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Least-cost model predictive control of residential energy resources when applying μCHP

Michiel Houwing, Rudy R. Negenborn, Petra W. Heijnen, Bart De Schutter, and Hans Hellendoorn

***Abstract*—With an increasing use of distributed energy resources and intelligence in the electricity infrastructure, the possibilities for minimizing costs of household energy consumption increase. Technology is moving toward a situation in which households manage their own energy generation and consumption, possibly in cooperation with each other. As a first step, in this paper a decentralized controller based on model predictive control is proposed. For an individual household using a micro combined heat and power (μCHP) plant in combination with heat and electricity storages the controller determines what the actions are that minimize the operational costs of fulfilling residential electricity and heat requirements subject to operational constraints. Simulation studies illustrate the performance of the proposed control scheme, which is substantially more cost effective compared with a control approach that does not include predictions on the system it controls.**

***Index Terms*—Distributed energy resources, distributed generation, model predictive control, μCHP**

I. INTRODUCTION

A. Electricity Infrastructure with Distributed Energy Resources

DISTRIBUTED energy resources (DERs), comprising distributed power generators, electricity storages, and load management options, can play a crucial role in supporting the European Union's key policy objectives of market liberalization, combating climate change, increasing the amount of electricity generated from renewable sources, and enhancing energy saving. Large-scale diffusion of DERs will have a profound impact on electricity infrastructure functioning: it will bring radical changes to the traditional model of generation and supply as well as to the business model of the energy industry [1].

A wide body of literature states that distributed generation (DG) of electricity, e.g. via photo-voltaics, wind turbines, or micro combined heat and power plants (μCHP), has a good chance of pervading the electricity infrastructure in the future (e.g. [2], [3]). Also, several electricity storage technologies are under development (e.g. lithium-ion batteries, plug-in hybrid electric vehicles [4]). Furthermore, demand side management options are foreseen for the future power system [5]. Drivers for DG are the environmental benefits (renewable energy sources, efficient use of fossil fuels), reduced investment risks, fuel diversification and energy autonomy, and increased energy efficiency (less line losses, cogeneration options). Drivers for DERs are the generation and sale of electric energy based on DERs on several markets (economic drivers) and the provision of balancing and ancillary services to network operators (technical drivers).

With an increase in DERs combined with more ICT and intelligence in the electricity infrastructure, the options for consumers with respect to energy demand fulfillment increase. The increased system complexity due to DER application is described in detail in [1], [6]. This paper specifically focusses on residential DERs (micro level). Households with DERs operate more independently of energy suppliers, they can devise new contractual arrangements with suppliers and/or network managers, they can buy and sell power among each other, and to and from their supplier. In that way smarter power systems arise in which households become so-called power 'prosumers'.

In this paper we consider the situation in which a household has the capability of generating its own power with a μCHP unit. The household can store heat and electricity and can trade electricity with an external energy supplier. Here we do not consider demand side management schemes. The household has full control over its DERs and there is no interaction with other households regarding electricity trade. This control strategy can therefore be characterized as *decentralized* [7].

B. Model Predictive Control

In [8] several decentralized control strategies are described and simulation results with these strategies shown. Here we propose a more sophisticated local household controller in terms of cost minimization. The controller has the task to automatically determine which actions should be taken in order to minimize the operational costs of fulfilling residential electricity and heat requirements subject to operational constraints. The controller uses a *model predictive control* (MPC) strategy such that it can:

- take into account the decision freedom due to heat and electricity storage possibilities;

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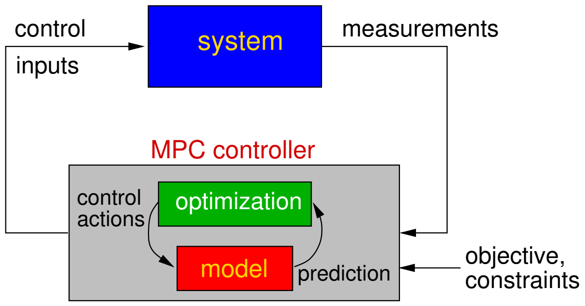


Fig. 1. Model predictive control scheme [9].

- incorporate predictions on residential electricity and heat demands;
- incorporate models of the dynamics and constraints of installed generators and storages.

MPC [9] is based on solving at each control step an optimization problem over a prediction horizon subject to system dynamics, an objective function, and constraints on states, actions, and outputs, see Fig. 1. At each control step the optimization yields a sequence of actions optimizing expected system behavior over the horizon. Actions (control inputs) are implemented by the system until the next control step, after which the procedure is repeated with new system measurements. MPC is successful mainly due to its explicit way of handling constraints, its possibility to operate without intervention for long periods, and its built-in robustness properties. Due to the prediction horizon it can take benefit of knowledge it may have over the future, e.g. forecasted energy demand based on historical data of energy consumption patterns. In this paper the focus is on daily operational costs pertaining to residential energy usage when adopting MPC in DER deployment.

This paper is organized as follows. In Section II we describe the system under study and give salient modeling assumptions. Section II also shows the developed mathematical system model. Section III gives the control objective and formalizes the control problem. Section IV illustrates the performance of the proposed controller through simulation studies. Section VI finally gives conclusions and suggestions for further study.

II. System Description

The system under study consists of a household interacting with its energy supplier (environment), as depicted in Fig. 2. Among the household and its energy supplier energy flows are present as shown.

Households fulfill their electricity and heat consumption requirements through several alternative energy supply and consumption means. The μCHP unit is based on Stirling technology, see e.g. [3]. The unit consists of a Stirling engine prime mover, conversion 1, and an auxiliary burner, conversion 2, which can provide additional thermal power. The Stirling engine converts natural gas (f_1) into electricity (g) and heat (h_1). The heat is supplied to the heat storage in the form of hot water (h_s). The auxiliary burner also converts natural

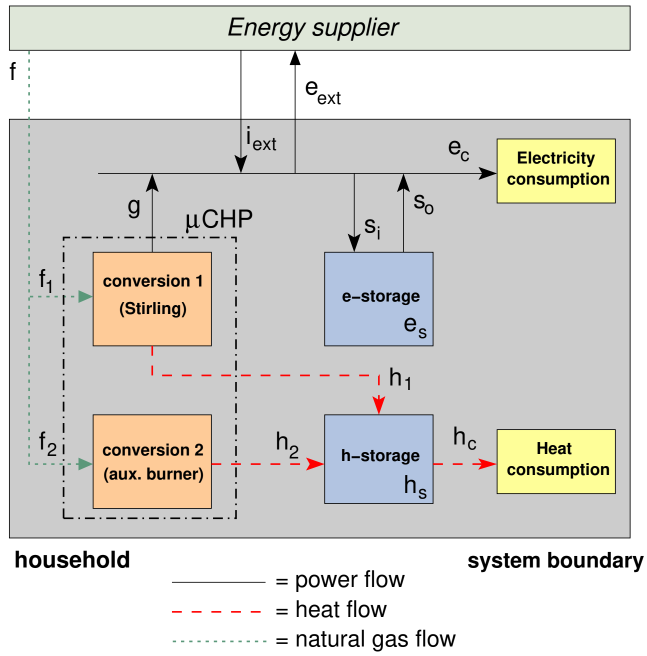


Fig. 2. Conceptual overview of the system under study.

gas (f_2) and provides additional heat (h_2). Heat consumption (h_c) is taken from the heat storage. Electricity can be stored in a battery (e_s) (e.g. lithium-ion). Electricity can flow to and from the battery, represented in Fig. 2 by (s_i) and (s_o) respectively. Locally generated electricity can be used directly by the household (e_c), it can be stored or it can be sold to the supplier (e_{ext}). Electricity can also be imported from the supplier (i_{ext}). The supplier thus sells primary fuel ($f = f_1 + f_2$) for fueling the μCHP unit as well as additionally required import electricity for households. The supplier buys any electricity that is produced by households in excess of their own consumption.

A. Modeling Assumptions

This section gives the most important assumptions made in modeling the system.

- Different configurations of a μCHP unit can be thought of in relation to its balance of plant equipment (i.e. heat storage, piping, pumps, heat exchangers). We envisage one large heat storage from which all heat can be extracted (see [10]). So we consider aggregated space heating and hot sanitation water needs.
- Produced heat cannot be dumped; all heat should be used.
- In [11] an efficiency value of 105 % for space heating purposes is mentioned. All efficiency values are based on fuel Lower Heating Value (LHV). Current heating efficiencies for sanitation water are 75 % and future values (2015) are predicted to be 89 %. In [12] an average natural gas consumption (2004) of 1736 m^3 is given (1300 for heating, 300 for hot water, and the rest for cooking). For the total efficiency of a (future) μCHP unit we therefore assume a value of: (13/16) $\cdot$ 105 % + (3/16) $\cdot$ 85 % =

101.25 %.

- The μCHP unit comprises a Stirling engine and an auxiliary burner. The WhisperGen® and the Microgen® μCHP systems are taken as a basis for our model [13], [14]. The modeled system has a full load power output (g) of 1.1 kWe. Part-load capacity is assumed at 0.55 kWe. The auxiliary burner capacity is assumed to lie between 0 and 20 kWth. The electric efficiencies of current state-of-the-art Stirling engines lay around 15 % [11].
- Stirling engines have a warm-up and cool-down time of around three minutes [15]. Our simulation time step represents 15 minute periods. We therefore neglect these warm-up and cool-down periods.
- Stirling engines cannot be subjected to too many start/stop cycles as this limits the engine's lifetime. A minimum up-time of half an hour and a minimum down-time of 15 minutes are therefore assumed for the Stirling engine [15].
- Water temperature in the heat storage should lie between 60 and 80 °C. With these temperatures the energy content limits of the heat storage can be calculated.
- There are no thermal losses in the conversion and storage systems. Combustion in the μCHP unit and in conventional high efficiency boilers is complete.
- The hot water storage has a volume of 100 liters. The maximum electricity storage capacity is 2 kWh.
- The Stirling engine gets priority over the auxiliary burner in heating the water.
- Natural gas consists purely of methane.
- Parasitic load from balance of plant equipment (compressors, pumps, etc.) is neglected.
- There are no capacity constraints in the physical electricity network between the supplier and the household.

B. Mathematical System Model Formulation

A substantial part of our mathematical model is based on [16]. Our model differs from the one in [16], however, in that we consider the μCHP unit as a combination of a prime mover and an auxiliary burner. Further, we incorporate electricity storage and we also consider varying electricity import prices.

Analogous to [16] we first define the following binary variables. v_k^{CHP} and v_k^{aux} indicate whether the μCHP prime mover and auxiliary burner are in operation at time interval k. The binary variables $u_{\text{up},k}^{\text{CHP}}$, $u_{\text{down},k}^{\text{CHP}}$, $u_{\text{up},k}^{\text{aux}}$, $u_{\text{down},k}^{\text{aux}}$ are start-up and shut-down indicator for the μCHP prime mover and auxiliary burner at time interval k.

An electricity balance relating the power output of conversion unit 1, the input and output of the electricity storage, the electricity consumption, and electricity bought or sold to the aggregator, has to hold. This power balance is given by:

$$\eta_{\text{e}} \cdot f_{1,k} + i_{\text{ext},k} + s_{\text{o},k} - e_{\text{ext},k} - s_{\text{i},k} - e_{\text{c},k} = 0 \ , \tag{1}$$

where $g_k = \eta_{\text{e}} \cdot f_{1,k}$ and η_{e} is the electric efficiency of the Stirling engine.

For the Stirling engine, part load and full load operation is modeled by

$$f_{1,k} = v_k^{\text{CHP}} \cdot f_{1,\text{part}} + x_{1,k} \cdot (f_{1,\max} - f_{1,\text{part}}) \tag{2}$$

$$x_{1,k} \leq v_k^{\text{CHP}} \ , \tag{3}$$

where $x_{1,k}$ is a binary variable deciding whether the Stirling engine will operate at full or part load.

The auxiliary burner operation is modeled by

$$v_k^{\text{aux}} \cdot f_{2,\min} \leq f_{2,k} \leq v_k^{\text{aux}} \cdot f_{2,\max} \ . \tag{4}$$

The electricity and heat stored should be between the minimum and maximum values:

$$e_{\text{s},\min} \leq e_{\text{s},k} \leq e_{\text{s},\max} \tag{5}$$

$$h_{\text{s},\min} \leq e_{\text{s},k} \leq h_{\text{s},\max} \ . \tag{6}$$

The electricity flows to and from the battery are limited by

$$s_{\text{o},\min} \leq s_{\text{o},k} \leq s_{\text{o},\max} \tag{7}$$

$$s_{\text{i},\min} \leq s_{\text{i},k} \leq s_{\text{i},\max} \ . \tag{8}$$

Lithium-ion batteries can be fully charged and discharged four times per hour [17]. Therefore $s_{\text{o},\max} = s_{\text{i},\max} = e_{\text{s},\max} =$ 2 kWh (per time step).

The constraint that forces the prime mover to stay in operation until at least the minimum up-time (2 time steps) is reached is:

$$v_{k+n}^{\text{CHP}} \geq u_{\text{up},k}^{\text{CHP}} \quad \text{for } n = 0, \ldots, t_{\text{up}} - 1. \tag{9}$$

The variables v and u have to be linked. This is modeled by:

$$v_k^{\text{CHP}} - v_{k-1}^{\text{CHP}} = u_{\text{up},k}^{\text{CHP}} - u_{\text{down},k}^{\text{CHP}} \tag{10}$$

$$v_k^{\text{aux}} - v_{k-1}^{\text{aux}} = u_{\text{up},k}^{\text{aux}} - u_{\text{down},k}^{\text{aux}} \tag{11}$$

$$u_{\text{up},k}^{\text{CHP}} + u_{\text{up},k}^{\text{CHP}} \leq 1 \tag{12}$$

$$u_{\text{down},k}^{\text{CHP}} + u_{\text{down},k}^{\text{CHP}} \leq 1 \ . \tag{13}$$

The heat in the heat storage is modeled by:

$$h_{\text{s},k+1} = h_{\text{s},k} + (\eta_{\text{tot}} - \eta_{\text{e}}) \cdot f_{1,k} + \eta_{\text{tot}} \cdot f_{2,k} - h_{\text{cp},k} \ , \tag{14}$$

where $h_{1,k} = (\eta_{\text{tot}} - \eta_{\text{e}}) \cdot f_{1,k}$, $h_{2,k} = \eta_{\text{tot}} \cdot f_{2,k}$ and η_{tot} is the total efficiency of the μCHP unit. The electricity in the electricity storage is modeled by:

$$e_{\text{s},k+1} = e_{\text{s},k} + s_{\text{i},k} - s_{\text{o},k} \ . \tag{15}$$

III. MPC Formulation

The objective of the MPC controller is to minimize the daily operational costs of residential energy use. These costs depend on the price p_{f} for gas consumption, the price $p_{\text{i,ext}}$ for importing electricity and the price $p_{\text{e,ext}}$ at which electricity can be sold. The cost function for control step k with a prediction horizon of N is therefore defined as

$$J(\cdot) = \sum_{m=0}^{N-1} \Big((f_{1,k+m} + f_{2,k+m}) \cdot p_{\text{f}} + i_{\text{ext},k+m} \cdot p_{\text{i,ext},k+m} - e_{\text{ext},k+m} \cdot p_{\text{e,ext}} \Big) \ . \tag{16}$$

The prediction horizon considered by the MPC controller consists of subintervals m, $m = 0, \ldots, N-1$. The length of one prediction step is defined as 15 minutes.

The control problem model the controller uses is similar to the system model as mathematically described in Section III (i.e. the controller uses a *perfect model*). The mixed-integer, linear programming, problem to be solved by the controller at each time step k involves minimizing (16) subject to the equality and inequality constraints (1)–(15) over the prediction horizon N.

We define an additional constraint for the controller such that the Stirling engine gets priority over the auxiliary burner in providing heat to the heat storage. This constraint is modeled by:

$$v^{\text{aux}}_{k+m} \leq v^{\text{CHP}}_{k+m} \quad \text{for } m = 0, \ldots, N-1. \tag{17}$$

At each k the controller uses initial system measurements in making its control decision. The problem is classified as linear because all relations (1)–(17) are linear and as mixed integer because the problem involves real and binary variables. The MPC controller determines values for the following control inputs for each prediction step: $x_{1,k+m}$, v^{CHP}_{k+m}, $f_{2,k+m}$, $i_{\text{ext},k+m}$, $e_{\text{ext},k+m}$. For each k the control inputs of the first prediction step are sent to the system. The minimization process is repeated for $k+1$, $k+2$, $\ldots$ until the end of the simulation.

IV. Simulation Results

A. Simulation Input

This section describes further input data for the simulations, besides parameters already given in Sections II and III. Residential electricity and aggregated heat demand profiles have been created with 2006 data from 'EnergieNed', the Dutch Federation of Energy Companies. Heat profiles have a resolution of one hour and electricity profiles of 15 minutes. We have chosen a winter day for the simulations. Fig. 3 shows the energy demand profiles used.

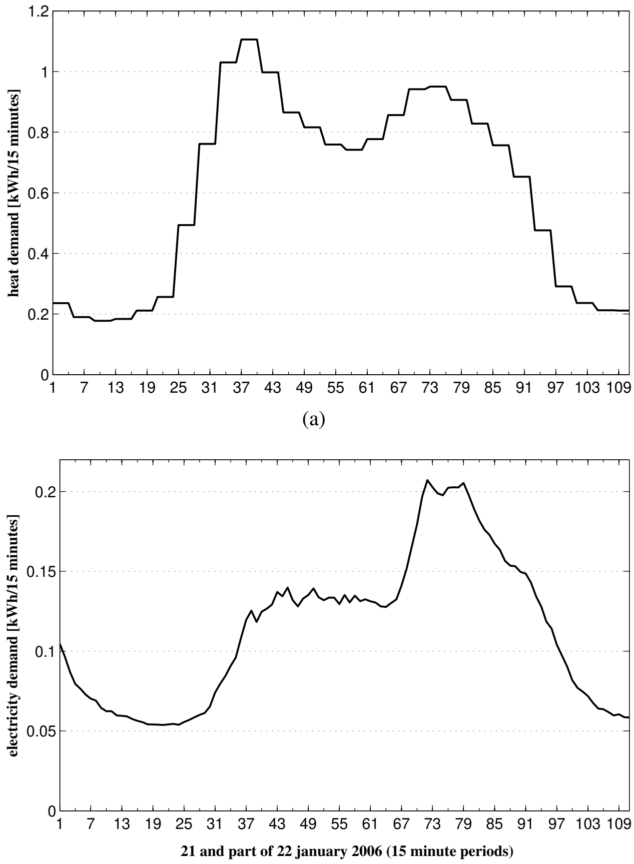
We also show data for a part of 22 January as the decision made by the controller at control step $k = 96$ should incorporate data for the prediction horizon relative to that time step.

The variable electricity import price has been constructed as follows. The Dutch central bureau of statistics states a total electricity tariff for small consumers for 2006 of 194 €/MWh [18] (household class: single tariff, 3000 kWh). The variable part of the total tariff (including energy and VAT taxes) is around 90 % of the total tariff [19], so this becomes 0.1746 €/kWh. The variable supply part of the total tariff accounts for 32 % of the total tariff [19]. For this variable supply part we have substituted Dutch power exchange values. We took Amsterdam Power Exchange data for 21 and 22 January. In this way we devised an import price as shown in Fig. 4.

For the value of the feed-back tariff we have taken average 'EnergieNed' data for 2006, which gives 0.0601 €/kWh.

In [18] a total gas tariff for small consumers of 552 €/1000 m^3 is given (for consumer class: 2000 m^3). According to [19], 91 % of the gas tariff is variable (including taxes). This leads to a value of 0.50232 €/m^3.

Because power exchange prices are known a day in advance, the electricity import price, $p_{\text{i,ext},k+m}$, is also known to the controller on forehand. As a first step we have taken the predicted residential heat and electricity demand for prediction horizon N with which the MPC controller works as being equal to the actual demand in that horizon.



(b)

Fig. 3. Energy demand data for average Dutch household (a = heat, b = electricity).

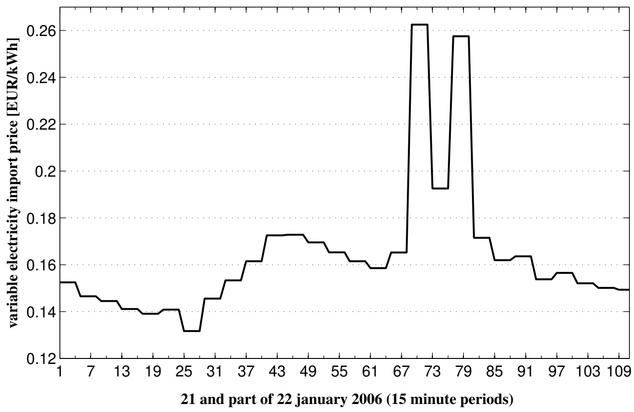


Fig. 4. Electricity import price.

The starting values for the simulation of the system are, for $k = 1$:

$$v_1^{\text{CHP}} = v_1^{\text{aux}} = u_{\text{up},1}^{\text{CHP}} = u_{\text{down},1}^{\text{CHP}} = u_{\text{up},1}^{\text{aux}} = u_{\text{down},1}^{\text{aux}} = 0\,,$$

$$e_{\text{s},1} = (e_{\text{s,min}} + e_{\text{s,max}})/2 = 1\,\text{kWh}$$

$$h_{\text{s},1} = (h_{\text{s,min}} + h_{\text{s,max}})/2 = m \cdot c \cdot \Delta T = 100 \cdot 4.18 \cdot (70 - 20) = 20900\,\text{kJ} = 5.81\,\text{kWh}.$$

In calculating $h_{\text{s},1}$ we have used the heat storage volume of 100 liters, an environmental temperature of 20 °C and the specific heat capacity of water of 4.18 kJ/kg·K.

V. Results

We have implemented the mathematical simulation model in Maple™. We have simulated the MPC controller and the resulting system outcomes per time step k for a full day period, for various prediction lengths between $N = 1$ and $N = 15$. For a specific value of N, the optimization solver gave different results for repeated simulation runs (around 6 runs per N), showing that the solver finds local minima in the solution space. The results given here are the ones resulting in the lowest daily costs.

The results for $N = 1$ are not very interesting to depict. The resulting daily operational energy costs as defined in (16) are 4.085 € for $N = 1$. The results shown in Fig. 5 are for $N = 3$. The daily operational energy costs are then 4.063 €.

The distinction between part load and full load operation of the Stirling engine (f_1) can be clearly seen.

For $N = 10$ the daily costs are 3.96 €. In Fig. 6 the results for $N = 15$ are shown.

For $N = 15$ the daily energy costs are 3.89 €, which is a 4.8 % reduction as compared with $N = 1$. For $N = 15$ the electricity imports are 0 during the peak import price period between $k = 69, \ldots, 80$. This effect is not observed for $N = 3$. What is interesting to see, is that for $N = 15$ the MPC controller fills the electricity storage before the peak import price period so that the household can profit from the relatively lower price before that peak period leading to lower daily energy costs. For $N = 3$ this behavior is not observed. This shows that model predictive control, anticipating future change, can result in better system outcomes.

VI. Conclusions and Further Study

We have proposed a model predictive control (MPC) strategy to be employed by households to control residential energy resources to minimize operational costs of energy use. A micro combined heat and power (μCHP) unit based on Stirling prime mover technology provides heat to the households and simultaneously generates electricity for use in the household or for export to the external grid. Results of the MPC controller have been discussed, and it has been shown that MPC gives better outcomes in terms of daily energy costs when a substantial prediction horizon is adopted by the MPC controller.

Interesting options for further study include the following.

A longer prediction horizon than 15 steps could be researched. Due to computation time limitations, a horizon of 15 steps was the highest value used for this paper. The prediction time step could then be of a larger time resolution (e.g. one hour) than the simulation time step.

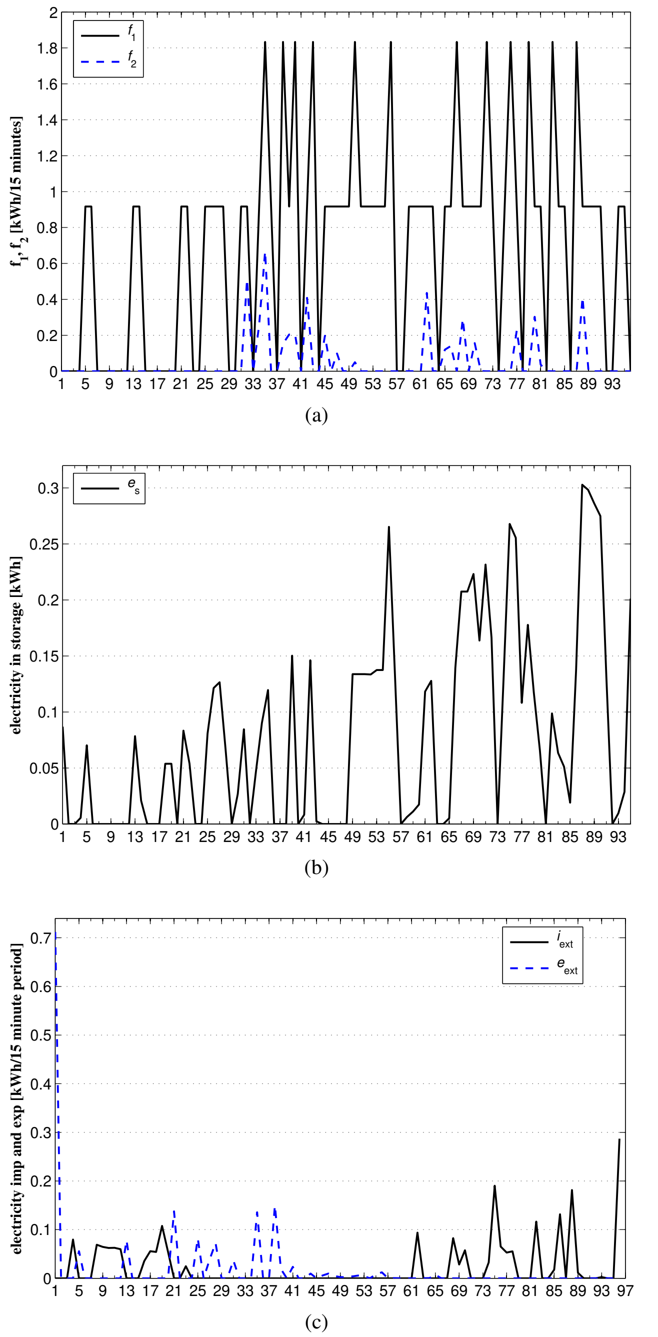
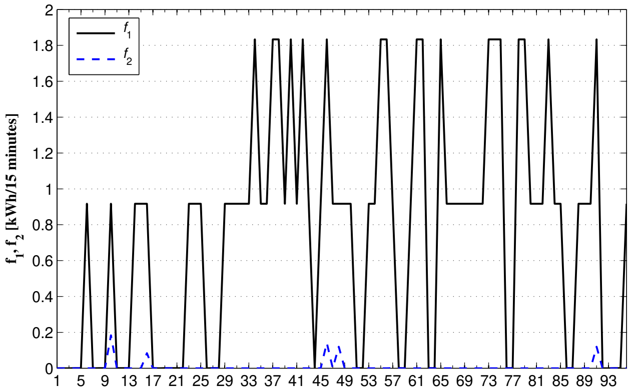
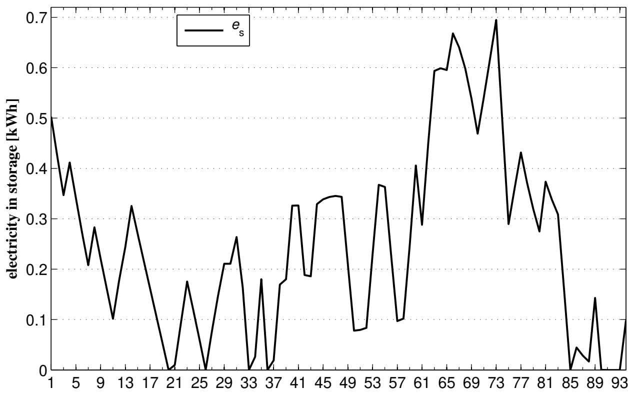


Fig. 5. Simulation results for January 21st, $N = 3$ (a = gas supply to μCHP prime mover (f_1) and auxiliary burner (f_2), b = energy level in electricity storage, c = electricity import and export).

In this paper we have not observed significant anticipative behavior by the μCHP unit (which could then be observed in the heat storage energy level), as importing electricity is always cheaper for a household than making it from gas via the μCHP. Also the feed-back tariff was fixed and too low to outweigh the costs of self-generated electricity via the μCHP.



(a)



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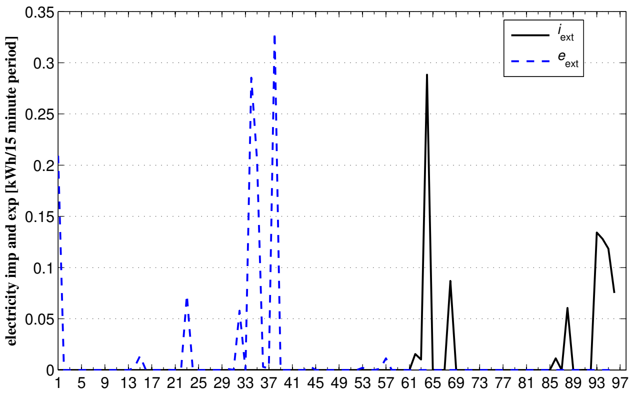

(c)

Fig. 6. Simulation results for $N = 15$ (same sequence as $N = 3$).

Variable electricity export prices (equal to the variable import price) are expected to lead to more anticipative behavior of the μCHP unit conversion units. With the μCHP unit anticipating future electricity export prices, the total system can prepare itself as such for taking as much advantage of higher export prices as possible.

The import price could be taken fixed and results researched.

A simulation with a Stirling engine operating only at full load could be undertaken.

Other μCHP technologies (e.g. fuel cells, internal combustion engines, microturbines) could be modeled as well.

Different seasonal days could be researched besides the winter day taken in this paper.

Predictions on residential energy demand which differ from actual values (made with a forecast model) could be experimented with.

The operational cost savings could be placed in more comprehensive cost benefit analysis of μCHP systems to see if variable cost savings outweigh additional investment costs.

Distributed control, in which multiple households can trade power amongst themselves, is also an interesting further step in which model predictive control could be used.

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