeably reduce over-heating, energy (including fossil fuel based) and $\mathrm{CO_2}$ emissions compared to a classic heating curve controller [24].
As highlighted in a joint work [21] within the IEA-EBC Annex 67 [1], further benefits of model predictive control could be identified in research through the use of a number of other indicators (e.g. export of local power production to the grid, shifting of energy from high to low price times). This is because current research on model predictive control seems to be narrowed down to the conventional performance indicators explicitly addressed through the choice of the objective function adopted.

[1] `http://www.annex67.org/`

3.4 Trade-offs arise between control strategies for heating using MPC

Once the choice is made to implement a predictive controller, an appropriate optimality criterion needs to be chosen, leading to the selection of a specific *objective function*. As previously mentioned, objective functions options are numerous. Trade-offs exist between these objectives for example, a controller leading to a minimal cost does not necessarily lead to the lowest consumption as was illustrated in [25].
Such compromises were studied in the context of a low energy single family house in Danish winter conditions in [20], where predictive controllers optimising either total energy use, cost, non-renewable energy use or $\mathrm{CO_2}$ emissions were compared. The results of the study suggested that there is a need to question classic assumptions that SPOT price minimisation would lead to optimal use of renewable power (due to null marginal cost of renewables) or minimisation of the total energy use would result in minimised $\mathrm{CO_2}$ emissions.

3.5 Automated model identification is a barrier to wider implementation of MPC

Model predictive controllers require the identification of a dynamical numerical model of the thermal behaviour of the building and its heating to be controlled. It has been found that this process among the costliest in the development of a predictive controller [26, 27, 28].
Such models can be built using three different approaches. In a physical approach (known as *white-box modelling*), equations dictating the behaviour of the system are used, and numerical values of the parameters are calculated from blueprints and tabulated material characteristics from references. This is often done with building simulation software packages such as IDA-ICE, TRNSYS, Modelica and EnergyPlus[2]. Statistical approaches (known as *black-box modelling*) rely on local measurements and mathematical methods to identify a model, for example in the form of an ARX, ARMAX, *transfer function* [18], subspace (4SID) [27] models or *artificial neural networks* [29]. Last but not least, the *semi-physical* approach (known as *grey-box modelling*) combines usage of simplified principles providing the model structure and local measurements allowing to identify the numerical values of the model parameters.
The semi-physical approach tends to draw significant attention as a modelling approach supporting predictive control. Its cost (particularly in terms of engineering hours) is significantly lower than for the physical approach which is both very labour intensive and resulting in complex models poorly suited to time-constrained optimisation. On the other hand, its structure and physical interpretability make it more attractive than pure statistical methods which are very vulnerable to the quality of the dataset used for modelling [30].
In practise, grey-box models are identified on a one by one basis using dedicated software tools such as CTSM-R [3] (as was done in studies [31] and [32]) or the MATLAB System Identification toolbox[4] (used in e.g. [33]).

[2]More details about the tools on http://equa.se/en/ida-ice, http://www.trnsys.com/, https://www.modelica.org/, and http://apps1.eere.energy.gov/buildings/energyplus/
[3]http://ctsm.info/
[4]https://se.mathworks.com/products/sysid.html

The author supports the statements from [26] and [34] that the absence of a framework for automated dynamical model identification is a blocking point for large scale deployment of model predictive in buildings. An attempt to facilitate user actions and automate part of the process was made in [35]. However, further research in this direction seems to be needed to achieve a more complete automation and unlock the benefits from model predictive control in practise.

3.6 Conclusions

This research focused on modelling for thermal loads in order to improve the efficiency of operation of thermal systems. First, a predictor of heat load for large individual consumers in a district heating system was evaluated on historical data, showing that even a simple forecast would significantly reduce uncertainty on future consumption. Then, focus was made upon model predictive control of individual residential buildings, where a number of benefits were identified compared to classic thermostatic control, consistently with the conclusions of a large amount of literature on the topic. The research also highlighted that trade-offs can arise between objectives to be used in control, and that these should be selected carefully by the designers. Last but not least, it was highlighted that a barrier in the expansion of model predictive control on a large scale is the absence of an automated robust model identification framework, which should be addressed by further research.

4 WP1 - Overall Conclusions

The research results of Working Package 1 (WP1) team are focused on enabling technologies for Smart Home applications.
In particular, the WP1 focuses on:

1. wireless machine-to-machine (M2M) communication technologies
2. smart modelling and optimization technologies for home heating systems.

In the domain of communication technologies, the work is focused on the evolution of public wireless cellular systems 4G-LTE/5G towards supporting massive and critical M2M. M2M will enable automatized and human-free interaction among the devices, enabling smart systems to automatically provide optimal performance. Smart Homes are combination of the sensors placed in home-based devices which measure predefined parameters, acquire data and send them to storage/processing capacities for further analysis. Depending on the results of analysis, Smart Home can create an automatized action, as home lighting control, heating control, etc. Specifically, as one case study of Smart Home system, optimization of home heating systems from the perspective of thermal load monitoring and control for power system energy savings and demand response functionalities is considered. The goal of the home heating system optimization was to create energy-saving and cost-decreasing system with the same or better quality of the service for the customers. This is obtained by heat load prediction/forecasting techniques based on historical data from which predictive control models are developed that revealed significant potential for improving the operational efficiency of heating systems.

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