

Using heat demand prediction to optimise Virtual Power Plant production capacity

Vincent Bakker, Albert Molderink, Johann L. Hurink and Gerard J.M. Smit
University of Twente, Department of EEMCS
P.O. Box 217, 7500 AE Enschede, The Netherlands

Abstract—In the coming decade a strong trend towards distributed electricity generation (micro-generation) is expected. Micro-generators are small appliances that generate electricity (and heat) at the kilowatt level, which allows them to be installed in households. By combining a group of micro-generators, a Virtual Power Plant can be formed. The electricity market/network requires a VPP control system to be fast, scalable and reliable. It should be able to adjust the production quickly, handle in the order of millions of micro-generators and it should ensure the required production is really produced by the fleet of micro-generators.

When using micro Combined Heat and Power micro-generators, the electricity production is determined by heat demand. In this paper we propose a VPP control system design using learning systems to maximise the economical benefits of the microCHP appliances. Furthermore, ways to test our design are described.

Keywords: Artificial Neural Networks, Weather Sensitive Short-term Load Forecasting, Distributed Generation, Algorithm design.

I. INTRODUCTION

Traditionally, most western countries have supplied domestic electricity demand through generation in large central power stations, with subsequent transmission and distribution through networks. The generation efficiency of the power stations varies between around 35% for older coal stations to over 50% for modern combined cycle stations, averaging to about 39%. When transmission and distribution losses are considered, the average overall efficiency of the system drops to 35% [5].

In the coming decade a strong trend towards distributed electricity generation (micro-generation e.g. solar cells, micro Combined Heat and Power (microCHP) appliances, micro gas turbines, micro-windmills, heat exchangers, etc.) is expected.

A microCHP appliance is a system that consumes natural gas and produces heat and — as a by-product during the heat production — electricity. It can generate electricity at the kilowatt level which will allow these units to be installed in an individual home. They can be connected directly to the domestic heating and electrical systems, which leads to a very high

efficiency (up to 90%) in usage of primary energy. The heat is used for the heat demand in the home such as central heating, showering, hot water taps etc. The electricity can be used in the home or, when not needed, be exported to the electricity distribution network. It is expected that microCHP appliances will replace the current high efficiency boilers [8]. This will increase the amount of microCHP appliances on the grid in the near future.

In case of a microCHP, adding a heat buffer (hot water tank) decouples the demand and production of heat. This gives some flexibility in the electricity production, allowing the production of electricity on more beneficial periods. For example, we may fill the hot water tank when people get home from work during the evening peak. The hot water can be used the next morning for showering, while the produced electricity can be used by the appliances switched on when people get home.

When the number of microCHP appliances becomes high enough, generators can be grouped together and become a Virtual Power Plant (VPP). By controlling and smart scheduling such a fleet of generators a Virtual Power Plant may replace a conventional (less-efficient) power plant. Using a Virtual Power Plant instead of a conventional one will result in a significant reduction in costs and CO₂ emission due to a more optimal use of primary energy sources.

Another use of the Virtual Power Plant is to use it for balancing. Electricity networks always have to be in balance. There cannot be more demand than production and it is impossible to dump electricity. In order to cope with this problem, in case of the Dutch electricity market, suppliers (producers) and consumers (retailers) of electricity have to specify one day in advance what their electricity production/demand is going to be for each hour of the day. Every deviation from this specification will result in an imbalance. All deviations have to be compensated elsewhere in the network, which is controlled by a central watchdog. The causer of the imbalance is penalised for this imbalance.

To minimise the penalties given by the central watchdog, it is useful for a player on the electricity market to have some production capacity which can be

controlled in real time. This way, when a deviation is detected on time, you can produce your own balancing power to minimise the mismatch.

Conventional power plants have a quite slow response time. Especially (old) coal station need in the order of a quarter of an hour or more to alter their output. This is too slow to use for balancing.

Retailers (buyers on the electricity market) cannot even use a power plant to minimise the mismatch because they can only buy from the market. The only way to compensate a mismatch is to change the demand (of their consumers). However, the demand of consumers is impossible to control.

When a player on the market has control over a Virtual Power Plant, it can use the VPP to reduce the electricity demand by producing electricity locally. However, in practice only a retailer will have control over a fleet, because it is very unlikely a producer will have a contract with individual households.

The start up time of a microCHP appliance is within a couple of minutes and thus very short. When the electricity is produced in-home, it does not have to be transported to the household and thus not bought on the electricity market. However, for such an approach, central real-time control of the fleet of microCHPs is required. The fleet may consist of hundreds of thousands or even millions of households, which is difficult to control. Controllability is thus a key success factor in such a system.

One import parameter in deciding which microCHP to use for electricity production is the availability of microCHPs for production. When a household has no space left in its heat buffer, the microCHP cannot start since it cannot get rid of the heat. The central Virtual Power Plant control has to know the production capacity of each household to decide which microCHP to switch on when. The production capacity of the Virtual Power Plant is thus dependant on the production capacity of the fleet. As a consequence, to use a Virtual Power Plant, the production capacity of the fleet has to be predicted at reasonable accuracy. This will ensure the promised production capacity is really available. In this paper, we present a system design which is able to control a large fleet of microCHPs.

In the following section, we start by begin a global overview of the control system. In Section III, we describe a learning system to help maximising the controllability of the system. In Section IV the approach of testing our system is described. We close this paper with the conclusions.

II. SYSTEM OVERVIEW

Our proposed system consist of two parts: a global scheduler and a local control system (see Figure 1). The global scheduler (GS) is placed at the energy

supplier and controls all local systems. The local control system (LCS) is located at each households and controls the microCHP.

A. Global system

The purpose of the global scheduler (depicted left in Figure 1) is to give the energy company control over the fleet. It should co-operate with the already available management system of the energy company in order to gather information about the required electricity production of the VPP (and thus the fleet). When the required production is known, the system will search for a schedule of microCHPs start- and stop times which optimally matches this production requirement. It will then send the LCS their schedule, so they know when to start- and stop their microCHP.

Although the basic concept of this approach looks simple, multiple problems and limitations have to be addressed. Like stated before, the fleet can grow to a size of millions of households. Bi-directional communication with such a fleet will result in serious bandwidth problems. Therefore it is important to minimise communication and use an optimised infrastructure [3].

Scheduling such a large fleet can also result in serious computational problems. Finding an optimal solution using information about all LCSs would require a lot of computation power, which might not even be available. To make the system more scalable, it is preferable to do as much processing as possible on the LCSs.

Another limitation in the scheduling are the locations of the microCHPs. Electricity is transported from power station to different adjacent areas. Dependant on the area, different voltage levels are used to minimise transport losses. Nearby the end-points (households and industrial area's), the electricity is transformed into the lower voltage levels we obtain from our sockets. To minimise wearing of the transformers, it is preferable to let them transform in only one direction. In other words, it is undesirable to transport electricity produced in one neighbourhood (via microCHPs) to another one via a high-voltage link. For the global scheduler this adds a soft location constraint. It should only enable microCHPs at the locations where the electricity is required.

One of the biggest problems is to determine the production capacity of the fleet. Like stated before, electricity production is coupled and limited by the heat demand of each household. In our approach, we let the LCSs determine its electricity production capacity using a learning system. It then communicates this to the global scheduler, which is then able to make a schedule using the production capacity information about the fleet.

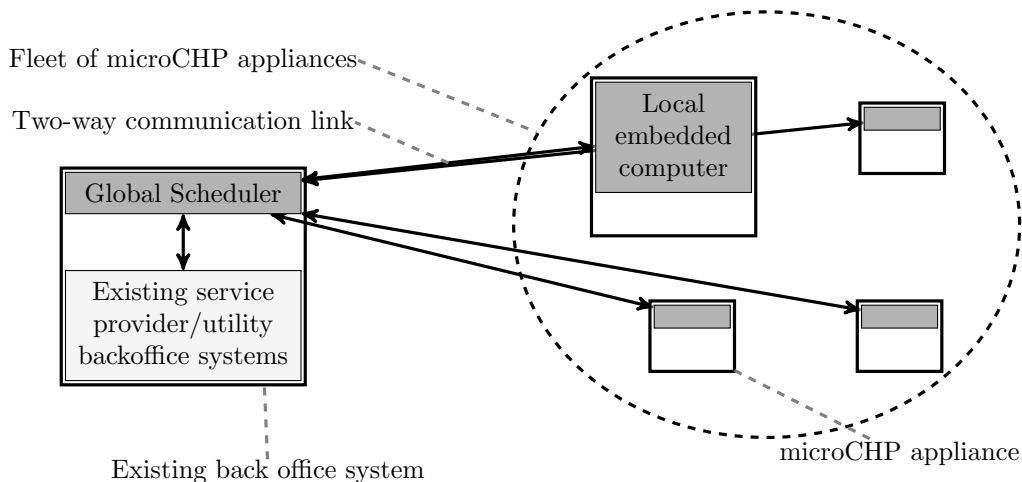


Fig. 1. System overview

B. Local system

The local control system placed in the households is the mediator between the requests of the global controller and the required (heat) comfort of the household. It should obey the request of the global scheduler as much as possible, but without any loss of comfort for the residents. This means it must keep track of the heat level available in the tank. When the level in the tank gets below a certain level, it might be possible the residents cannot get as much heat as they request due to limited heat production capacity of the microCHP. Therefore, the microCHP has to start, whether it is on a beneficial period or not. The level in the heat buffer and the heat demand determines the run-time of the microCHP. When a heat buffer is empty, the microCHP can run for a long time to fill the buffer. Due to wearing of the microCHP, it is desirable to minimise start-ups and thus let the microCHP run for longer time-periods.

The goal of the local controller is to maximise electricity production on beneficial periods, considering the limitations of the heat buffer, wearing and the comfort of the residents. When we only consider the current level of the heat buffer, we can easily optimise for long run-periods by filling the tank and letting it empty as much as possible. This will improve the electricity production, however maybe on less beneficial periods.

When we can predict the heat demand of the household, we know when heat is required and can predict the production capacity of the microCHP. When we inform the global scheduler about our production capacity, the global scheduler can calculate an overall schedule which is most beneficial. When our predictions are good, we can optimally control the microCHP and hopefully come to a global optimum for our electricity production and thus electricity costs

for the fleet. A good heat demand prediction is thus key in our approach.

III. LEARNING SYSTEM

Purpose of the LCS is to maximise (economical) benefit of the microCHP. For this, the LCS will be a learning system that can learn the heat demand behaviour pattern of the residents to accurately determine the electricity production capacity for the whole day. In our approach, we choose to let each LCS determine its own households heat demand. When each LCS predicts its own heat demand, the overall systems performance will increase. First of all, the LCS can use local information to improve its own prediction. This means that each individual prediction can be better, thus the global prediction of the production will improve. Furthermore, when all processing is done locally, the global scheduler is released from this task. This improves scalability.

Heat demand is determined by multiple factors like weather, the type of house, the insulation of the house, the type of family living in the house, etc. Furthermore, behaviour of the residents has a big influence and is always difficult to predict. To predict data with some noise and an unknown relation, neural networks are commonly used. Neural network techniques have already been used for electricity load prediction for big area's [4], [1]. Different in our approach is that we want to predict heat demand for individual households instead of electricity load for a whole area.

In our approach, we use three input groups for our neural networks. For influences of the weather, we use temperatures as an input. For each hour of the day, the forecasted temperature is used as input.

Factors like the type of house, insulation, type of family are more or less fixed for a longer period and

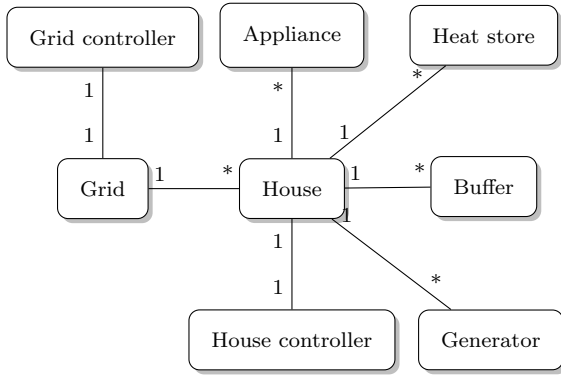


Fig. 2. Simulator overview

thus not used as input. The learning system should be able to learn these pattern.

To cope with the behaviour of the residents, we use two techniques. First, we assume people have a more or less fixed/repeating pattern. For example, when people have jobs, they get up quite regularly every morning, take a shower and go to work. However, during weekends, they might sleep late and stay at home. To learn the behaviour of a certain weekday, we use historical heat demand data. The data of the same (week)day one week earlier and the data the day before is used as input. To handle the different regular pattern on the different weekdays, we use seven different networks, one for each weekday.

In total you get seven networks, one for each weekday. Each network has the temperatures and earlier heat demand as input.

In [2] we have shown a good network structure to predict individual heat demand. Although the prediction still is not perfect, it already shows promising results.

IV. APPROACH

Because we are able to roughly predict the heat demand, we want to know the improvements of the system controllability using our new prediction scheme. Since we don't have a million of microCHPs installed, we have to simulate the effects of our new prediction scheme. Using the simulator described in [7], we want to embed our local controller into the simulation model.

The purpose of the simulator is to simulate multiple households within a grid. With the simulator, we are able to model energy (electricity and gas/heat) flows of a neighbourhood. Central in this design is a household, modelled in Figure 2 as a house.

A house consist of multiple energy consuming and producing objects:

Appliance Appliances entities model real-life appliances like a tv, computer, lightning and central heating. In general, these are electricity/heat consuming products. A house can have zero or more appliances.

Generators Generators are appliances which produce and/or transform energy into electricity and heat. For example microCHP appliances convert gas into heat and electricity. Other generators as micro-wind turbines or heat pumps also are categorised as generators. A house can have zero or more generators.

Buffers Buffers are used to (temporarily) store electricity. Currently, a battery is modelled with the KiBaM model [6]. A house can have zero or more buffers.

Heat stores Equivalent to storing electricity can heat be stored as well. In our simulation we use a Gledhill heat storage. This buffer can be used for both heating as hot tap water. A house can have zero or more heat stores.

House controller The house controller is used to control all entities in the house. In our case, this is the controller that will control the microCHP. A house requires at least one house controller.

Grid controller A controller that can communicate with all house controller. In our case is this the global scheduler. A grid requires at least one grid controller.

Energy (in the form of heat and electricity) can flow between entities. All flows are stored in the simulation results and can be processed later for plotting and/or manipulation.

To analyse the impact of (improvements of) our prediction, we use special versions of the grid controller and house controller. In the grid controller we will implement the scheduler. Here we can test different schedulers, optimisations, communication protocols and control strategies. This enables us to analyse the performance, controllability and scalability of the fleet control.

This house controller will incorporate the heat demand predictor. Using this controller we can analyse the impact of different learning strategies. The first strategies/changes we want to test are

- *Learn once vs continuous learning* When using neural networks, we can train the network once and reuse it many times. Using this approach requires less computational power on the LCSs, but makes the system less flexible. When the LCS is trained to learn a certain behaviour, it might be possible that the system is unable to detect changes in seasons. Using continuous learning the system can stay open for changes in the environment. Another interesting question is how much training is required to come to reasonable result.
- *Add more inputs* We want to improve our prediction. We hope to achieve this by adding more relevant input to our system. We want to add wind speed and illumination factor as weather inputs. Furthermore we want to add thermostat programs as an extra input group.

To measure our improvements, we need an performance indicator which we can easily compare. In [2], we used two error measurements. When predicting the production capacity, and thus the heat demand, two factors are important:

When The most important factor is when electricity can be produced. Two indicate the performance of our (trained) neural network, we determine the mean squared error on the average heat profile. The average heat profile is determined by calculating the average heat demand for each hour of the day over a longer period. The mean squared error between averages of the real heat demand and the predicted heat demand is then used.

How much Another important factor is the amount of electricity that can be produced. Although this is already partly covered in the first indicator, we use another performance indicator to handle profile shifts. If for example people get up an hour later, the heat profile might shift one hour. This would result in a poor performance, while the prediction might only be off one hour. Therefore, we determine the total heat demand for each day. The mean square error between the totals of the real heat demand and predicted heat demand is then used.

Different network sizes, network structures and inputs give different errors. As a result, the two performance indicators are different in order which makes them impossible to compare. Therefore, we normalise the indicators to make them comparable. Normalisation shifts and scales the errors such that their range

is between 0 and 1. After normalisation, we determine the performance of a prediction scheme by adding the two errors. Because the profile error is more important than the heat total error, we give the profile error and weight of 0.75 and the total error one of 0.25.

New prediction schemes might introduce different error sizes, which will result in other scaling factors for normalisation. This is unwanted, since we want to maintain one single performance indicator to measure improvements.

In order to compare performance indicators of other prediction strategies, we store all the results of previous approaches. New results are added to the results set. Every time new results are added, the whole set of results is normalised. This will ensure a fair comparison between different approaches.

V. CONCLUSION

We have proposed an control design system to control a large fleet of microCHP appliances. Embedding this control system design in the simulator, we are able to research the impact of the large fleet on the grid. We can use different schedulers, optimisations, communication protocols and control strategies.

Furthermore, we are able to model the impacts of improvements of the global scheduler and local control systems.

REFERENCES

- [1] A.-U. Asar and J.R. McDonald. A specification of neural network applications in the load forecasting problem. *Control Systems Technology, IEEE Transactions on*, 2(2):135–141, Jun 1994.
- [2] V. Bakker, A. Molderink, J. L. Hurink, and G. J. M. Smit. Domestic heat demand prediction using neural networks. In *Proceedings of Nineteenth International Conference on Systems Engineering, Las Vegas, Nevada, USA*, pages 189–194, Los Alamitos, August 2008. IEEE Computer Society Press.
- [3] M.G.C. Bosman, V. Bakker, A. Molderink, J. L. Hurink, and G. J. M. Smit. Load control in low voltage level of the electricity grid using μ chp appliances. In *19th Annual Workshop on Circuits, Veldhoven, The Netherlands*, Proceedings of the STW programs 2008, Utrecht, November 2008.
- [4] S.-T. Chen, D.C. Yu, and A.R. Moghaddamjo. Weather sensitive short-term load forecasting using nonfully connected artificial neural network. *Power Systems, IEEE Transactions on*, 7(3):1098–1105, Aug 1992.
- [5] Arjen de Jong, Ernst Jan Bakker, Jan Dam, and Hans van Wolveren. Technisch energie- en CO₂-besparingspotentieel van micro-WKK in Nederland (2010-2030). Technical report, Werkgroep Decentraal, July 2006.
- [6] J.F. Manwell and J.G. McGowan. Lead acid battery storage model for hybrid energy systems. *Solar Energy*, 50(5):399–405, 1993.
- [7] A. Molderink, V Bakker, J.L. Hurink, and G.J.M. Smit. Simulation of the effect of introducing micro-generation, energy buffers and accompanied optimization algorithms on the energy efficiency. In *19th Annual Workshop on Circuits, Veldhoven, The Netherlands*, Proceedings of the STW programs 2008, Utrecht, November 2008.
- [8] United States Department of Energy. The micro-CHP technologies roadmap. *Results of the Micro-CHP Technologies Roadmap Workshop*, December 2003.