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**ADVanced communicAtions and iNformaTion processing in smArt Grid systEms**

# WP1 D.1.2
# Initial Findings on Smart Home Research

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| **Abstract** | This deliverable will explore the initial literature study and research directions for WP1 of the ADVANTAGE project. This deliverable will consider how communications within the home can enable future smart grid systems. The first topic to be studied relates to how wireless technology can support communication between electronic devices within the home and to the power supplier – so called machine-to-machine communications. The second topic relates to modelling and control of heating systems within the home, so they can be integrated effectively into the smart grid network. |
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# WP1 - Introduction

Work package 1 focuses on the "Smart homes" aspect of Smart-Grids. In the first part of this section, communication protocols for machine to machine communications to support intelligent operation of dwellings are presented. Then, optimised control of dwelling heating within the smart grid is introduced from an applied point of view.

# 1 ALOHA Model for Random Access Control in Massive M2M Communications

## 1.1 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 the Internet of Things (IoT). 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 will be faced with increased density both in terms of user and base station deployments. In such a scenario, there is a focus in the design of simple and efficient random access solutions able to support the expected surge of MTC traffic in the future.

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 a (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 wireless sensor networks (WSN), where devices occasionally transmit small amount of data and are usually unpredictably triggered by events, the RA solutions are more favourable.

The ALOHA protocol was 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*. Later upgrades that improved throughput are well-known as *Slotted ALOHA* (SA) or *Framed Slotted ALOHA* (FSA). Finally, recent years have brought increased interest in the ALOHA protocol enhanced by Successive Interference Cancellation (SIC) and a number of research proposals dramatically increased the throughput of classical ALOHA, such as *Contention Resolution Diversity Slotted ALOHA* (CRDSA), *Irregular Repetition Slotted ALOHA*, *Frameless Slotted ALOHA*, *Coded Slotted ALOHA*, etc.

## 1.2 System description, techniques and scientific methodology

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 [2]. Using the analogy with sparse-graph codes and iterative erasure decoding, SA with SIC has been further optimized to reach close-to-optimal throughputs [3]. Motivated by increased density of cellular networks due to the introduction of small cells, SA algorithms with SIC operating cooperatively in multi base station (SA-MBS) systems were recently considered [4]. 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 is connected to 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 [5][6].

### 1.2.1 Placement Model

Placement model supposes 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 $\lambda_{BS}$, while for UEs it has intensity $\lambda_{UE}$. 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. Users are denoted as $U_i$, $i = 1, 2, ...$, and BSs as $B_j$, $j = 1, 2, ...$ Unless otherwise stated, focus will be 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.

### 1.2.2 Random Access Model

The system applies *Slotted ALOHA* random access model in the *Multi Base Station* (SA-MBS) scenario [4]. The time domain is discrete and 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 $p$ referred to as the activity factor. Due to high BS density, the UE packet transmission may be detected at several neighbouring BSs. BSs are interconnected via a backhaul network and any BS may collect any UE's data packet (i.e., there are no a-priori UE to BS associations). The UE's packet is 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, activity factor is $p = 1$. This is sufficient, as any other $p < 1$ will only thin the PPP describing UE placement to intensity $p\lambda_{UE}$.

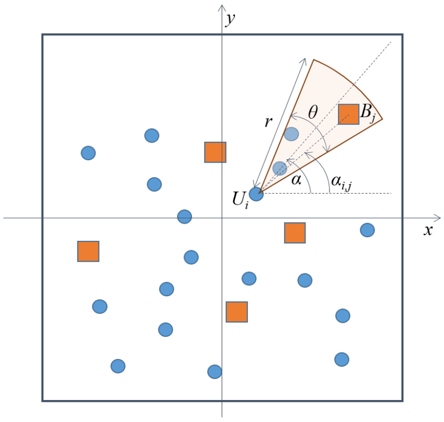


Figure 1: The user directional transmission model

### 1.2.3 User Transmission Model

In contrast with the previous work on SA-MBS [4], UEs use *directional antennas*, e.g., by exploiting beamforming techniques, to direct their transmission beams [8]. The system uses a simple randomized beamforming model in which UEs choose the main lobe direction $\alpha$ uniformly at random from the interval $[0, 2\pi)$, as shown in Figure 1 [9], 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 the assumption that the density of infrastructure $\lambda_{BS}$ (e.g., small cells) is very large. The main lobe angular width $\theta$ is equal for all UEs. The UE signal range $r$ is a constant, assumed equal for all UEs. In other words, the system model is homogeneous where each UE transmits using the same power. The signal propagation model is simplified by considering only path loss (shadowing and fading effects are neglected).

## 1.3 Results and findings

The following research results are presented in the paper "Slotted ALOHA with Multiple Base Stations and Directional Antennas", which is currently under review for the IEEE GLOBECOM 2016 conference at the moment of writing of this report.

In particular, the focus is on a simple randomized beamforming strategy where, for every packet transmission, a user orients its main beam in a randomly selected direction. For this research work, the total achievable system throughput is investigated 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.

Both scenarios work under the assumption of ideal synchronization of arriving packets and their alignment with time slots on base stations, without beamforming alignment delay, propagation

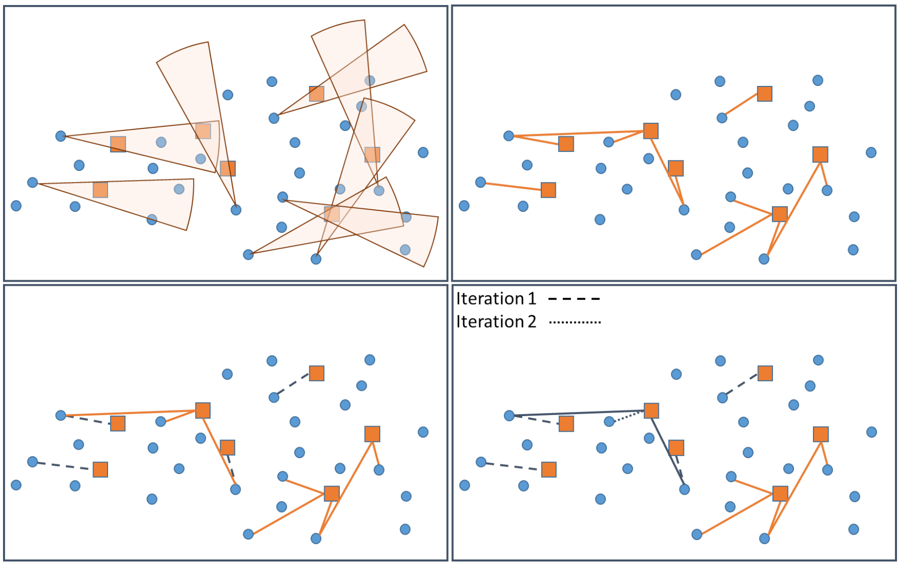


Figure 2: *Upper-left subfigure:* Randomly directed UE transmissions in a given time slot; *Upper-right subfigure:* Resulting network connectivity graph; *Lower-left subfigure:* Non-cooperative SA-MBS decoding example - only UEs connected via dashed edges will be collected; *Lower-right subfigure:* Cooperative 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* [11]).

delay and other processing delay effects. Upper system throughput limits are presented and compared against the simulation results.

In the following paragraphs, two algorithms for the decoding model are suggested.

**Non-Cooperative SA-MBS Decoding:** in this case, 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 decoding proceeds on a "slot-by-slot" basis, where the TSs are independent of 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, 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, 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) [2]. In short, if UE's transmission is decoded as a singleton at any BS, its signal can be subtracted from collisions

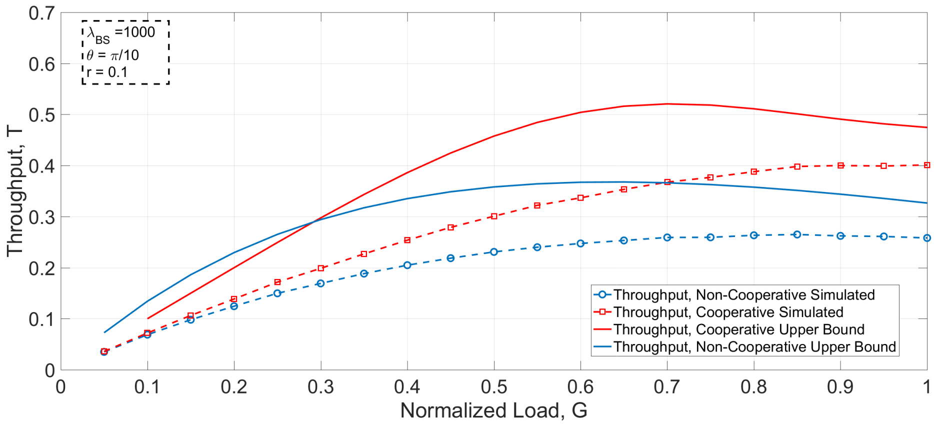


Figure 3: Average system throughput $T = T(G)$ for cooperative and non-cooperative SA-MBS decoding (simulation results and upper bound).

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 [3][4] (Figure 2, lower-right subfigure).

## 1.4 Conclusions and future work

Investigated SA-MBS scenario considers 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 results obtained demonstrate that the cooperative SA-MBS decoding can significantly outperform non-cooperative SA-MBS decoding. In addition, the bounds obtained 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, the model 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).

For the future work, the following topics will be investigated:

- design and compare two approaches: **synchronous** vs. **asynchronous** Slotted ALOHA, where packet-level asynchronism is present, 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 of advanced ALOHA algorithms such as CRDSA, CRSDA+, IRSA, for both synchronous and asynchronous approach without time slots, with implementation of novel approaches for collision avoidance and resolution.

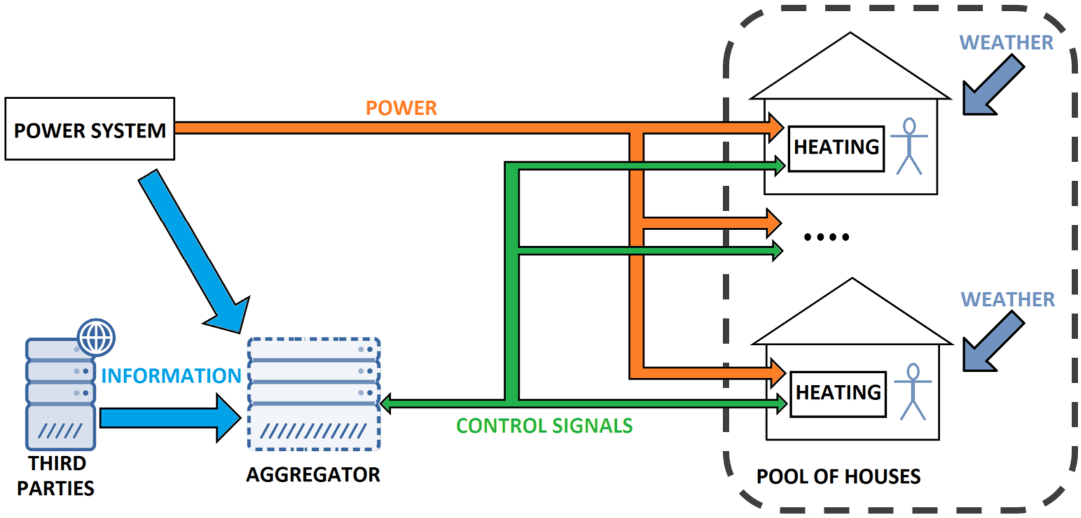


Figure 4: Structure of the system considered

# 2 Optimised control of building heating operation in the smart grid

The focus of this research is on the control of heating appliances in buildings, with an aim to reduce the overall cost and environmental impact of building heating. This includes making use of flexibility in energy use to support the grid and participate in the integration of renewable energy, as well as taking into account weather influence and user behaviour to improve comfort and improve energy efficiency.

The current control of heating in buildings is based upon simple thermostatic control. This was appropriate in times where computations were expensive and little communication was economically feasible, when power production was more centralised and easily controllable. However, in a system that is increasingly powered by renewable energy with greater need for demand response, it is now time for a more efficient and flexible heating control to be implemented. As shown in a Danish study [13], substantial socio-economic benefits can be expected at a national level as a result of such a flexible operation of heat pumps (which the study estimated to be around 50 M€/ year in the Danish energy system in 2035, excluding the worth of energy savings due to optimised control to use free heat gains from sun and occupants).

## 2.1 System description and scientific methodology

In this research, the system consists of a pool of houses with electrical heating connected to a power system. The controllers of the heating system are communicating with an aggregator that has access to data from the power system (e.g. the operational requirements) and third parties (e.g the weather forecast, power price previsions) in Figure 4.

### 2.1.1 Predictive control for building heating

Receding horizon control (RHC, also known as model predictive control) is a technique to improve the operation of a system by optimising the future control inputs towards some objectives, given a model of the dynamics of the system. A framework for RHC is presented in [14], where the focus is on linear systems and implementation using MATLAB [15].

RHC relies on extensive use of optimisation. Provided that a linear system model is available, the system constraints can be formulated as linear matrix inequalities, and the cost function is a convex function (most often linear or quadratic), the problem can be solved using *convex optimisation* techniques which is a widely covered topic in the literature [16, 17, 18].

The application of receding horizon control to building climate management is an active field of research. In [19], a simple simulation approach in energy systems is presented, including applications to heat pump heating of building, from a simulation point of view. In [20], model predictive control formulations for building climate control are introduced, with a particular focus on handling of uncertainties either from weather prediction or occupant behaviour.

### 2.1.2 Model identification for building heat dynamics

A model of the dynamic behaviour of the system is required in order to implement predictive control. Building such a model based upon experimental data is a process known as *system identification* in the field of control, which is extensively described in [21]. When it comes to the field of statistics, building such a model of a dynamical model based upon an extensive amount of observations is known as *timeseries analysis* [22].

There are two main approaches to building models using experimental data: *grey-box* modelling and *black-box* modelling.
Black-box modelling relies on the sole usage of data to extract a model that is statistically representative of the system behaviour in the experiment. Common techniques for black-box modelling are ARX (*Auto Regressive with eXogenous inputs*) [22], ARMAX (*Auto Regressive Moving Average with eXogenous inputs*)[22], subspace identification [21, 23].
On the other hand, grey-box modelling incorporates a-priori knowledge of the physics of the system, so that numerical values of physical parameters of the chosen model structure are identified using statistical methods. Grey-box model structures for a single zone building are introduced in [24, 25, 26, 27].

## 2.2 Results and findings

### 2.2.1 Tools for model identification in practise

A variety of tools available for practical model identification were identified. The System Identification Toolbox [28] for MATLAB [15] provides a broad range of tools for model identification, from black-box models (e.g. ARX, ARMAX, subspace methods) to grey-box models. When it comes to building greybox models using a continuous stochastic timeseries framework, the

CTSM-R package [29] for R [30] allows parameter identification using maximum likelihood techniques. Investigation on real world data from individual houses using these tools is an ongoing task.

### 2.2.2 Optimisation programs for predictive control

A variety of objectives functions can be formulated, depending on the aims of the control, including: energy cost (e.g. [31], [32]), energy consumption, non-renewable primary energy use (e.g. [33]).
As highlighted in [34], there can be a conflict between those objectives, for example a price optimal heating schedule will not necessarily be energy optimal. It is therefore important to select an objective function that is consistent with the aim to be achieved.

Simple (linear and quadratic programming) formulations of the control problem were obtained, that can be solved with either linear or quadratic programming (depending on the chosen objective to be achieved) at low computational cost and with commonly available tools (e.g. MOSEK [35], Gurobi [36] or the dedicated toolbox for MATLAB [37]). However, an identified model of the building in a state space form is a pre-requisite for the numerical definition of the optimisation problem in practice.

### 2.2.3 Linear regression for weather compensation in heating performance comparison

A predictor of heat demand based upon historic data was developed as part of the research, resulting in the paper [38] that was submitted to IEEE Multi-Conference on Systems and Control 2016 (currently being reviewed). The aim is to fit a simple model to historic consumption data, so that given environmental conditions for a day (ambient temperature, solar radiation and wind) one may compute an estimation of the associated heat demand and its uncertainty. Currently, such a model is fitted using only ambient temperature as an explanatory variable of the heat demand. This is expected to be insufficient for comparison of advanced controllers that would take into account further environmental variables such as solar radiation or wind.

The study focused on 6 individual houses in Danish climate with a year of data for each, which had been collected as part of the project *Styr din Varmepumpe* [39]. The data was processed into daily values of the following variables: heat consumption for space heating, indoor temperature, local and forecast ambient temperature, direct sun radiation on an horizontal surface and diffuse sun radiation, wind speed, product of wind speed and ambient temperature, humidity and day of the week.

A p-value based criterion was introduced to identify the relevant explanatory variables to be successively added to the model, that was computed using linear regression tools from the stastistics toolbox in MATLAB [40].

It was found that the significant explanatory variables vary from house to house, although the main influence from the ambient temperature was always found to be the strongest. For example, in some houses, the wind was found to have an influence on the heat load, while in others sun radiation played a larger role. Therefore, there is a need to convey the modelling work on each house to find out an appropriate model.

## 2.3 Conclusions and future work

The structure of a future control for heating in residential buildings within the Smart-Grid was presented, together with the available tools and theoretical frameworks to support this development.
A simple methodology relying on linear regression was developed, allowing a better practical assessment of benefits resulting from a change in building heating control, as it accounts for differences in weather conditions beyond the simple outdoor temperature influence.

Further work will focus on the following aspects:

- Development of practical model identification algorithms at individual building level
- Forecasts of heat consumption in individual buildings
- Controller structure and algorithms to enable practical deployment, including the provision of flexibility in energy use (collaboration within the IEA EBC Annex 67 research group on Energy Flexible Buildings [1])
- Quantifying the improvements in heating operation efficiency resulting from a change of the controller in practice

[1] http://www.iea-ebc.org/projects/ongoing-projects/ebc-annex-67/

# 3 WP1 - Overall Conclusions

In this section, research focuses and initial findings of the "Smart homes" work package were introduced.
First from a communication point of view, where cooperation was found to significantly improve machine to machine communication performance in simulations using SA protocols. Then, from a control point of view, where methodologies and tools for implementing a more efficient control of building heating were presented, together with a methodology to assess improvements in performance in practise.
In both cases, future directions for the remainder of the research project were presented.

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