# An OPC UA-based Energy Management Platform for Multi-Energy Prosumers in Districts

Denis Bytschkow[1] bytschkow@fortiss.org
Alexandre Capone[2] alexandre.capone@tum.de
Jan Mayer[1] mayer@fortiss.org
Michael Kramer[2] michael.kramer@tum.de
Thomas Licklederer[2] thomas.licklederer@tum.de

***Abstract*—Control and optimization in smart energy systems rely heavily on mathematical models of power system engineers. Simultaneously, software engineers that create control and monitoring systems are faced with questions for designing appropriate system interfaces, such that different kinds of interaction schemes are supported. Often, the data specifications required by the interfaces are implicitly available within the mathematical models. Moreover, control and optimization schemes sometimes require data to be transferred to be able to operate. Despite these synergies, these tasks are generally treated separately. In this work, we aim to reduce the gap between those activities to facilitate the development of interactive and collaborative systems. We model a system consisting of multiple buildings and multiple energy networks to optimize their operation. We work with the model in a follow up step to create an industrially applicable interface that relies on the OPC UA communication protocol, which is widely used in industry and is easily integrated in modern SCADA systems. We finally demonstrate the application of the proposed approach using a co-simulation.**

***Index Terms*—Smart Grid, Smart Energy Systems, Model Predictive Control, Energy Platforms, Open Interfaces.**

## I. INTRODUCTION

The energy landscapes in many countries face a dramatic change due to strong investments in renewable energies in order to reduce $CO_2$ emissions. Accompanied with the increasing penetration of electrical and thermal storage systems, heat pumps, CHP units and electric vehicles, the future energy system will be characterized by a high number of distributed resources interacting across energy sectors. The authors in [1] stress the need for the integration of demand side management from buildings to provide flexibility for the electrical grid in city districts. Buildings and their technical equipment will no longer be only passive heat and electricity consumers, but have own (renewable) generation and storage capacities. They are connected as sector-coupling *prosumers* in district energy systems [2]. For the concrete implementation, two challenges have to be faced. Firstly, many of the technical systems, which could be integrated beneficially, are located at the lower level of the energy system, e.g. the distribution grid. Secondly, the subsystems are equipped with different forms of control systems and use domain specific communication protocols. Hence, any form of coordination system must lend itself to handle this inherent variety through an interoperable communication interface. The OPC Unified Architecture (OPC UA) standard is one possible solution to address this challenge. The authors in [3] map BACnet objects from single building automation systems into an OPC UA information model. In [4] OPC UA is used in a model to merge building automation and factory automation systems for the use of industrial waste heat in office buildings.

While older automation systems usually employ standard control or rule-based approaches for each individual device, modern systems are tightly integrated in energy management systems (EMS) with higher computational power and forecasting. Thus, the choice of control approach depends on the technical capabilities of the individual building system. Model predictive control (MPC) has been employed to control multiple building in different settings. Compared to other control methods, MPC has the advantage that it enables system constraints to be taken into account [5]. Examples of MPC for districts include distributed approaches for linear models, such as [6], where reduced communication and a high degree of autonomy for the EMS is enabled, as well as centralized approaches [7], where a complex nonlinear model is considered.

Our work contributes to bridge the gap from theoretical control approaches to real world implementation to enable increased energy efficiency with less costs and optimization on city district level. A central MPC controller is introduced and employed in an OPC UA-based coordination system. Every *prosumer* EMS has an OPC UA interface to communicate parameters and operational boundary conditions and to receive optimal control set points. Finally, we implement and test the developed system and the MPC with a co-simulation framework [8].

The following parts of the paper are organized as follows. The model and the MPC controller to dispatch the prosumers is formulated in Section II. Section III introduces the OPC UA system architecture and explains mapping in the controller. The system is evaluated and discussed with a test scenario in Section IV. Finally, we summarize and conclude our paper in Section V.

The authors would like to thank the German Federal Ministry for Economic Affairs and Energy for the financial support under the grant 03ET1413.
[1] fortiss GmbH, Research Institute of the Free State of Bavaria, Munich, Germany
[2] Munich School of Engineering, Technical University of Munich, Germany

978-1-5386-8218-0/19/$31.00©2019 IEEE

## II. Model Predictive Control

MPC is a control method used in settings where system constraints need to be taken into account [5]. At every time step, MPC aims to optimize a cost function over a finite-time horizon of length $N_H$ by employing a mathematical model of the system at hand. For an $n_x$ dimensional linear system, this is achieved by solving an optimization problem of the form

$$\min_{\mathbf{x}} \boldsymbol{\lambda}^{\mathrm{T}}\mathbf{x} \tag{1a}$$
$$\text{s.t.} \quad \mathbf{A}\mathbf{x} = \mathbf{b} \tag{1b}$$
$$\mathbf{G}\mathbf{x} \leq \mathbf{h} \tag{1c}$$
$$\mathbf{x_{lb}} \leq \mathbf{x} \leq \mathbf{x_{ub}}, \tag{1d}$$

where $\mathbf{x}$ is the $n_x N_H$-dimensional vector of optimization variables, $\boldsymbol{\lambda}$ is the cost vector, $\mathbf{A}$ and $\mathbf{G}$ are constraint matrices, and $\mathbf{b}$, $\mathbf{x_{lb}}$, $\mathbf{x_{ub}}$, $\mathbf{h}$ are constraint vectors. To achieve higher modularity, all vectors and matrices are composed of sub-vectors and sub-matrices. For instance the demand vector $\mathbf{b}$ contains an electrical sub-vector $\mathbf{b_{el.}}$ and a thermal one $\mathbf{b_{th.}}$. This applies to $\mathbf{A}$ and $\mathbf{G}$ as well. The first entry of the solution of (1) is applied to the system at hand, after which the MPC optimization problem is solved again. By repeating this process, MPC enables to guarantee optimal behaviour and system constraints over the receding horizon.

In order to employ an MPC method, the district heating network is modelled as a system of linear equations with sampling time $\Delta t$, which are obtained as follows. We assume that the heat network can be described by a quasi-static model, and that delays caused by the mass flow rate of water are negligible. Moreover, we assume that the heat network is lossless. Hence, the heat network can be described by the following power conservation law:

$$\sum_{i=1}^{n} P_i^k = 0, \tag{2}$$

where $k$ denotes the time step, $P_i^k$ is the rate of heat flow corresponding to the $i$-th building, and $n$ is the total number of buildings in the district. The heat flow rate of a single building is given by

$$P_i^k = \sum_{j=1}^{m_i} P_{j,i}^k \eta_j - P_{Co,i}^k, \tag{3}$$

where $m_i$ is the number of power producing devices in building $i$, $P_{j,i}^k$ is the production device $j$, and $\eta_j$ is the respective efficiency coefficient, which is assume to be constant. $P_{Co,i}^k$ denotes the consumption rate in building $i$. Storage devices are considered simultaneously as part of user consumption, when charging, as well as production devices, when discharging. Production is limited for every device, i.e.,

$$0 \leq P_{j,i}^k \leq P_{j,i,\max}^k, \tag{4}$$

where $P_{j,i,\max}^k$ is the maximal power of device $j$ in building $i$. Storage devices must satisfy capacity constraints given by

$$-C_{j,i}^0 \leq \Delta t \sum_{k=1}^{N_H} P_{j,i}^k \leq C_{j,i}, \tag{5}$$

where $C_{j,i}$ is the storage capacity of device $j$ in building $i$, $C_{j,i}^0$ is the initial state of the storage device.
The power grid model is modelled using the electric power equivalent of eqs. (2) to (5), and is omitted here for the sake of brevity. Coupling devices, such as heat pumps, are modelled by a consumption term in one network and a generation term in the other. We aim to minimize the total operation costs of the entire district. This is achieved by considering the following cost function:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{m_{\mathrm{i}}} \sum_{k=1}^{N_{\mathrm{H}}} c_{j,i}^k P_{j,i}^k, \tag{6}$$

where $c_{j,i}^k$ denote the operation costs of device $j$ in building $i$. In settings where $CO_2$ emissions need to be minimized, $c_{j,i}^k$ is employed to denote emissions instead of costs. By defining the vector of variables $\mathbf{x} = (P_{1,1}^1, \cdots, P_{1,1}^{N_H},\ P_{2,1}^1 \cdots P_{2,1}^{N_H} \cdots)$, the heat and power networks are written in the form required for the MPC optimization, i.e., (1).

## III. System

The introduced mathematical model, which is similar to the optimal dispatch of the energy hub presented by [9], is a straight forward solution to determine the cost optimized power injections in combined multiple energy networks. It is however not sufficient to build the desired systems, since it still lacks many system details to achieve an interaction with real systems. For instance, it is not clear who communicates which data, which systems are present and how the corresponding interfaces looks like. Fortunately, the MPC formulation contains enough information for such missing system specifications. Thus, we can use it to facilitate the specification for the desired interactions with the prosumers, or more concretely, the interface specification for their EMS.

Before we explain further specification details, we introduce available system architecture options. The desired system, which we denote as *coordination system* in the following, is a remote application running on a server. This allows a higher redundancy and facilitates the maintainability. Its major task is to reach an energy efficient operation in a neighbourhood area with optimal energy dispatch schedules. Therefore, the system connects to a number of buildings or more precisely to their EMS interfaces, which provide the required information. Architectural options concern the choices how to connect the systems. They define which systems initialize connections (client functionality), who is addressable and listens to requests (server functionality), what data is communicated (information model) and how is the data communicated (protocols). A general overview and the choices are depicted in Figure 1. They cover details about the desired interfaces, information model and protocols[1].

From the architectural choices presented in Figure 1 the information model is frequently discussed for development. The MPC is a great input for that. Other choices like servers, clients and protocols are usually available as libraries.

[1]Choices for interfaces are for instance REST, MQTT or OPC UA plus the desired information model.

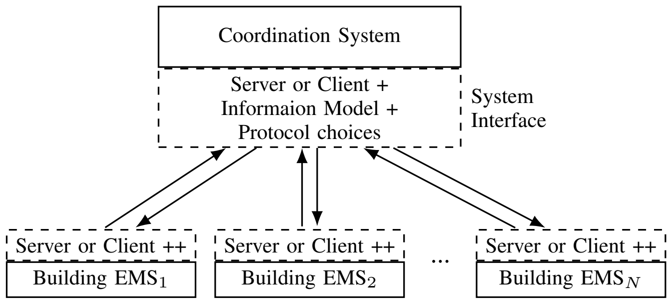


Fig. 1. System architecture with different choices.

The MPC dispatch matches available energy production within the buildings with the expected demands. We identified five different input types from the MPC: `ControllableGeneration`, `VolatileGeneration`, `Coupler`, `Storage` and `Demand`. They represent five different resources types, that are available in the system. Table I presents the required resource parameters for the model.

TABLE I
INPUT DATA MODEL FOR THE COORDINATION SYSTEM

| ***ComponentType*** | ***Attribute*** | ***Type*** | ***Unit*** |
|---|---|---|---|
| `Controllable Generation` | InstalledPower | Double | $kW$ |
| | Efficiency | Double | % |
| | NetworkType | El./Heat(range) | - |
| `Volatile Generation` | InstalledPower | Double | $kW$ |
| | Efficiency | Double | % |
| | NetworkType | El./Heat(range) | - |
| | Forecast | Array⟨Time,Value⟩ | ⟨Time,Double⟩ |
| `Coupler` | NetworkType1 (NT1) | El./Heat(range) | - |
| | NetworkType2 (NT2) | El./Heat(range) | - |
| | Efficiency (NT1) | Double | % |
| | Efficiency (NT2) | Double | % |
| | InstalledPower (NT1) | Double | $kW$ |
| `Storage` | Capacity | Double | $kWh$ |
| | SOC | Double | $kWh$ |
| | MaxCharging | Double | $kW$ |
| | MaxDischarging | Double | $kW$ |
| | ChargingEfficiency | Double | % |
| | DischargingEfficiency | Double | % |
| | NetworkType | El./Heat(range) | - |
| `Demand` | Forecast | Array⟨Time,Value⟩ | ⟨Time,Double⟩ |
| | OptimizationGoal | EUR/CO2 | - |
| | NetworkType | El./Heat(range) | - |
| `All Components` | OperationalCost | Double | €$/kWh$ |
| | CO2Cost | Double | $g/kWh$ |
| | Name | String | - |
| | ID | String | - |

The types and parameters for the information model were chosen so that the MPC model can be directly created from them. For instance, the efficiencies are the input for the matrix elements $a_{i,j}$ of $\boldsymbol{A}$. The installed power parameters (and the dis-/charging rates) determine the boundary conditions $\boldsymbol{x}_{ub}$. Further, the forecasts of the volatile generation additionally restricts $\boldsymbol{x}_{ub}$, while the forecast of the demand represents the desired input of the demand vector $\boldsymbol{b}$. Storage constrains and SOC values are further used for $\boldsymbol{h}$. The network types determine whether the matrix elements belong to the electricity sub-matrix or the heat sub-matrix. Further, each component has operational costs and the costs for $CO_2$. This input belongs to $\lambda$. Finally, each component has a name, and an identifier. This is used to create indices mappings for the model and the solution $\mathbf{x}$. The mapping represents the MPC set points.

The information model for the resources is used twice in our system implementation, for which we use the Smart Energy System SIMulation (SESSIM) framework[2]. It allows to create a co-simulation environment that combines simulations with real systems using messages for interaction [8]. First, the resource model is represented as plain JAVA objects. This allows us to create the MPC from a list of objects that are expected to be available from the interfaces by creating the demand vector $\mathbf{b}$ as the sum of all demands for the corresponding network type, the matrices $\mathbf{A}$ and $\mathbf{G}$ from the efficiencies of the resources, the boundary conditions $\mathbf{x_{lb}}$ and $\mathbf{x_{ub}}$ from installed power and forecast values of variable generation. The solution vector $\mathbf{x}$ represents the MPC set points. They are sent to the corresponding EMS interfaces with the mapping from the identifiers. Second, we use the resource objects to directly convert them into established industrial interfaces. Currently we support REST and OPC UA interfaces. In automation, we work mainly with OPC UA, since it is widely adopted to SCADA and automation systems of system manufacturers. An EMS implements an OPC UA server. It supports publish/ subscribe mechanisms to reduce communicated data, provides security and supports reconnection mechanisms, to increase the reliability. The OPC UA interface creation from our objects is automated and has two steps, as depicted in Figure 2.

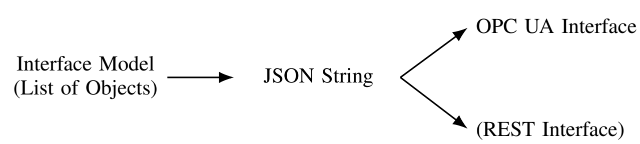


Fig. 2. Steps for an automated interface creation.

It starts with the object JSON string serialization (e.g. with GSON). The creation of the interface relies on JSON strings. To create OPC UA interfaces, we use JSON data fields, like booleans, numbers or strings to create OPC UA data nodes, which are subscribable. JSON containers, like arrays and objects are converted into OPC UA folders, which contain data nodes. The result is an OPC UA server interface that can be accessed with arbitrary OPC UA clients. We show in Figure 3 the automatically generated OPC UA server interface. It contains the information model and additional information for the current status of the EMS. With the presented OPC UA server interfaces the EMS provides enough information for the coordination system to carry out the optimal dispatch calculations. The coordination system subscribes to an arbitrary number of EMS systems to obtain those values and to write the MPC solution as set points into the available variables. Each EMS system reacts to those set points individually. The reaction is validated with the EMS metering values to close the feedback loop.

[2]Open source: https://github.com/SES-fortiss/SmartGridCoSimulation

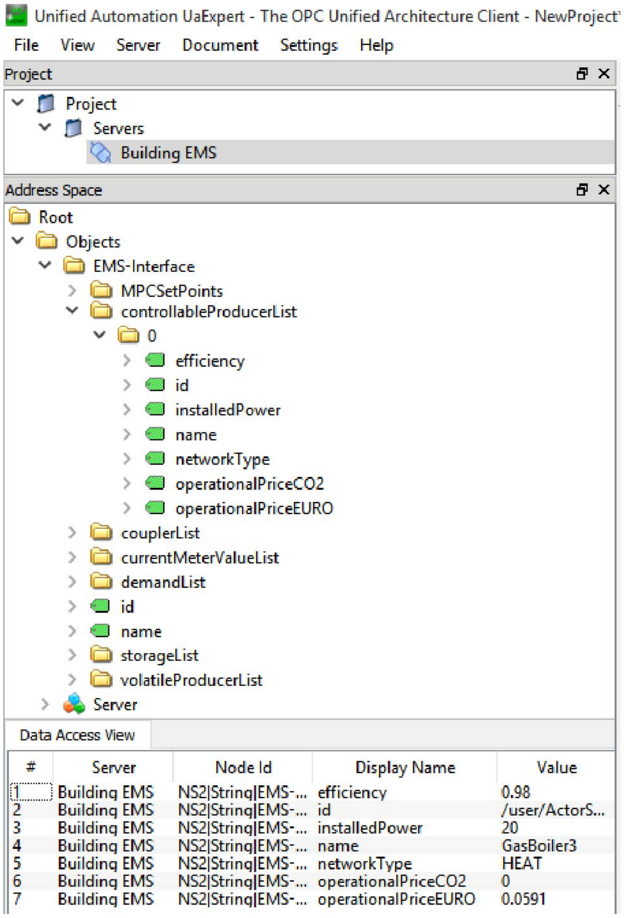


Fig. 3. OPC UA client connection to our OPC UA server.[3]

In Section IV, the system is evaluated with a co-simulation framework with multiple EMS systems connected to district heating and an electrical system.

## IV. Example

In this section, we present a coordination example for five buildings, numbered from 1 to 5. All buildings correspond to single family homes, except for buildings 3 and 4, which are a large and small multi-apartment home, respectively. The demand profiles were generated according to [10] for electricity and [11] for heat, and were scaled and modified with additive white noise. The average thermal and electrical demands, and plant configuration of each building can be seen in Table II. The plant parameters can be seen in Table III. We used the system presented in Section III to model and simulate the EMS of individual buildings with their respective demand and production.

To evaluate our example, we compare two extension stages. In the first stage, each EMS performs the optimization itself. This leads to the most cost effective schedule for a single building. This solution represent our reference scenario. The second stage is the optimization with the coordination system.

[3]We used the available UaExpert client software, a registered trademark of Unified Automation GmbH, to connect to our OPC UA server implementation.

TABLE II
Average building demands and building plant configurations

| | *Avg. heat demand* | *Avg. power demand* | *Heat gen.* | *Power gen.* | *Storage* |
|---|---|---|---|---|---|
| B1 | 14.4 kWh | 51.4 kWh | Oil boiler | / | / |
| B2 | 16.5 kWh | 50.0 kWh | Gas boiler | PV | Battery |
| B3 | 147.8 kWh | 457 kWh | Gas boiler; heat pump | PV | Thermal st. |
| B4 | 127.5 kWh | 286.5 kWh | CHP | CHP | Thermal st. |
| B5 | 80.5 kWh | 316.9 kWh | CHP; Solar thermal plant | CHP | Thermal st. |

TABLE III
Plant parameters

| | *Size* | *Capacity* | *Efficiency* | *Fuel costs* |
|---|---|---|---|---|
| Oil boiler | 20 $kW$ | / | 0.95 | $6.81^{ct}/_{kWh}$ |
| Gas boiler | 20 $kW$ (B2 and B3) | / | 0.98 | $5.91^{ct}/_{kWh}$ |
| PV | 5 kW (B2) 40 kW (B3) | / | (0.3) | / |
| CHP | 70 kW (B4) | / | 0.29 (el.), 0.61 (th.) | $5.91^{ct}/_{kWh}$ |
| CHP | 70 kW (B5) | / | 0.28 (el.), 0.6 (th.) | $5.91^{ct}/_{kWh}$ |
| Heat pump | 10 kW | / | 2.5 (COP) | El. costs |
| Solar thermal | 20 kW | / | (0.95) | / |
| Battery | 9 kW | 12 kWh | 0.98 | / |
| Thermal storage | 60 kW | 100 kWh | 0.9 | / |

This optimization takes all production options of all buildings into account and provides a global schedule for the neighbourhood. All optimizations are carried out on the presented interface data. The optimization results and the comparison of both stages is displayed in Figure 4 for heat and in Figure 5 for electricity for a day schedule with 15min planning intervals and an MPC forecast horizon of 6 hours. Due to space limitation, we show the operation on a building level.

Our results demonstrate a signification production adaption with the coordination system. Components with higher costs, like oil and gas boilers in B1 and B2 are not used anymore. Instead, the more economic CHP plants are preferred and here, the more efficient CHP of B4 first, and then the one from B5. The cogenerated electricity is used additionally for the heat pump. The MPC combines the generation from CHPs and heat pump such successfully, so that even storages are not used at their full capacities. With this, the coordination system increases the self-consumption of the system, while covering the heat demand quite successfully. In fact, the buying of electricity is reduced to zero with the MPC, since all electrical demand is covered by CHPs, solar power and batteries. This greatly reduces the operational costs of the system. Finally, we show a cost comparison of the reference scenario (intelligent EMS) with the coordination system in Table IV. In this simple example, with the chosen parameters, we see that costs are decreased by around 20% when combining multiple buildings with the presented equipment.

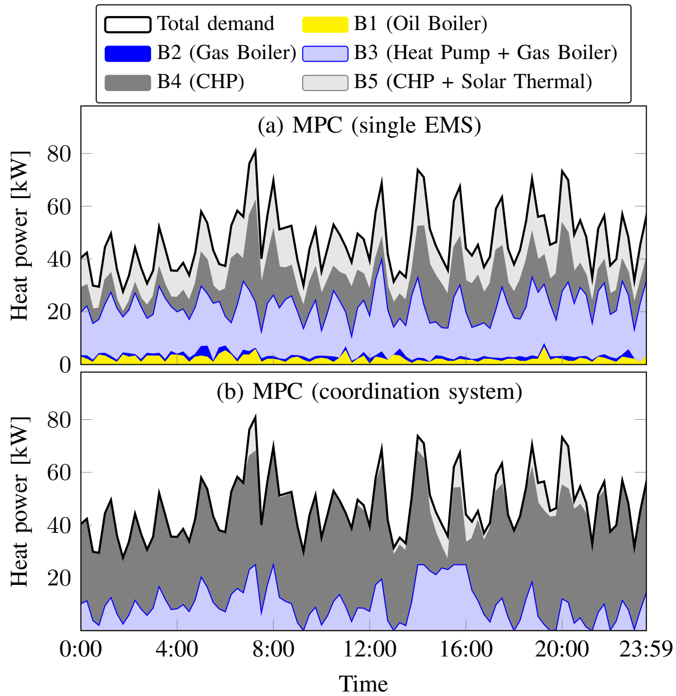


Fig. 4. Comparison of both extension stages: a) each EMS perfoms its own optimized MPC vs. b) the coordination system perfoms the optimised MPC.

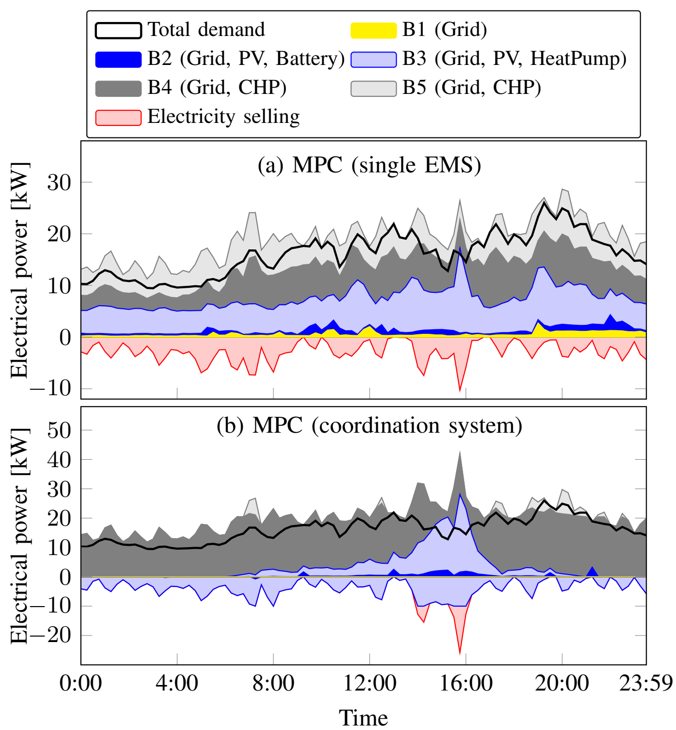


Fig. 5. Same comparison as Fig. 4, but for the electricity network.

TABLE IV
MULTI ENERGY PROSUMER COST COMPARISON FOR ONE DAY OF OPERATION IN [€]. INDIVIDIAL SYSTEMS VS. INTEGRATED APPROACH.

| B1 | B2 | B3 | B4 | B5 | SUM | MPC system |
|---|---|---|---|---|---|---|
| 7.4 | 3.5 | 48.3 | 31.5 | 25.7 | 116.4 | 94.8 |

## V. CONCLUSIONS

We presented an implementation of a framework to coordinate and optimise multi-energy prosumers with a centralized MPC. The industrial interface OPC UA is used for the integration of the EMS into a coordination system. Thereby, the MPC is able to use data from the distributed EMS. Each building EMS remains an individual system, with its own equipment thresholds, control logic, user access rules, firewalls and other configuration details. Connected systems can be stopped, restarted, updated and redeployed independently. Such a loose coupling enables independent system development and the compatibility of our system for different types of EMS. Furthermore, we have shown that the proposed optimization works for multiple energy prosumers using a co-simulation to simulate buildings. We carried out an exemplary co-simulation for a reference case, and achieved cost savings of around 20% by replacing costly fossil fuel production by cheap energy from renewables. The coordination system facilitates the optimal use of storage and generation units among participating buildings. Future work will integrate and test the coordination system in a laboratory environment to overcome the co-simulation with real technical devices.

## ACKNOWLEDGMENT

The authors would like to thank all project partners for their support and great work environment during our multi energy management and aggregation platform (MEMAP) project.

## REFERENCES

[1] D. Müller et. al., “Demand side management for city districts.” Building and Environment, 91, 283-293, 2015.
[2] E. Vesaoja et al. ”Hybrid modeling and co-simulation of district heating systems with distributed energy resources” Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES), 2014.
[3] A. Fernbach, W. Granzer and W. Kastner, “Interoperability at the Management Level of Building Automation Systems: A Case Study for BACnet and OPC UA.” in In Proc. of 16th IEEE Conference on Emerging Technologies and Factory Automation (ETFA ’11), 2011.
[4] S. Mätzler et. al., “An OPC UA cross-domain information model for energy management in automation systems.” In Proc. IECON 39th Annual Conference of the IEEE Industrial Electronics Society, 2013.
[5] J. B. Rawlings and D. Q. Mayne, “Model predictive control: Theory and design.” Nob Hill Pub. Madison, Wisconsin, 2009
[6] M. Kramer, A. Jambagi, V. Cheng, “Distributed model predictive control for building energy systems in distribution grids.” In Proc. IEEE PES Innovative Smart Grid Technologies Conference (ISGT) Europe, 2017.
[7] G. Sandou et al. “Predictive control of a complex district heating network.” IEEE Conference on Decision and Control (CDC). 2005.
[8] D. Bytschkow, M. Zellner and M. Duchon, “Combining SCADA, CIM, GridLab-D and Akka for smart grid co-simulation.” Innovative Smart Grid Technologies Conference (ISGT), IEEE, 2015.
[9] M. Geidl and G. Andersson, “Optimal power flow of multiple energy carriers.” IEEE Transactions on Power Systems, 22(1), 145-155, 2007.
[10] A. Jambagi, M. Kramer and V. Cheng, “Residential electricity demand modelling: Activity based modelling for a model with high time and spatial resolution.” 3rd International Renewable and Sustainable Energy Conference (IRSEC), IEEE, 2015.
[11] Association of German Engineers (VDI), ”Guidelines for demand profiles of single- and multi-family houses for the use of CHP plants”, VDI 4655, 2008.
[12] F. J. Rooijers and R. A. M. van Amerongen, “Static economic dispatch for co-generation systems.” IEEE Transactions on Power Systems, 1994