Computational Intelligence Techniques Applied to Flexible and Auto-adaptive Operation of CHP Based Home Power Supply

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***Abstract*--Micro Combined Heat and Power (CHP) systems for single or small ensembles of (residential) buildings are seen advantageous to combine both decentralized power supply and rather high overall efficiency. The latter presupposes flexible and adaptive plant management which has to mediate between energy cost minimization and user comfort aspects. The successful use of Computational Intelligence (CI) techniques for this purpose is focused and shown with several examples.**

***Index Terms*--Distributed generation, Combined Heat and Power (CHP), Energy management, Computational Intelligence (CI)**

I. Introduction

MICRO Combined Heat and Power (CHP) systems powering up to approximately 10 kW_{el} are considered as a future key technology for energy supply of buildings and settlements from the viewpoints of both heating systems manufacturers and energy suppliers; such CHP plants can be based on conventional Diesel, gas or biomass motors, gas or steam turbines, as well as Stirling engines or fuel cells [1]. In combination with public gas and electricity supply these technologies are well suited for cardinal provision of electric and thermal energy in single or multi-family residences and buildings with mixed occupancy of habitation and business establishments. It is evident that reasonable economic operation of CHP systems can only be achieved if peak demand is being moderated; for electrical peaks the public grid connection provides a sound basis, whereas thermal peaks can be smoothed out by both thermal storage and an auxiliary boiler. Efficient operation of such plants pivotally depends on both their sound design for the particular building under regard as well as on powerful strategies for energy and load management. *Energy management* in this context means cost-efficient supply of all (electrical and thermal) loads by intelligent and anticipatory operation of all interacting system components, in particular the CHP unit. *Load management* means the controlled arresting and releasing of the operation of certain devices, especially larger electro-thermal loads with a significant power demand – for instance a washing machine.

So far, commercial CHP plants do not include sophisticated control structures for flexible and automatic adaptation of their operation to the individual customer behavior, given tariffs and local infrastructure. The existing conventional energy management systems usually control the power of the CHP unit with respect to the actual heat consumption, but do not apply past or forecasted quantities; user specific consumption behavior as well as dynamic weather influences (such as outside temperature, wind, insolation) are not adequately considered. The potential of installed CHP plants therefore cannot completely be exploited.

In the frame of a current research project – accompanied by manufacturers of CHP plants, network operators and natural gas service providers – efficient strategies for a powerful energy and load management of a micro CHP based energy supply for buildings has been developed and verified on a sound simulation of the complete CHP system [2]. Besides regarding the operational demands and boundaries of the plant components involved, the *energy management* is designed to fulfill comfort demands by flexible adaptation to user habits (evaluation of past and consequential prognosis of future consumption) as well as local tariffs and infrastructure, and therefore provides economic generation of electricity and heat under inclusion of environmental compatibility. The *load management* controls the operation release time of certain (mainly larger electro-thermal) devices based on evaluation of past user behavior – considering both comfort demands and economic aspects. The management functionalities were elaborated and verified on a detailed operational simulation of the complete CHP system under regard; system characterization and first results were presented in [2].

Both flexibility and user adaptability of this system greatly result from the internal employment of various techniques of Computational Intelligence (CI) which were only briefly mentioned in [2]; therefore, the specific focus of this paper is on the customization and successful application of these CI techniques to the given purpose.

II. System under Regard

The principal structure of a micro CHP system for domestic supply including electricity (el) and thermal (th) flows is shown in Fig. 1. The CHP unit supplies the electrical and thermal circuits of the building(s). Heavy variations of the thermal load are smoothed out by both the thermal storage and the peak boiler, whilst the public electric power system acts as an (expensive) electricity buffer, limited by the admitted exchange power only.

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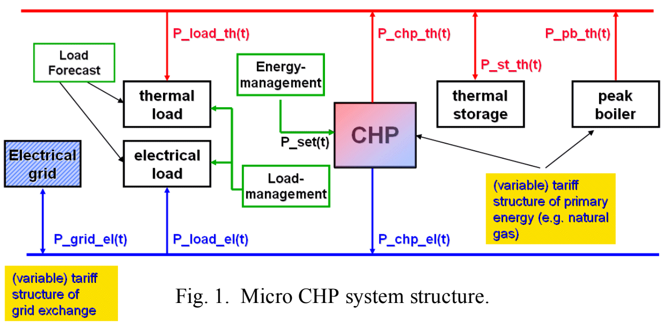

Fig. 1. Micro CHP system structure.

Anticipatory and cost optimal ad hoc determination of devices commitment and time dependent CHP power set-points is a demanding task under regard of the following diversified constraints [2]:

- current system state (e.g. electrical and thermal load, storage filling level);
- operating point dependent component characteristics (e.g. electrical vs. thermal output of the CHP unit);
- operational constraints (e.g., minimal operation times or intervals between activation of components);
- interdependencies in components' co-operation;
- varying tariffs for both electrical power exchange with the public grid and CHP fuel (e.g., natural gas from public supply);
- forecasted electrical and thermal loads;
- potential commercial contracts.

Flexible and cost-optimal system operation under these conditions as well as continuous adaptation to the local infrastructure, given tariffs and the individual customer behavior were achieved by development of the CI based modules of *energy management, load forecast* and *load management* which are focused on in the following. Coupling of these management modules with a Matlab/Simulink® based simulation of the CHP system in high temporal resolution and simulation fidelity [3] (60 sec calculation step rate was applied here) allows to test and verify the CHP management modules under operational realism before their implementation into a real residential supply system.

III. Flexible and Adaptive System Management

The three developed powerful management modules consisting of

- *energy management* providing prudent and cost optimal CHP unit set-points,
- *load forecast* incorporating anticipated load trajectories into current decisions and
- *load management* enhancing system efficiency by means of controlled arresting and releasing large electro-thermal loads

are based on predefined system features and exhibit on-line data processing.

A. Energy Management

The energy management generates the actual CHP set-points based on past, current and forecasted loads, tariff information as well as current and past operating states, Fig. 2; in particular the constraints as listed in section II. are regarded.

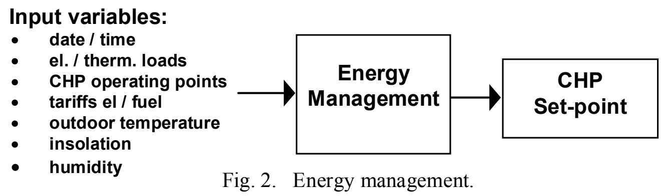

Fig. 2. Energy management.

The relevant features are allocated to an *Adaptive Network Fuzzy Inference System* (ANFIS [4], see section IV. *A.*) as inputs; if required, the selection of these features can be supported by correlation methods which are also implemented. The adaptation to local tariffs and changing user habits is done by off-line application of the well-known procedures of *optimization* and *generalization*: In a first step archived load curves are used to determine the corresponding optimal CHP set-points based on metaheuristic optimization techniques (see section IV. *B.*). In a second step the identified set-points as well as the corresponding input features (see Fig. 2) are used to extend the knowledge base by means of the implemented training algorithm (see section IV. *A.*). Periodic appliance of this process results in a continuously improving on-line management of the CHP system. Even though the user is free to select the objective function (e.g. minimization of emissions), overall *cost* minimization will be most commonly used in practical applications, achieved by proper CHP power set-point setting and – if actually applied – load management:

$$cost_{total} = cost_{fuel} + cost_{el\,from\,grid} - revenues_{el\,to\,grid} + cost_{assets} \quad (1)$$

$$\min_{CHP\ set\text{-}point,\ load_{managed}} cost_{total} = f(CHP\ set\text{-}point,\ tariffs_{el,fuel},\ load_{managed}) \quad (2)$$

B. Load Forecast

As determined above, the prospective electrical and thermal loads are influential input features of the energy management; thus, an effective forecast has to be provided. While numerous load forecast tools for large electrical grids are existing [5], little information is on-hand about applications in distributed systems (e.g. residential buildings or settlements). Therefore, as a first approach, general features such as outdoor temperature, global insolation, humidity and others were used as inputs for an ANFIS – test data were available from [6]. The investigation revealed that, based on these features, a data set of at least one year was necessary in order to generate acceptable forecast results for residential buildings. Hence, the time delay between installation and operability as well as the computational time demand of several days (PC with 512 MB, 1300 MHz) ruled out the practical application of this method for distributed systems. As another approach, by means of autocorrelation, characteristic features for the forecast of electrical and thermal loads in residential buildings could be identified. In both cases current and archived loads proved to have the highest information content. Thus, the load prognosis was transformed from reasoning based on general features to an identification of typical load sequence patterns as exemplarily shown in Fig. 3 with an excerpt of a real load curve; in consequence, the task of ANFIS became a multidimensional non-linear extrapolation.

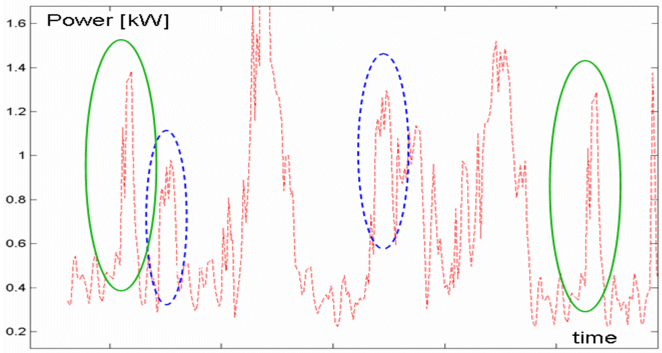

Fig. 3 Recognition of typical load sequences.

Fig. 4 exemplifies the forecasted discrete load values for the following 90 minutes based on 13 past electrical load values (over 3 hours) in a 15 min time pattern. Based on this principle the electrical load at specific, discrete times in the future (e.g., i = 15, 30, 60, 120 minutes ahead) is continuously predicted.

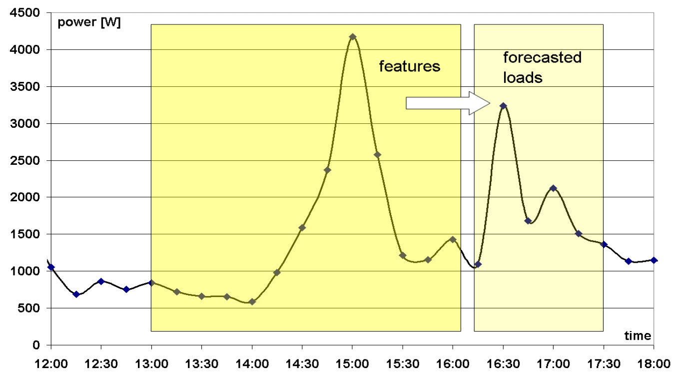

Fig. 4 Time-frame for load forecast.

The quality of the prognosis, in this case characterized by the mean forecast error $mfe(T_i)$

$$mfe(T_i) = \sum_{t=1}^{n} \frac{\left| P_{prog+T_i}(t) - P_{meas+T_i}(t) \right|}{P_{meas}(t)} \cdot 100\% \qquad (3)$$

with
- n: number of 15 min time steps, e.g., for 3 days: n = 3 · 96 = 288
- T_i: forecast horizon, e.g., 15 min
- $P_{prog+Ti}$: forecasted load at T_i
- P_{meas}: measured load at T_i

over 3 days, is shown in Fig. 5.

It is evident that for a one-family house the *mfe* appears relatively high compared with, e.g., load forecast for a large power system, since the usage of each particular device strikes through; under this aspect and consideration of the tremendously higher max/min load ratio of a single house the prognosis quality achieved is acceptable, see Fig. 6, and could not be exceeded by other means. For instance, the result of conventional forecast based on general input features (e.g., temperature etc.) – which was also entered in Fig. 5 for comparison – proves to be significantly worse.

From Fig. 5 it can further be seen that a data set of one day for the load pattern based ANFIS training is insufficient while a period of two weeks training data already has a high information content concerning the consumer behavior in the near future (< 45 min).

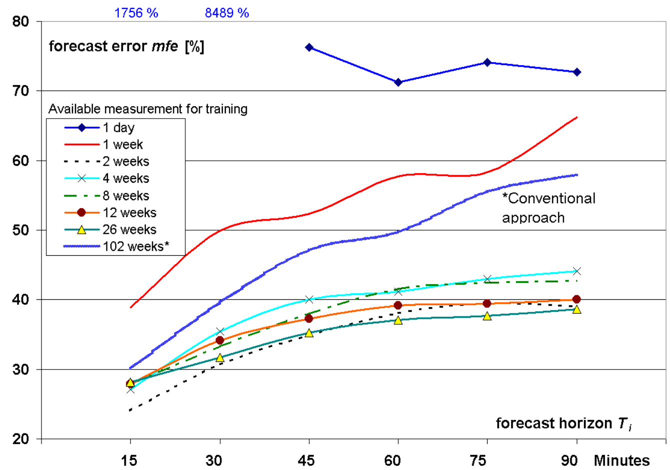

Fig. 5 Forecast error and adaptation.

Further extension of the training data period even leads to slight worsening of forecast results in consequence of over-fitting. With a training data set of 26 weeks maximal prognosis quality is achieved for longer term forecast (> 45 min).

Comparative investigation of the load pattern based forecast method for an ensemble of 69 one-family houses procured forecast errors in the range of 5…7% only, thus proving the cardinal qualification of the approach. Besides the improvement of prognosis quality the applied method of load sequence pattern recognition could reduce both the data set required for sound training (from ca. 2 years to 2 weeks) – thus leading to faster adaptation to the consumer behavior on site – as well as the ANFIS training time from ca. 2 days to few minutes.

Owing to the chaotic and hardly predictable instantaneous values of the hot water demand in single houses, the *expected*

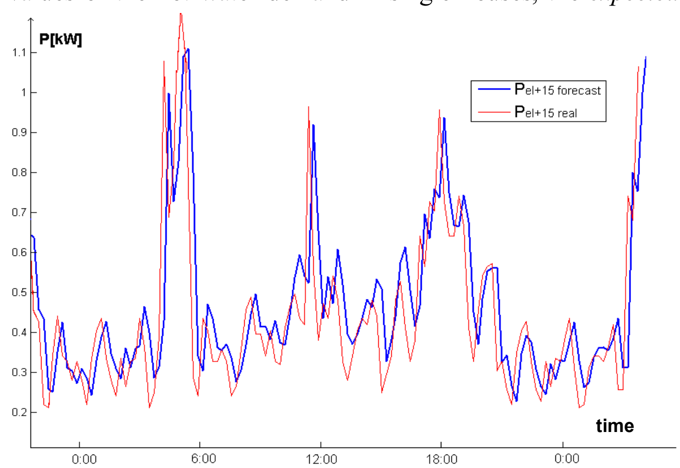

Fig. 6 Example of electrical 15 minutes load forecast.

cumulative thermal energy demand (hot water and heating) within the next 2 hours is forecasted. The actual difference is balanced by the thermal storage, see Fig. 1.

Both the electrical and thermal sequence recognition based load forecasts purely rely on past and current power consumption. By continuous subjoining of the actual load data to the existing data archive and periodic ANFIS training week by week the knowledge base is steadily amended, thus incrementally adapting the system to the consumer attitudes.

C. Load Management

In excess of the energy management described above the load management – optionally applicable as concomitant module – procures further enhancement of CHP system efficiency by

- attempt to preferentially achieve in-house consumption of electricity generated by the CHP unit,
- peak power shaving and
- operation of flexible loads at lower tariff times.

The basic idea lies in splitting the sum of consumption into the particular electrical and thermal loads $flexload_{load\_no}$ taking part in the load management, as well as a remaining part *restload* which cannot be influenced.

$$load_{el}(t) = \sum_{load\_no=1}^{n} flexload_{el,load\_no}(t) + restload_{el}(t) \qquad (4)$$

and

$$load_{th}(t) = \sum_{load\_no=1}^{m} flexload_{th,load\_no}(t) + restload_{th}(t) \qquad (5)$$

with n: number of electrical loads taking part in load management
m: number of thermal loads taking part in load management

Consumer acceptance studies have been carried out regarding load management appliance; Table I highlights general findings, whereby the heavy electro-thermal devices such as washing machine and dishwasher have been identified to have the highest acceptance.

TABLE I
CONSUMER ACCEPTANCE STUDIES REGARDING LOAD MANAGEMENT

load type	light	hot water	kitchenware
acceptance	no	no	hardly
load type	dishwasher, washing machine, dryer		refrigerator, freezer
acceptance	yes		yes

An individual time-frame is assigned to each device participating in the load management in order to restrain the management's influence to practicable and accepted time horizons, and thereby customizing the load management module. As an example, the load management is admitted to release operation of the washing machine within a period not later than 2 hours after the user has initiated the starting procedure if the corresponding time-frame is set to 120 minutes.

Enabling the load management is treated as an additional variable within the optimization process of the energy management which already was described in section III. *A.*, thus adapting the favorable operating times of participating devices to the CHP set-points and actual tariffs. As a result the load management module provides a schedule of preferential operation times for each participating device one week in advance.

By overruling the proposed schedule, the user still can give emphasis on his comfort demands in which higher associated costs have to be accepted. Automatic communication between the management module and the participating devices avoids additional user effort. Even if remote control particular devices is not yet state of the art, there is current work in progress to establish such techniques, using for instance power line or wireless communications [7], [8].

IV. Application of Computational Intelligence

As mentioned above the energy management – optionally complemented by the load management functionality – is based on the two procedures of optimization and generalization. While the *optimization* is applied periodically in off-line mode (e.g., for the upcoming week in advance) thus admitting the employment of metaheuristic approaches (subsection *B.*) , the *generalization* means adaptation of the optimized CHP operation patterns to the actual influence factors (input features according to Fig. 2); this task was solved by application of an *Adaptive Network Fuzzy Inference System* (ANFIS, [4]) which had already proven of value in the load forecast functionality (section III. *C.*) as well as in many other on-line applications worldwide.

A. ANFIS Generalization

While the membership functions and rules of a conventional fuzzy inference system typically are set up by a human, for complex systems this task can be automated by use of an ANFIS which in the meantime is available as tool within the Matlab/Simulink® environment. The adaptation of parameters is achieved by a hybrid learning algorithm (least-squares method and back-propagation), whereby the computational effort is essentially determined by the number of rules. In case of *grid partitioning* this number of rules directly follows from the combination of all system input variables and the membership functions of each input; in this case, known under the name of *curse of dimensionality*, the number of rules can be tremendously high even if the number of inputs is only moderately large (above ~ 5). Given that only few of the formed rules really contribute to the requested mapping of input features to the output signal, most of them are subsequently restrained within the learning process by slashing their firing strength. Due to the high number of rules this process takes considerable computation time.

The alternative method of *subtractive clustering* [9] allows for dimension reduction by classifying the input data into clusters belonging together, and thus generates only the minimum number of rules required to distinguish between them. Due to the significant reduction in computational time this method was applied here. Based on an ANFIS with subtractive clustering of rules both the derivation of actual CHP set points according to given input parameters in *real time*, as well as the periodic (weekly) adaptation to user habits, local tariffs and infrastructure changes within few minutes are successfully fulfilled.

B. Optimization

As to be seen from the enumeration of system operating conditions in section II. the optimization of CHP unit operation and device arresting and releasing is a high-dimensional mixed integer problem. Therefore, *metaheuristic* methods appear eligible, the more so as they are robust, unpretentious in application and do not tend to be captured in local minima; furthermore, computation time demand seems uncritical in consequence of their off-line application (see section III. *A.*). Three typical metaheuristic approaches were comparatively applied to the described plant optimization task:

- *Genetic Algorithm (GA) [10];*
- *Particle Swarm Optimization* (PSO) [11];
- *Ant Colony Optimization* (ACO) with the extension to mixed-integer problems as presented in [12].

Finally the optimization efficiency was enhanced by co-operative application of these approaches.

For efficiency comparison the three approaches were alternatively employed for the determination of CHP (gas motor driven generator set) power set points over one week, based on given measured shapes of electrical and thermal consumption of a one-family house as well as a time variable electricity and gas tariff structure; objective was the cost optimal energy supply. As commensurable measure of the efficiency of approaches the number of objective function calls NO was evaluated which were needed to undercut a given operation cost limit; for all three approaches investigated this number of objective function calls is likewise the product of the number of individuals involved and the number of generations required. Since all approaches applied have a stochastic search behavior the investigation – as a compromise between significance and temporal effort – was actually based on 5 runs. The results are summarized in Table II. All approaches were able to accomplish the optimization task but the duration was rather different ranging from numbers of minutes up to several hours. Therefore, in order to enhance the efficiency, a combined co-operative application of two or even all three algorithms was implemented:

- The different approaches handle the optimization in parallel, with independent individuals.
- The approaches run on separate LAN coupled computers.
- Each approach transmits its current best result and the appertaining variables to a central database before every start of a new generation.
- Each approach grabs the actual database entry as new start parameters before the next generation is initiated in case that a better solution is found there, and thus takes profit of the advances made by the other approaches.

In Table II the results gained with this co-operative method applying the metaheuristic algorithms ([10], [11] and [12]) are opposed to those of single approach application (all results are based on 5 runs, see above). It can clearly be seen that the Ant Colony Optimization (ACO) behaves superior to the other two approaches, and that by co-operation a further significant improvement is achieved. In consequence of the stochastic search behavior of all three approaches the ratio of the maximal and minimal number of objective function evaluations NO_{max}/NO_{min} can be considered as a measure for the robustness of the approach and points out the favorable co-operation for the given task.

TABLE II
NUMBER OF OBJECTIVE FUNCTION EVALUATIONS NO IN COMPARATIVE SINGLE AND CO-OPERATIVE APPLICATION OF METAHEURISTIC APPROACHES

	Single use			Co-operation	
Method	**ACO**	**GA**	**PSO**	**ACO**	**GA**
NO_{min}	1930	3100	9780	945	1750
$NO_{max/min}$	2,1	5,4	5,4	1,3	1,5
	Co-operation			**Co-operation**	
Method	**ACO**	**GA**	**PSO**	**GA**	**PSO**
NO_{min}	1830	3375	3375	1750	1400
$NO_{max/min}$	1,3	1,3	2,0	4,0	6,1

V. OPERATING RESULTS FOR CHP SYSTEM

The operating results exemplarily presented in the following were achieved by application of the described management functionalities to the simulation of a commercially available gas motor driven micro CHP system according to Fig. 1 with the modeling tool as described in [2]. Measured electrical and thermal consumption curves of a one-family house over more than one complete year in 15 min steps were available from [6], and time variable electricity tariffs as well as a constant gas tariff were applied. All operational constraints as mentioned in section II. were considered by the management.

In Fig. 7 the plant operation during one sample day, procured by the management system in real time, is shown. At first glance a coherency of electrical consumption and operation of the CHP unit cannot be recognized. But if the electricity tariffs for both delivery and feed-in – also shown in Fig. 7 – are considered, too, there is more evidence: generally the plant is operated if there is a noticeable local electricity consumption forecast during times of high tariff for electricity drawn from the public system. The thermal storage – see Fig. 1 – decouples electrical and thermal consumption; in the example shown here this permits the energy management to shut down the CHP unit at night time and in the afternoon, Fig. 7. The cost factor for each start-up of the unit and the limitation of set-point changes which are considered by the management as well lead to a sparing plant operation (few operation cycles and power changes) which can also be recognized in Fig. 7.

The *load management* was released for several electro-thermal devices – Table I – with an admitted operation time shift by max. ± 24 h in this particular example; the effect can immediately be noticed in Fig. 7 by comparison of the originally forecasted and the actually managed electrical load curves. The load management essentially effects that

- the flexible loads are preferentially operated at times of low tariff for electricity drawn from the public system (Ia in Fig. 7) or when the CHP unit is running (Ib and Ic) and
- load peaks are significantly reduced (IIa,b in Fig. 7).

A *monetary comparison* of different CHP operation modes is finally shown in Table III; in the right column the total operation costs of the system over one sample winter week are entered. It is apparent that CHP operation with the energy management enabled is saving approximately 17% of cost compared to no CHP operation (that is, complete electricity demand covered by external grid and thermal demand covered by peak boiler). Having the load management released for one day (see above) is saving another 6%. In contrast, blindfold CHP operation at either nominal or minimal constant power is even more expensive than no CHP operation at all.

TABLE III
COMPARISON OF ENERGY COSTS IN DIFFERENT OPERATIONAL MODES.

CHP operation mode	Weekly cost [€]
Constant nominal power	139,16
Constant minimal power	54,14
No CHP operation	53,22
CHP with energy management only	44,00
CHP with energy and load management	41,07

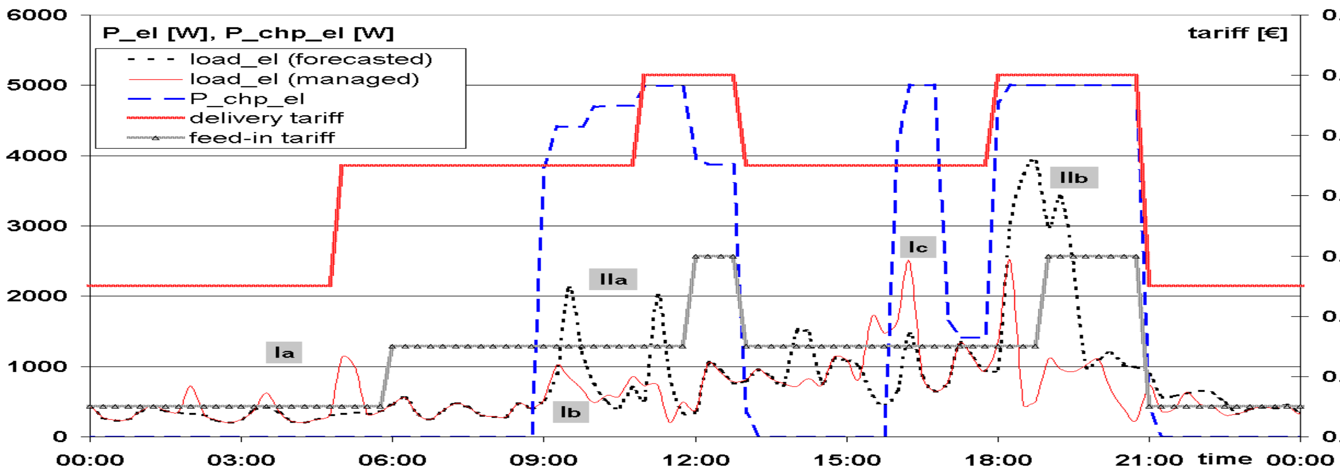

Fig. 7 Plant operation over one sample day.

VI. Conclusion and Outlook

The developed and described management system for micro CHP plants based on CI techniques proved excellent performance in various scenarios simulated under operational realism on a PC as exemplarily shown: the (economic) efficiency of system operation is significantly enhanced and flexible adaptation to given and changing user habits is afforded. Practical application of the approach in a real CHP plant appears feasible by

- relocation of the management software from PC to a micro-controller based control box installed at the site of the CHP plant;
- connection of controllable electrical devices (first models providing an external interface are already available in the upper market segment of, e.g., washing machines) by domestic bus, (W)LAN or power line communication, Fig. 8.

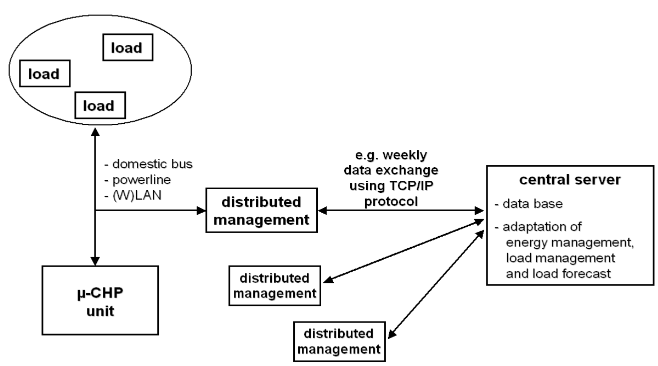

Fig. 8 Integration of domestic CHP plant control.

In this context it appears also possible to couple the local control of the domestic CHP plant – for instance via the internet – with a central server which then could undertake the system training and adaptation remotely as external service delivery, Fig. 8. This would disburden the local control from these tasks – admitting to implement it on a simpler and less expensive type of controller – and would also give the perspective to integrate the operation of many micro CHP systems into superior central control as a virtual power plant.

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