

Production planning in a Virtual Power Plant

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Abstract—Distributed electricity generation is increasingly applied in the electricity grid. This generation can be more energy efficient than conventional generation; however, a large scale introduction of distributed generators implies possible instability in the grid. A Virtual Power Plant (VPP) deals with this problem by controlling the distributed generators in such a way, that the complete group acts like a normal power plant. All generators need to be steered individually, which makes the control more complex than the control of a normal power plant.

The VPP we describe in this paper consists of a large number of microCHP (Combined Heat and Power) appliances. As the produced heat of such a microCHP is completely consumed locally, the production opportunities of the distributed generators are determined by the local heat demand. This heat demand can be predicted one day ahead, see e.g. [2]. A feasible schedule of a single generator ensures that the heat demand is supplied in time. The objective is to generate at the most profitable times.

In [3] a dynamic programming formulation is described which schedules one generator optimally (for local objectives) within reasonable time. We extend this method to the case of a Virtual Power Plant. The costs of the basic state changes in the dynamic programming formulation of the individual generators are altered, according to the objective of the VPP, which is to generate a predefined electricity pattern for a full day. Starting from the point of view of local objectives of individual generators the global objective of the VPP is gradually (iteratively) incorporated. This results in a production planning that can be done in reasonable time, compared to the planning horizon.

Keywords: distributed generation, scheduling

I. INTRODUCTION

Many types of small-scale electricity generators are introduced in the electricity network. Examples are photovoltaic cells, wind turbines and Combined Heat and Power (CHP) appliances. The size of these electricity generators may vary from small, household-scale appliances to larger, neighbourhood-scale installations. Compared to large fossil-fuel or nuclear power plants these generators are at micro- to mini-level in the field of electricity generators.

A single micro-generator has limited influence on the electricity grid; it cannot destabilize the grid. However, very large amounts of such generators can have impact on the grid; once they simultaneously decide to deliver electricity to the grid this can lead to grid instability. Although individual micro-generators seem harmless, a large-scale introduction of them needs to be controlled and regulated.

The paper is organized as follows. In Section II the concept of a Virtual Power Plant (VPP) is introduced. Section III gives our approach to the production planning of a VPP. A distributed scheduling method for this planning problem is

proposed in Section IV. The paper ends with results in Section V and conclusions and recommendations in Section VI.

II. PRODUCTION PLANNING OF A VIRTUAL POWER PLANT

A Virtual Power Plant (VPP) combines many small electricity generating appliances into one large, virtual and controllable power plant. This VPP is comparable to a normal power plant in production size. However, the comparison ends here. Due to the geographical distribution of generators, the physical electricity production from a VPP has a complete other dimension than the production from a large generator that is located at a single site. The wide-spread distribution of generators asks for a well-controlled generation method. Instead of steering one large generator all generators in a VPP can be individually steered. These generators must be scheduled to generate at different times of the day in such a way, that the combined electricity production of all generators matches the production of a normal power plant. Although the steering of a VPP is more complex than the steering of a normal power plant, the use of large amounts of generators with small capacity (and limited runtime) results in more flexibility in the production of electricity. This means that a VPP should be better capable of adapting its production, in the scenario of fast changing differences between demand and supply (which is likely in case more renewable resources as wind, sun or water are used for electricity production). Control methods for a VPP may focus on two different elements:

- **offline methods**

The planning of the production of individual generators for a longer period (e.g. 24 hours), resulting in an aggregated production that matches the production of a normal power plant;

- **online methods**

The need for online (re)scheduling methods for the production of individual generators, due to fast changing demands or deviating properties of the individual generator (e.g. changes in actual runtime or actual power output).

In this work, we focus on the first element; in particular, we focus on the production planning for one day ahead.

A. Problem description

We assume that the VPP has decided to produce a certain amount of electricity for the next 24 hours. This decision can be based on predictions of energy market prices, energy consumption in the market and production opportunities of the distributed generators. Once a decision for a particular

production scheme is made, this scheme must be followed, especially if the VPP acts on the energy market. To guarantee stability in the electricity grid, the VPP is supposed to deliver the specified amounts; otherwise severe price penalties are given. So, the problem is to match the decided, and thus fixed, production pattern given by the scheme. The way to do this is by planning the production runs of the distributed generators.

The problem now can be reduced to the assignment of production runs to different generators, subject to the global requirement of matching a given production pattern and to the local requirements for the availability of ready-to-produce generators at different times of the day.

The VPP production scheme is assumed to be known to a central entity within the VPP. The problem of using the production opportunities of the distributed generators to assign concrete production runs to specific times on the day, can be challenged in many ways. For example, the central entity itself may compute a schedule for all generators, based on production opportunity information from the generators. However, this task of globally matching production and demand is known to be NP-complete in the strong sense [4]. Therefore, we propose a method to distribute the scheduling of production runs.

In this work the focus is on microCHP (Combined Heat and Power) appliances as distributed generators. This type of generator generates heat and electricity simultaneously and on a household scale. Due to the use of a heat buffer, the electricity generation in a house can be partly decoupled from the household's heat demand. In combination with a heat demand prediction of the house this gives the scheduling freedom to plan the runs of the generator.

III. PROPOSED APPROACH

A VPP can be organized in different ways. For example, in [6] a multiagent approach is presented; the results of field tests are shown in [5]. For an extended overview of literature on distributed energy markets we refer to [8]. Below we introduce our own approach to organize a VPP.

The production opportunities of the individual microCHP appliances (which we use in our VPP) are limited by the heat demand, since the basic use of the generator is to supply heat to the house. In our case this means that a prediction of the heat demand of the next day determines the available run hours of the generator. Based on the predicted heat demand profile and the heat level of the heat buffer at the start of the planning horizon, the total amount of potential (maximal) production and the total amount of necessary (minimal) production are known. Note that potential production cannot be utilized at each moment in time; the runs are subject to other constraints and, therefore, production must be spread over the day according to these constraints (e.g. the spread heat demand over the day or the limited maximum heat production per time interval and the limitations of the heat buffer that is used). In a VPP the sum of the potential production of all generators gives the VPP production capacity. This potential also cannot be utilized at free will, for similar reasons as in the case of a single house. Based on the potential production a planning can be made for

the production within a house, but also for a group of houses. However, the potential production is based on predictions and may not be accurate anymore when the system is running. For this reason, the individual generators in the VPP need to be realtime controlled.

Our approach consists of three steps:

- **Prediction**

In the first step a prediction of the heat demand must be done for each house. This local information is necessary to decide the local production potential of the micro-generators. A neural network approach is used for this prediction [2].

- **Planning**

In the second step the local production potential is assigned to actual runs, based on local (domestic) and global (VPP) objectives. The planning process is known to be NP-complete in the strong sense [4]. Therefore, heuristics, as proposed in this work, need to be developed.

- **Realtime control**

Whereas the first two steps can be done offline, the microgenerator needs to be realtime (online) controlled too. In this realtime control the runs of individual micro-generators need to be rescheduled, if the reality differs too much from the prediction. A generic method for realtime control can be found in [7].

A. Structure

In this subsection we introduce the structure that is used in our approach. This structure forms the basis for the planning method in Section IV. We use a hierarchical structure for planning the runs. For scalability reasons the method divides the distributed generators into groups of comparable and limited size. The group size should not increase with an increasing number of generators, since the method iteratively finds a schedule (see Section IV). When the number of generators per group would increase, the method could use more iterations to find a good match. However, the number of iterations, that the scheduling method uses to match the production to the demand, needs to be limited; otherwise the process of scheduling takes too much time. For this reason we limit the amount of generators per group. A hierarchical structure facilitates the division into groups of limited size by the use of a number of levels, corresponding to the total number of generators.

Algorithm 1 gives the creation of the hierarchical structure. The scheduling process requires the structure to be capable of handling increasing amounts of generators. Therefore the generators are divided into groups of limited maximum size y . Based on the number of generators different levels are introduced at which groups of lower levels are aggregated in higher order groups, again of maximum size y . The lowest level consists of the generators. The level above divides these generators over the minimum possible number of groups (based on y). In the next levels these groups are included in larger groups (consisting of maximally y sub groups), until there is only one group left in the highest level. The algorithm has as input the lowest level (all generators) and returns a

structure H consisting of all higher order levels H_1 up to and including H_L .

An example is shown in Figure 1. In this example a set of 14 generators is used to create a structure with a maximum group size of 3.

The structure has the advantage that there is a difference of at most one sub group in the group division at each level. This extra sub group has size smaller or equal to the smallest sub group in the group with the least number of sub groups. This means the imbalance in the structure (measured as the difference in number of generators between largest and smallest branch at level 2) can at most grow to:

$$y^{L-2},$$

compared to the difference it could grow to in case all groups are filled from the left:

$$y^{L-1} - 1.$$

Algorithm 1 Create groups G_i and structure $H = (H_1, \dots, H_L)$ from generator set $X = \{x_1, \dots, x_n\}$ with maximum group size y

Require: $X \neq \emptyset, y \geq 1$

Ensure: $\bigcup G_i = X$, $G_i \cap G_j = \emptyset$ ($i \neq j$) and $|G_i| \leq y$

$L \leftarrow \lceil y \log |X| \rceil$

$N \leftarrow \lceil \frac{|X|}{y} \rceil$

for $i = 1$ to N **do**

$G_i \leftarrow \emptyset$

$j \leftarrow i$

while $j \leq n$ **do**

$G_i \leftarrow G_i \cup x_j$

$j \leftarrow j + N$

end while

$H_{L,i} \leftarrow G_i$

end for

$H_L \leftarrow \{H_{L,1}, \dots, H_{L,N}\}$

$k \leftarrow L$

while $k > 1$ **do**

$k \leftarrow k - 1$

for $i = 1$ to $\lceil \frac{N}{y} \rceil$ **do**

$H_{k,i} \leftarrow \emptyset$

$j \leftarrow i$

while $j \leq N$ **do**

$H_{k,i} \leftarrow H_{k,i} \cup H_{k+1,j}$

$j \leftarrow j + \lceil \frac{N}{y} \rceil$

end while

end for

$N \leftarrow \lceil \frac{N}{y} \rceil$

$H_k \leftarrow \{H_{k,1}, \dots, H_{k,N}\}$

end while

$H \leftarrow (H_1, \dots, H_L)$

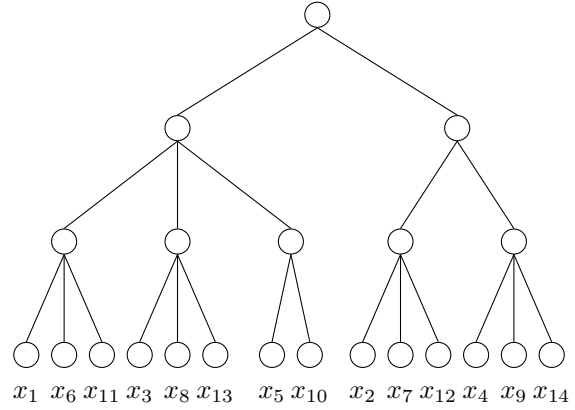


Fig. 1. An example of the hierarchical structure, produced by algorithm 1

we give an overview of the way we plan the generator runs of a single generator in Section IV-A, using a Dynamic Programming approach. Then, this approach is extended in Section IV-B to a form that can be used to solve the global (VPP) production planning problem. The notion of distributed DPs leads to the idea for an *approximation* heuristic. Section IV-C completes this method, by introducing iterative rescheduling methods to match the resulting global schedule to the fixed production pattern scheme. In this process the communication structure, given in Section III-A, is used.

A. Assignment of production runs based on heat demand predictions: a Dynamic Programming approach

In [3] a Dynamic Programming formulation (DP) of the planning problem in a single house is proposed. It divides the planning horizon T in N intervals of equal size and introduces a state tuple (A, B, C) to describe the situation in each interval. So, each interval has a set of states (A, B, C) . A denotes the number of intervals that the state of the microCHP (on or off) is unchanged until the start of the current interval (positive values indicating that the microCHP is running and negative values indicating that the microCHP is off). B is the total number of intervals the microCHP has been running for the whole planning period until the current interval and C is the number of runs of the microCHP which have already been finished. For each interval $j \in T$ and state (A, B, C) we define the cost function $F_j(A, B, C)$, which aims at minimizing the costs from interval j until the end of the planning horizon, N , assuming that the current situation is characterized by the state (A, B, C) . The costs between two consecutive states in sequential intervals can vary for different intervals and states. These costs represent the objective function (e.g. the inverse price on the electricity market [1]); on the other hand, the hard constraints on heat comfort, minimum runtime and minimum offtime can be deducted from the state description and are represented by costs of ∞ . The total amount of generated heat can be deducted from the combination of A , B and C . Since the demand of each time period and the start level of the heat buffer are known, we can deduce for each state in each time period whether lower and upper levels of the heat buffer are exceeded or not. In case there is a violation, a penalty of ∞ is

IV. DISTRIBUTED SCHEDULING METHOD

In this section we propose a distributed method to create a schedule for the production runs of distributed generators. First

given to the corresponding state. The minimum runtime and offtime constraints now can be taken into account by looking at the value of A and penalizing ‘wrong’ state changes in the DP with a value of ∞ .

The main challenge in the creation of a DP is to limit the number of states in the description. In this DP formulation a selection of states is formed for (the start of) each interval, based on the available states in the previous interval and the binary decision to switch the microCHP on ($x = 1$) or off ($x = 0$) in the previous interval. In this way the state space grows exponentially with the intervals (2 new states for each previous state). However, many states are visited multiple times from different previous states and the requirement to offer guaranteed heat comfort excludes many states. So, in practice the number of states could be limited sufficiently. Figure 2 shows an example for two state changes that are possible from a certain state $(3, 13, 2)$. In the given case, switching the microCHP off ($x_j = 0$) is not possible, either due to minimum runtime constraints ($MR > 3$) or due to heat demand (in this case the lower level is reached at the start of time period j). The decision to leave the microCHP running ($x_j = 1$) has attached costs of 2, based on the relative desire to let the microCHP run in period j .

$$\dots \begin{pmatrix} \dots \\ \dots \\ (3, 13, 2) \\ \dots \\ \dots \end{pmatrix}_{j-1} \begin{matrix} \xrightarrow{(x_j=1)} 2 \\ \xrightarrow{(x_j=0)} \infty \end{matrix} \begin{pmatrix} \dots \\ \dots \\ (4, 14, 2) \\ \dots \\ (-1, 13, 3) \\ \dots \end{pmatrix}_j \dots_{j+1}$$

Fig. 2. State changes from $(3,13,2)$ with corresponding costs

Via a backtracking algorithm the value of $F_0(0, 0, 0)$ can be calculated. The path(s) corresponding to this value give the state tuple changes which correspond to the x_j values.

1) *Properties of the DP:* Since there are $O(N^3)$ state tuples and there are N time periods to evaluate, the dynamic programming approach of the single house model has runtime $O(N^4)$. In practice, the DP approach is a suitable method to solve the problem of scheduling single houses to optimality within reasonable time, when the interval length of the decisions is > 5 minutes. This is indicated by the dashed vertical line in Figure 3. In this figure, the computation time of the DP is plotted against the number of intervals (each of a fixed size) of the scheduling problem for 24 hours. Two cases are used; the first one represents a day in winter, where in case 2 the heat demand is halved (heat demand is an important factor, since this represents the production potential, which is reflected in the total number of states and, thus, in computation times). In the case, when the interval length of the decisions is > 5 minutes, the state space of the DP has an acceptable size and the optimum is found within ± 5 minutes, given by the dashed horizontal line in Figure 3. An interval length of 5 minutes is a good trade-off between precision and data [9], so our choice for the interval lengths is acceptable.

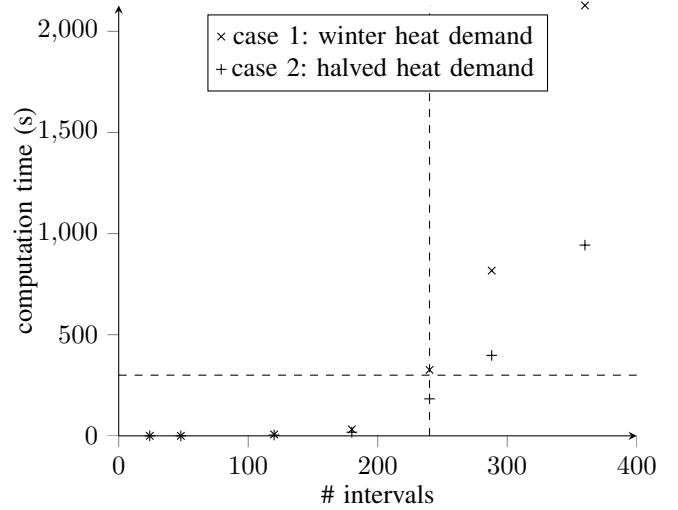


Fig. 3. Computation times for the DP approach for different numbers of intervals

B. Distributed DP

A DP can be a fast method to find an optimal solution for single houses. On the other hand, the problem of scheduling a fleet of houses introduces an extra dimension to the problem. Now, the houses need to cooperate in the sense of electricity generation. Together, they must produce a total electricity pattern that matches a predefined production plan. When this cooperation is applied to the DP formulation the state space explodes, since the DP needs to combine the information of all houses in a single state definition. This DP is not suitable to be used to solve the problem of scheduling a fleet to optimality within reasonable time, if we want to be able to solve instances with similar interval lengths as in the problem of scheduling single houses.

However, the single house DP can still be used in an approximation heuristic. The concept of the single house DP is that it produces an optimal planning for the runs of the generator, where the objective is market price-oriented. Our idea of distributed DP is to match the desired production and the planning of the VPP, by using the local computation capacity of the houses. The local production is still planned from the viewpoint of local comfort and price optimization. However, the globally decided production plan must eventually be matched. This is done by steering the market prices that are used in the local DPs. So, relatively fast local DPs are used in a VPP perspective and steering elements are introduced to rearrange these local schedules.

A central entity within the VPP is located at the top of the hierarchy as in Section III-A. Since the total production plan is known here, the central entity can steer temporary schedules into the right direction. This entity can ask lower level nodes to produce a certain part of the total production plan. The steering goes via artificial costs, which can be interpreted differently by the various end groups or can be surpassed differently by the levels in between. For example, if a node at a certain level has fulfilled its part of the total production plan, it suppresses new artificial cost changes and leaves the substructure unchanged.

Of course it takes several iterations to eventually match the total production plan at the top of the hierarchy with the distributed planning. A detailed description of this iterative steering is given in Section IV-C.

C. Iteratively reassignment of production runs via steering signals

As mentioned before, each group has an entity, which collects the planned runs from the generators and reports back to the central entity. Within the structure, communication takes place between some elements of subsequent levels. We make a distinction between two types of communication:

- the planned production runs, which are the results of local scheduling methods;
- steering signals, which are used as input for the local scheduling problems.

Aggregated production plans are forwarded to higher level entities, whereas steering signals are sent to lower level entities. The idea behind the structure is that at each level different steering signals can be given, such that locally more or less independent adjustments to the generator schedules are made. The balancing properties of the structure play an important role in this, since substructures can be copied with in a similar way, at the same level as well as at different levels. Therefore a generic way of using steering signals can be applied to the method at all levels, which allows substructures to be copied with based on the actual deviations of the local plan and the realisation.

Once this generic way of using steering signals can be shown to need a limited amount of iterations to reach the matching of the underlying substructure, we can apply the method on large scale. In combination with the use of the local matching, we define two ways of choosing steering signals:

• steering 1

In the first steering method, the artificial additional costs that is used in the steering process, decreases linearly with each iteration. This cost is added to the current costs for the state changes, only at state changes where the current planned production of the substructure exceeds the desired production. The idea is that exceeding planned production is rescheduled at other times, by increasing the costs attached to the current states, where the planning exceeds the desired production. The starting value of the artificial costs is in the order of the maximum cost in the original DP and decreases linearly to 0.

• steering 2

The second method uses the same idea of decreasing additional costs as in the first steering method. In addition to this method, each individual DP now only changes its planning, if at least a minimum number of decisions is changed with respect to the previous DP calculation. This is done to introduce a certain threshold for individual houses, before the current production plan is altered.

V. RESULTS

In this section we show the results of our distributed scheduling method. We give the iterative and distributed

production planning of one subgroup. However, due to the balancing properties of the structure, subgroups are comparable and it should be possible to extend the method to a large scale VPP.

The instances of our tests consist of a subgroup of 50 houses. Each house contains a microCHP and a heat buffer of 10 kWh, and has a heat demand of 84 kWh of a winter day. The costs for the state changes are the inverted prices of the APX day ahead market [1]. In Figure 4 the squared mismatch between the fleet production plan and the predefined production pattern is plotted against the number of iterations. The total production potential is divided equally over the intervals and defines the production plan of the VPP. It can

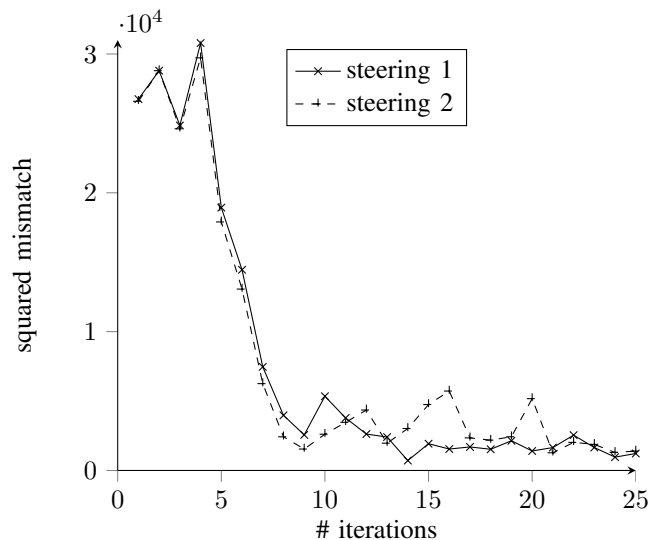


Fig. 4. Squared mismatch between fleet production plan and predefined production pattern

be seen in Figure 4 that the squared mismatch is drastically reduced within 10 iterations. The method overcompensates in some iterations, resulting in alternating improvements and deteriorations. This phenomenon also takes place, when the second steering method is applied. However, the overshooting stabilizes, since decreasing additional costs are used. Only minor differences between the two steering methods can be noticed. The first method seems to perform slightly better than the second method, if a large number of iterations is allowed, since small changes in local production plans are taken into account.

In Figure 5 the objective value (normalized profit on the APX day ahead market) is given. The dashed horizontal line with value 1 represents the optimal (normalized) profit of the 50 houses, when each of these houses uses a DP with only local objectives. The dashed horizontal line with value 0.91 represents the optimal (normalized) profit, when the houses cooperate in a VPP and the total production exactly matches the defined plan. After 10 iterations the objective value stabilizes close to the optimal value of 0.91. This shows that the squared mismatch in Figure 4 after 10 iterations has an acceptable size; this size can be used as a stop reference to decide after how many iterations a substructure has approximated its desired production plan ‘good enough’.

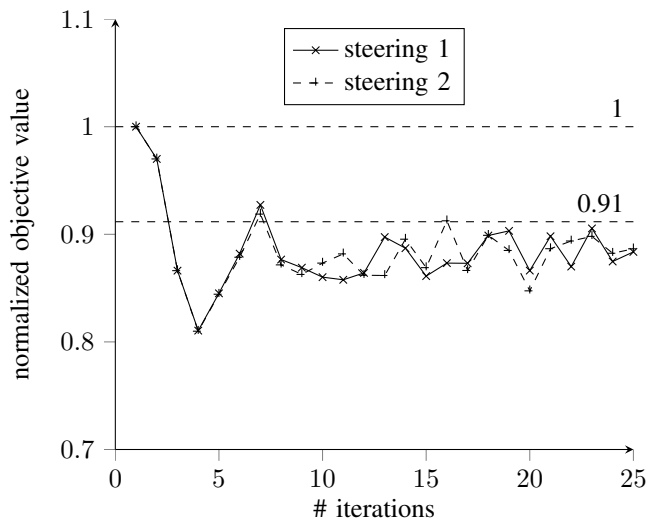


Fig. 5. Objective values

VI. CONCLUSION AND RECOMMENDATION

In this paper we describe a distributed scheduling method to plan the production of a Virtual Power Plant. A balanced communication structure is proposed, in which groups of a fixed maximum size are divided over a minimal number of levels.

From the results in Section V we conclude that the distributed scheduling method for a VPP is possible with a limited number of iterations. Within 10 iterations the method reaches an acceptable approximation of the global optimum.

In future work we want to extend the generic steering method to a large scale implementation. Also, other steering methods can be developed.

VII. ACKNOWLEDGEMENTS

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