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Using an ANFIS based short term load forecasting model for the optimization of micro-CHP operating strategies in domestic households

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Abstract This paper presents a comprehensive concept for the development of an auto-adaptive optimization model seeking to determine optimal operating strategies of micro combined heat and power (CHP) units in domestic households with special respect to the energy-economic framework conditions in Germany. The methods proposed to be applied are an adaptive network based fuzzy inference sys-tem (ANFIS [1]) coupled with mixed-integer-linear programming (MIP).

Nowadays, most of micro-CHP units are driven heat led, due to their limited technical ability of following the electric load profile (especially in case of fuel cell micro-CHP). However, the consumption-rate of locally self-generated electricity is crucial for the economics of micro-CHP systems. Therefore, the aim of this paper is to provide an economically optimized operating strategy which requires information about the household's future load situation and therefore an appropriate individual short term load forecast (STLF). Furthermore, the concept described considers battery and hybrid electric vehicles as additional consumers of electric energy which enforces the necessity of optimized operation. Keywords: ANFIS, STLF, MIP.

1 Introduction

The ongoing and intense research, development and funding activities regard-ing micro combined heat and power units (CHP-units) is likely to further intensify their distribution in small and middle sized German households. Especially in case of fuel cell based micro-CHP units, the coupled generation of electricity and heat provides for a more efficient use of primary energy [7] as well as minimized transportation losses compared with the still common decoupled generation. However, these key facts regarding micro-CHP are only valid if two important aspects are fulfilled:

1. Electricity is only generated if the co-product thermal energy is used in the local building,
2. the electricity generated on-site is used locally to the largest possible extent (which is also economically reasonable).

The legal framework in Germany takes account of these two key requirements through funding the whole electricity generated with micro-CHP units while obligating the local use of the co-produced thermal energy [2]. Due to the generated savings, it is reasonable to maximize the consumption-rate of self generated electricity. However, most of micro-CHP units in Germany are driven heat led because there is a lack of intelligent control algorithms which provide for an optimized operation with respect to the time dependent local demand of electric energy[1]. This is why this paper presents a concept for the development of a generic auto-adaptive optimization approach which takes each household's individual customs into account. Hence, the methodological approach described, supplements standard methods of optimizing the operation of CHP-units based on deterministic and perfect-foresight optimization models (cf. e.g. [6,8,9]). These standard methods usually neglect the lack of perfect information in reality, and therefore are not suited for the online optimization of the operating strategy. However, supplemented with an adaptive method of load forecasting as prior stage, the standard optimization methods can be also used online.

As described in the following sections a mixed integer linear program (MIP)[2] in combination with an adaptive network based fuzzy inference (AN-FIS) model seems to be suitable to address the challenges mentioned. While a lack of data formerly prevented corresponding approaches, recent developments in smart metering and the resulting improved data situation in households nowadays allow for the development of new household individ-ual forecasting methods.

This paper is divided into six sections. Section 2 addresses the optimization of micro-CHP operation with a MIP before section 3 describes the ANFIS model and its problem specific implementation as a possibility for data driven adaptive short term load forecasting (STLF). Sections 4 and 5 give some exemplary results of application before the paper sums up with conclusions and an outlook.

2 Optimized operation of micro-CHP units

The framework described in section 1 leads to the following composition of the household-revenues r_e for electricity generated through the operation of a micro-CHP unit. It is assumed, that a battery storage is lacking while a thermal energy storage is available.

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[1] If a sufficiently large local battery storage for electric energy is available, the maximization of self-consumption becomes trivial. However, due to still high battery investments, the approach selected is intended to minimze the necessary storage capacity or to completely avoid its necessity.

[2] The MIP approach is selected due to the consideration of several distinct points of operation.

$$r_e = x_{e,f} \cdot (p_{e,f} + r_{e,g} + r_{e,chp}) + x_{e,l} \cdot (p_{e,l} + r_{e,chp}) \tag{1}$$

with

r_e	: revenue of a houshold for locally generated electricity	$[€]$
$x_{e,f}$	: amount of generated electric energy fed into the grid	$[kWh]$
$x_{e,l}$	: amount of generated electric energy locally used referred to as own-consumption	$[kWh]$
$p_{e,f}$	: payment for electric energy fed into the grid	$[€/kWh]$
$p_{e,l}$	: avoided payment for electric energy out of the grid	$[€/kWh]$
$r_{e,g}$	: payment for avoided grid use	$[€/kWh]$
$r_{e,chp}$	: CHP bonus payment	$[€/kWh]$

Today, the total revenue for CHP-electricity fed into the grid in Germany is approximately 0.11 €/kW h while the own consumption is funded with 0.051 €/kW h, and, depending on the customer's tariff, causes savings of about 0.25 €/kW h. Therefore, equation 1 shows that, out of the opera-tor's point of view and with the assumption of inflexible electricity prices, the revenue-maximizing strategy is to maximize the own consumption of locally generated electricity. Despite of the common presence of a thermal (hot water) storage, which partly decouples thermal demand from generation, this goal is not easily achievable because especially fuel cell micro-CHP units are not flexible enough to follow the household's load curve in real time. This leads to the necessity of a cost-minimizing optimization model for the determination of an economically optimized operating strategy for the micro-CHP unit. The availability of a battery electric vehicle reinforces this necessity due to the significant increase of electricity consumption (typically by 30-50 % of the yearly household electricity consumption) [10].

The optimal operating strategy is defined as the one with minimal costs C in the considered time horizon T which is expressed in the objective function:

$$\min C = \sum_{t}^{T} \begin{pmatrix} x_{ng,t} \cdot p_{ng,t} \\ + x_{e,g,t} \cdot p_{e,g,t} \\ - x_{e,l,t} \cdot r_{e,chp} \\ - x_{e,f,t} \cdot (p_{e,f} + r_{e,g} + r_{e,chp}) \end{pmatrix} \tag{2}$$

whereby $x_{ng,t}$ and $p_{ng,t}$ refer to the consumption and price of natural gas in time step t, while $x_{e,g,t}$ and $p_{e,g,t}$ are the amount and price of electricity obtained from the electric grid.

Of course, there are several constraints to be respected. The main purpose of covering the local thermal demand $D_{th,t}$ of the building with the CHP-unit has to be fulfilled at every time:

$$x_{th,t} \geq D_{th,t} \quad \forall t \in T \tag{3}$$

The power demand $D_{el,t}$ of the building has to be covered either through the micro-CHP unit or the power grid:

$$x_{e,g,t} + x_{e,l,t} = D_{el,t} \forall t \in T \tag{4}$$

It is to be noted, that the amount of thermal energy $x_{th,t}$ is assumed to be provided exclusively through the thermal storage, which itself is filled by the CHP-unit at any time of operation, expressed by $x_{chp,th,t}$. However, there are maximum S_{max} and minimum S_{min} storage level constraints for the thermal storage. The actual storage level is referred to as S_t and thermal losses are summarized with the storage efficiency factor η_S .

$$S_{t-1} * \eta_S + x_{chp,th,t} - x_{th,t} \leq S_{max} \tag{5}$$

$$S_{t-1} * \eta_S + x_{chp,th,t} - x_{th,t} \geq S_{max} \tag{6}$$

The complete optimization model includes more constraints which are mostly technical ones. However, for the purpose of this paper the reduced mathematical description is sufficient for the traceability of the problem.

3 Short term load forecasting based on ANFIS

The necessity of household individual short term load forecasting (STLF) is due to the non-generalizability of household load profiles. While literature reveals a wide variety of models for short term (electrical) load forecasting on an aggregated level (cf. e.g. [3,4]), the situation is different for approaches on load forecasting for distinct domestic households. Although, on an aggregated level, standard load profiles exist (e.g. in Germany the household load profile H0), individual households strongly differ due to different daily routines and habits. As described in chapter 2 the individual load forecast is one input of a model for the determination of optimal CHP-operating strategies.

3.1 Short term load forecasting modeling concept

The STLF modeling concept is based on an auto-adaptive approach utilizing a problem specific implementation of an adaptive network based fuzzy inference system (ANFIS [1]). This method provides for both the advantages of fuzzy inference and neural networks (especially the ability of learning) and is therefore appropriate to meet the requirements of individual STLF. Because of the rising accuracy of STLF, the smaller the considered time horizon and the nearer-term the learning data is, one iteration[3] per day seems to be suit-able. Hence, due to consistency reasons, in real applications the forecast data

[3] One iteration: Learning based on recent load profile and forecast of future load profile.

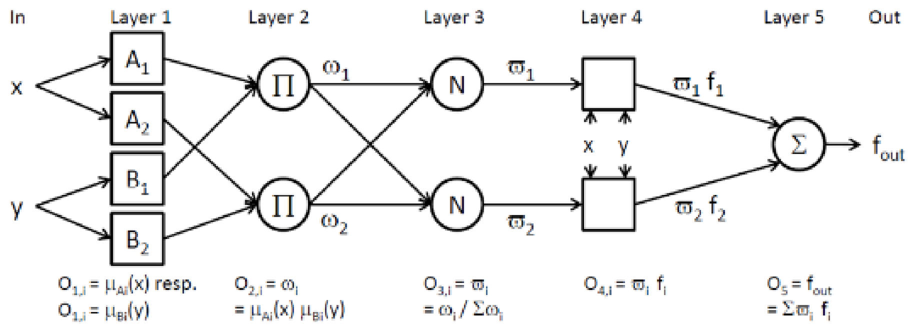

Figure1. Structure of ANFIS (based on [1]).

Table1. Forward- and backward-pass of the hybrid learning rule [1]

	Forward	**Backward**
Premise Parameters	Fixed	Gradient-descent
Consequent Parameters	LSE	Fixed
Signals	Node values	Error rates

should be supplemented with standard or historic load profile data for time slots further in the future for the subsequent optimization.

Figure 1 shows the structure of ANFIS as a composition of a fuzzy inference (FI) system and a neural network (NN). The structure of the underlying FI system is split over five layers. All parameters of the adaptive nodes are part of the FI system and modifiable during the learning procedure (cf. table 1) which is why this design provides for a *learning FI system*. The five layers and their individual characteristics are described in the following.

Layer 1: The adaptive nodes of this layer contain the membership func-tions as defined in the underlying FI system. The node function $O_{1,i}$ of each node i in layer 1 is a membership function of the form $\mu : X \rightarrow [0, 1]$. Its function is to fuzzify the crisp input value of each input variable. The node function for the input value x to node i and the linguistic label A_i is:

$$O_{1,i} = \mu_{A,i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{7}$$

where the membership function in this example is assumed to be bell-shaped according to its parameters (a_i, b_i, c_i). All parameters of the node functions in layer 1 are referred to as premise parameters which are adapted during the application of the so called hybrid learning rule (cf. table 1) [1].

Layer 2: The non-adaptive nodes of layer 2 represent the if-part of the FI system. The node-value is called firing strength w_i:

$$O_{2,i} = w_i = \mu_{A_i} \mu_{B_i} \tag{8}$$

Layer 3: Here, also non-adaptive nodes serve to normalize the node values of layer 2. This leads to a unified weight of all rules applied. The node values are referred to as normalized firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum_i w_i} \qquad (9)$$

Layer 4: All nodes of this layer are adaptive nodes which represent the then-part of the FI system's rules. In the Sugeno-type FI system all membership functions regarding the output values are linear functions. The parameters (p_i, q_i, r_i) of this layer are also called consequent parameters which are modified during the forward-pass of the hybrid learning algorithm (cf. table 1).

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x_i + q_i y_i + r_i) \qquad (10)$$

Layer 5: The single node of layer 5 is a non-adaptive node which serves to determine the overall output as the weighted sum of all incoming signals.

$$O_5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (11)$$

3.2 Problem specific implementation of ANFIS

Inputs: Due to security and availability reasons all input data needs to be accessible from the location of the micro-CHP unit. Furthermore, the input data has to have significant effect on the power demand of the building. In our first step, the selected parameters are the ones listed below. Each parameter's input space is partitioned with an individual number of bell-shaped membership functions (given in brackets). Due to the selection of a multi-model approach (cf. following section Design), no indicator for the day of the week is needed although it is a highly influencing parameter. The selected parameters are:

- time (hour) (7),
- corresponding load of the week before (3),
- corresponding load of the day before (3),
- indicator of presence resp. longer absence of occupants (2).

The parameter selection is due to the lack of availability of broader test data. Further developments may include more parameters if available which is likely to improve forecast quality.

The inputs for the learning algorithm are recorded load profiles connected with the corresponding input parameters. Therefore, the system needs a few weeks for good adaption on a household after the very beginning of operation.

In this first approach, the temporal resolution is set to one hour. This, on the one hand, partly neglects the highly fluctuating character of household loads (cf. e.g. [6]) but on the other hand is sufficient for the study's purpose at this early stage.

Design: As load profiles strongly differ on different type of days, the week is split up into four groups. The first group includes the weekdays from Monday to Thursday. Each of the other three groups covers one day of the week: Friday, Saturday and Sunday. Based on this pre-processing, an interative multi model approach is selected [5]. This means that for each type of day, a distinct instance of the ANFIS-model is used which is iteratively trained based on historical data of the corresponding group.

According to the model description in chapter 3, the input data is fuzzy-fied through bell-shaped membership functions. The initial setting for these functions is based on expert's knowledge, differs for the four type of days and covers the whole parameter's input space. The determining parameters of each function as defined in equation 7 are adapted within the learning procedure which provides for an adaption to each household's individual requirements. The rules, which are responsible for the input-output mapping are also based on expert's knowledge and intensive experimental studies. Owing to the ANFIS structure, each rule incorporates one linear output member-ship function. The parameters of these linear functions (cf. equation 10) are adapted within the forward-pass of the hybrid learning procedure.

Furthermore, the ANFIS structure (cf. figure 1) also illustrates a great advantage of the modeling concept, which is its expandability, e.g. with new or actualized expert's knowledge as well as with new load determining parameters. It is easy to add more rules and input or output membership functions due to the flexible structure.

4 Exemplary application

4.1 Standard Load Profile as Reference Model

The most intuitive way of "predicting" household load curves in Germany is to use the standard load profile for households (profile H0) which can be easily scaled up with the historical yearly consumption of electric energy. However, the application as forecast shows comparatively high error values. This is due to the non-generalizability of individual household load curves in contrast to the aggregated profile of numerous households. Therefore, the H0 profile serves as a good reference for the forecasting model in the following for being able to asses the advantages generated through the proposed forecasting method.

4.2 Error measure

Standard error measures in forecasting like the mean average percentage error or the root mean sqaured error do not completely reflect the purpose of this special approach which is to meet the principal characteristic of the household's load profile. Therefore, a problem specific error measure is used, which expresses the yearly deficient cover of energy (YDCE, eq. 12). It represents the amount of energy, which is not covered by the forecast at the correct time. Together with the comparison of the actual (AYED) and the forecasted (FYED) yearly energy demand, this error measure is sufficient to evaluate the quality of this special forecast. For being able to better classify the individual results, the YDCE is also stated as a percentage of AYED (cf. section 4.3). This improves the comparability of several results.

$$\mathrm{YDCE} = \sum_{t=1}^{n} \max\{0, (A_t - F_t) \cdot h_t\} \tag{12}$$

$$\mathrm{AYED} = \sum_{t=1}^{n} A_t \cdot h_t \tag{13}$$

with

A_t	: Actual loadvalue in t	[kW]
F_t	: Forecasted loadvalue in t	[kW]
h_t	: Duration of time interval t	[h]

4.3 Results of ANFIS application

The results of an exemplary application of the ANFIS based STLF are given in table 2 for three different households[4]. The underlying load profiles cover one year and therefore many different load situations. Moreover, it can be assumed, that the individual consumer behaviour is fully represented with a one year load profile.

In comparison with the reference model H0, the proposed ANFIS model shows remarkable advantages. The yearly deficient cover of energy could be reduced by approx. 50 % while the forecasted yearly energy demand meets the actual value pretty good. However, the results also clearly show the complexity of forecasting household individual loads. While forecasts on a higher aggregated level reach deviations of smaller than 1 % (cf. e.g. [3], [4], [11]) the model proposed only reaches 10 % at the minimum (cf. table 2). Nevertheless, taking the available data and the preliminary state of the work into account, the results show, that the approach is promising and delivers significant better input data for the optimization than the standard load profile does. Furthermore, the quality is hard to be rated due to the lack of comparable approaches.

[4] Another 30 load profiles were examined with similar results.

Table2. Selected Results of Exemplary Application

Profile	ANFIS		H0	Actual
	FYED	YDCE	YDCE	YED
01	5,420 kWh	546 kWh (10 %)	1,023 kWh (19 %)	5,412 kWh
02	4,454 kWh	596 kWh (14 %)	1,037 kWh (24 %)	4,385 kWh
03	6,154 kWh	719 kWh (12 %)	1,314 kWh (22 %)	6,048 kWh

5 Improved operation of micro-CHP unit

This section gives preliminary and exemplary results regarding the achievable improvement due to forecast-optimized micro-CHP operation in comparison with the heat-led operating strategy[5]. The household considered in the following has 4 inhabitants, a yearly electricity consumption of 6,664 kWh (2,496 due to an electric vehicle) and a yearly thermal energy demand of 12,448 kWh.

In case of the heat-led strategy, the only trigger which initiates the op-eration of the micro-CHP unit is the case of a thermal energy storage level below the defined minimum level. Due to the electrical load profile, which is not explicitly taken into account in the heat-led strategy, the produced elec-tricity is only used locally to the extent which is demanded just at the time of operation. Therefore, in total, a larger part of the electricity produced is fed into the grid. On the other hand, the optimized-strategy is based on the individual forecast and therefore takes all available data into account. The optimization tries to shift the times of operation to the times in which the local electricity demand is expected to be high. Simultaneously, technical constraints ensure the coverage of the thermal energy demand at any time.

The comparison of both strategies shows, that the optimized strategy increases the own consumption by 15 % which results in additional anual saving of approx. 102 E. Although this seems to be a small effect, the projection to the whole economic lifetime, which is assumed to be 20 years, shows an over-all improvement of the investment's net present value[6] of approx. 1,300 E. This economic advantage is almost equivalent to the current governmental investment funding for micro-CHP units with 1 kW_{el} [12].

6 Conclusions and Outlook

The application of the approach developed already shows advantages in comparison to a heat led operation of micro-CHP units. However, the forecasting

[5] The unit assumed has a maximum electrical power of 1.2 kW and a corresponding thermal power of 2.4 kW. Furthermore, three different points of operation are assumed: 0 %, 50 % and 100 % of maximum power.

[6] Assumed discount rate is 5 %.

quality still needs to be improved to justify the application in practice and to generate a reliable input for the optimization. Nevertheless, the appli-cation of intelligent and adaptive techniques for household individual load forecasting could be proved as a promising concept for the improvement of micro-CHP operation. This was demonstrated in an exemplary application for a real household with a time horizon of one year.

Future research will be concentrated on the identification of further influencing parameters to be used as input data and hence to improve forecast quality. Moreover, the selection and the initial settings of the membership functions needs to be further investigated. Another research question which will be dealt with, is the comparison of the model with other forecasting methods such as regression approaches or various kinds of neural networks. Regarding the overall concept, a subsequent simulation will be developed, which will give full information about the effects of forecasting errors on the stability of optimized operating strategies.

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