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UE-Based Estimation of Available Uplink Data Rates in Cellular Networks

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Towards Integrating Behaviour Demand Response into Simulation Based Heat Production Optimisation †

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Abstract: Behaviour Demand Response (BDR) is the process of communicating with the building occupants and integrating their behavioural flexibility into the energy value chain. In this paper we will present an integrated behavioural model based on well-established behavioural theories and show how it can be used to provide predictable flexibility to the production schedule optimisation. The proposed approach is two-fold: the model can be used to predict the expected behavioural flexibility of occupants as well as to generate optimal communication to trigger reliable BDR events. A system architecture will be presented showing how BDR can be integrated into simulation passed building/district operation.

Keywords: Behaviour Demand Response (BDR); flexibility; simulation-based optimisation

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1. Introduction

Optimisation of production schedules is usually based on co-simulation of the heating system taking the production and storage assets, the distribution network, and the expected heat loads into account. These load predictions are calculated from the heat demands of zones based on envelope and comfort parameters as well as expected occupancy. In this context, behaviour demand response (BDR) is based on the ability of building occupants to adapt their behaviour such that these parameters are positively contributing to the overall energy optimisation goals. The integration of building occupants into the process is enabled by the ability to send messages and monitor behaviour of building occupants. However, to predict the outcome of such messages and rigorously integrate this into the production scheduling optimisation a suitable model of behaviour next to the building asset model is required.

In this paper we will discuss how such a model can be created and propose a system architecture integrating all these components together. In Section 2 we will briefly introduce the behavioural model and outline how it can be used to compute behavioural parameters. In Section 3 we will then show how this behavioural model, estimating in particular the individuals' intention to act on real-time messages, can be integrated together with the co-simulation of the technical heating system and how this integration can help optimising production schedules, which not only take the physical building parameters into account but also make use of the flexibility created by the active participation of the building occupants in shaping their demand profiles.

2. Behaviour Modelling

Modelling behaviour is a well-established field and many theories have been developed over the years [1]. However, many of these theories have been developed in a very specific context and do not lend themselves directly to deriving mathematical models, which are required to integrate such approaches into numerical optimisation algorithms.

The approach presented here is based on a subset of well-stablished behavioural theories, such as the action-regulation-theory [2], the high-performance-cycle [3], the theory of planned behaviour [4], the self-determination theory [5], and the social cognitive theory [6] translated into an integrated probabilistic model of behaviour [7] enabling the sampling, and therefore probabilistic prediction, of identified behaviour relevant parameters (see Figure 1).

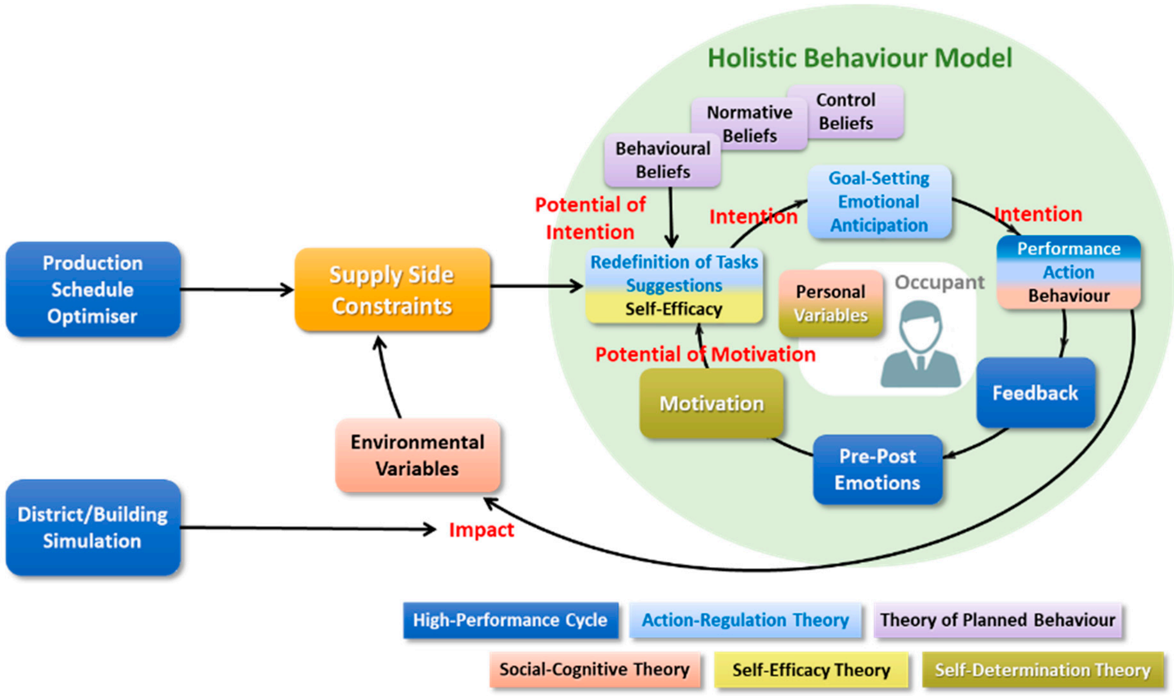

Figure 1. An integrated model of behaviour.

The model describes the processes how an individual is translating targeted constraints imposed on him/her by the energy supply into relevant demand response actions and behaviours to be carried out when requested (see [7] for a detailed description). Each of the underlying behavioural theories identifies parameters, their scales, and their mutual relations as well as inventories for measuring a subset of these parameters. The actions themselves are measurable through the actual interaction of the building occupant with the building itself, therefore providing another source of input.

In summary, this allows to derive a set of behavioural parameters $S = \{s_1, \ldots, s_N\}$ together with a set of mutual relations $N = \{n_1, \ldots, n_N \mid n_i \subset S \setminus \{s_i\}\}$ with other behavioural parameters. Each parameter can take on a value $x_i \in X_i$ and the behavioural model allows to easily define compatibility potentials between related parameters c_i: $X_i \times X{n_i} \mapsto \mathbb{R}$, which define a Gibbs distribution on the behavioural parameters

$$\pi[x_1, \ldots, x_N] = \frac{e^{-\beta \sum_i c_i[x_i, x_{n_i}]}}{\sum_{z \in X_S} e^{-\beta \sum_i c_i[z_i, z_{n_i}]}}$$

Computation of the normalising denominator of this joint distribution is infeasible, so we are using a Markov-Chain-Monte-Carlo algorithm [8] to be able to sample from the marginal distributions $\pi_1, \ldots, \pi_N$ of the behavioural parameters. This approach also allows to easily fix a subset of parameters, allowing to use every parameter as either input or output of the model.

The model can be trained using inventories as provided by the underlying behavioural theories as well as through ongoing interaction of the building occupants with the system. This means that we are sending dynamic questionnaires to the building occupants, fixing parameters relating to their beliefs and motivation based on their answers. Further to that we are observing how occupants are reacting to the messages sent to them by the system, enabling us to directly measure the intention-action-gap and adapt the relevant model parameters accordingly.

The main output of this learning process is amongst other quantities, like the individual's attitude, normative beliefs and control beliefs, an estimate of the intention to act for each building occupant. This enables the production optimisation to predict how much reaction to a BDR request could be expected from the building and factor this in to the overall optimisation strategy. This will be discussed in the next section.

3. Integration of BDR into Production Optimisation

In the previous chapter we briefly presented a behavioural model that can be used to predict the expected behaviour of building occupants with regards to reacting to targeted messages sent to them in order to trigger demand response events. We will now discuss how this model-driven approach can be integrated into a system architecture that is applicable to all simulation based building operation schemes (see Figure 2). This architecture has at its core the co-simulation of the building/district, which predicts the system's performance and allows the production schedule optimiser to provide optimal operational schedules to the facilities manager. During the operation a supervisory control component makes sure that all systems are operating optimally and notifies the production schedule optimisation to re-optimise in case unforeseen circumstances occur.

Thus far, this is the only situation in the model where building occupants have been implicitly considered. We propose to instead consider the building occupants explicitly as a vital part of the building operation itself. The proposed approach is considering two distinct phases, first the day ahead schedule optimisation taking into consideration the behavioural flexibility and then second the actual operation of the building including the behaviour demand response triggers. By considering the two phases together, the behavioural model is learned and continuously calibrated from the ongoing operation while at the same time the operation is controlled based on the optimised model parameters.

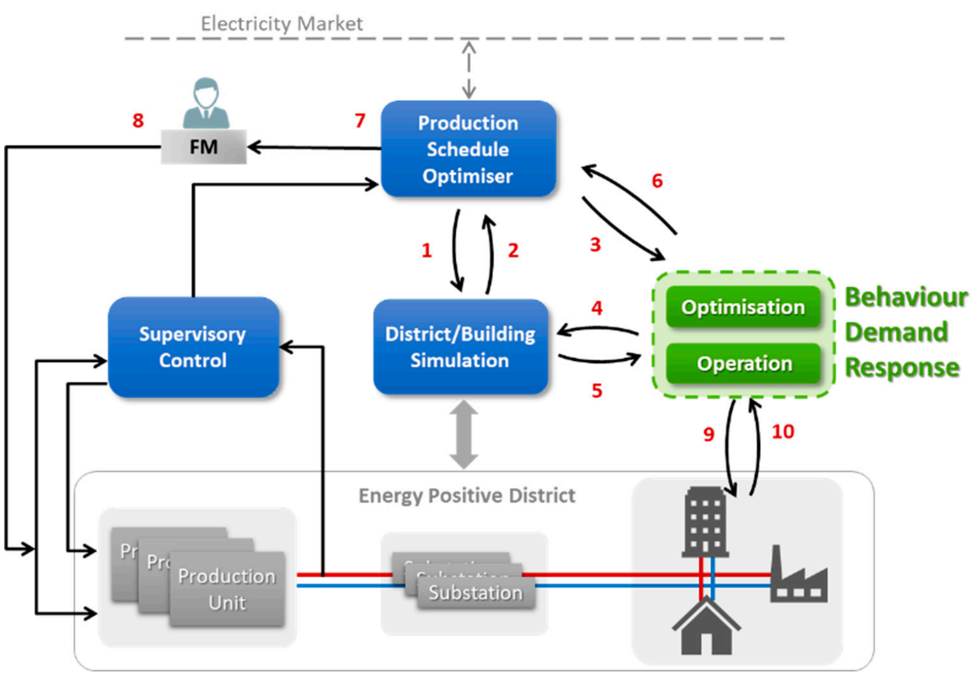

Figure 2. A system architecture integration all four key components of model-driven energy system optimisation.

The process can be broken down into the following subsequent steps (see Figure 2):

- The production schedule optimiser (PSO) uses the district simulator to predict the expected performance of the district (1, 2)
- Similarly, the PSO uses the BDR optimisation module to predict the expected behavioural flexibility offered by the building occupants (3)
- To compute this quantity the BDR module uses the behavioural model outlined above in conjunction with the building simulator to estimate the available behavioural flexibility (4, 5, 6)
- Taking into consideration both the predicted performance of controllable production assets and the predicted behaviour demand response flexibility the PSO creates an optimal production schedule with respect to the external context and electricity market conditions (7, 8)
- During the operation the BDR module uses the behavioural model to optimally trigger BDR events through communicating with the building occupants and measuring their reactions to continuously learn the model parameters (9, 10)

The key idea is to introduce Behaviour Demand Response as a predictable asset into simulation based production optimisation. A behavioural model is used to provide predictability of occupant behaviour similar to what the district simulator provides for the physical assets. It also helps to guide the communication with the building occupants in order to achieve optimal demand response results during operation. The integration of occupant behaviour and physical asset operation into one unified approach not only improves the prediction of the expected building energy performance but also unlocks otherwise unused demand flexibility.

4. Conclusions

The contribution of this paper is two-fold: we briefly introduced how well-established behavioural theories can be translated into a mathematical model of behaviour and presented a system architecture that integrates behavioural flexibility as reliable asset into the simulation based energy production and building operation optimisation. By modelling the processes how an individual is translating targeted constraints imposed on him/her by the energy supply into relevant demand response actions and behaviours to be carried out when requested it becomes possible to integrate the building occupants as active participants into the building operation. This model-driven Behaviour Demand Response approach creates three major additional benefits:

- More aggregated demand flexibility becomes available as tradable asset and otherwise unused capacity can be accessed by the production schedule optimisation
- Prediction and real-time management of behavioural flexibility enables de-risking such approaches, with building occupants being explicit components of the system rather than potential outliers of the operation
- Integration of users as active participants enhances acceptance and increases the reach of the optimisation to potentially also include non-connected and legacy systems

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