Stochastic Unit Commitment Considering Uncertain Wind Production in an Isolated System

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***Abstract*—Wind Energy has become the renewable energy with the highest installed capacity in some European countries mainly due to its advanced technology and to political incentives. In countries such as Spain installed wind capacity amounts 17% of total installed power capacity today. As wind-produced power is enlargening even more, some of its difficulties above all insufficient exactness of one day-ahead wind forecasts and its volatility will complicate the operation of the network even more. Stochastic programming has been proposed as adequate way to handle this uncertainty. In this paper the unit commitment problem is modelled taking into account stochastic wind production. The model is applied to the isolated power system of Gran Canaria. The impact of increasing installed wind capacity and the value of having to deal with the uncertainty of wind in this power system as well as the influence of electric cars in the system operation is analyzed.**

***Index Terms*—Stochastic Unit Commitment, Wind prediction error, Renewable Energies**

I. Introduction

UNCERTAINTY has always been present in electrical power systems for example through possible unit failures and errors in demand prevision. In the last years electricity production by wind has increased significantly and thus as well associated problems regarding uncertainty in wind previsions. Policy makers are willing to support renewables energies and especially wind energy as well in the future. Thus wind energy and its special characteristics have to be taken into account when planning and operating electrical power systems even more. This means on the one hand that investigation in wind prediction has to be enforced to make wind previsions more exact. On the other hand new flexible and fast-reacting generation technologies as well as new types of electricity storage have to be applied to manage the variability of wind electricity production.

To cope with the mentioned uncertainty in wind previsions stochastic optimization is used in this paper to obtain optimal unit commitment decisions taking into account various representative wind production scenarios.

New storage facilities have to be available in the future to cope with large-scale integration of wind energy. One storage facility might be the use of the batteries of plug-in electric cars. These cars represent firstly an extra consumption for the system, since batteries are charged connecting the car to the grid. Secondly they might be used to consume wind overproduction in offpeakhours and to reduce peaks during the day slightly.

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The paper will be structured as follows: A short literature review explaining modelling approaches in chapter II is divided into two parts. In the first part the general modelling of stochastic optimization problems as well as the modelling of stochastic integer problems and the corresponding literature is presented (part II-A). In the second part, II-B, recent works treating uncertain wind production and its impacts on the power system are resumed. The modelling approaches applied to the case of unit commitment with stochastic wind production used in this paper are described in section III. These approaches from section III are applied to the Case of Gran Canaria. Results are displayed in section IV and finally conclusions can be found in section V.

II. Literature Review

A. Stochastic optimization

In stochastic programming optimization problems are treated which contain uncertainty of at least one of the input parameters. This is the opposite of a deterministic optimization model which assumes all input parameters to be certain. Basic textbooks on stochastic optimization can be found with [1], [2] and [3]. In [4] stochastic programming is applied to different application in power systems.

A special case of a stochastic program, stochastic integer programming, has become interesting for various fields such as capacity expansion, energy planning or power system operation. Here either some variables are of integer nature. In many cases these variables might be binary as in the unit commitment case formulated and calculated in this paper in chapters III and IV. This is expressed with a further restriction to the stochastic optimization problem assigning the corresponding decisions variables a solution space in integer numbers.

Special consideration of stochastic problems with integer variables is given to in [5]. The author looks at implications on analysis and algorithm design of including integer variables in stochastic programming. He remarks that the breakdown of convexity and the inclusion of integer variables are the main problems when changing from stochastic linear programming to stochastic integer programming. [6] as well as [7] give an introduction to stochastic integer programming. They survey structural properties of this special type of problem and algorithms to solve them. The authors analyse mainly linear two-stage models with mixed-integer recourse and their multi-stage extensions. Multistage stochastic integer programs are the focus of the paper written by [8] who apart from looking at the dynamic formulation of this problem examine the conditions for optimality and stability of the solutions. A stochastic integer programming is used by [9] to incorporate day-ahead trading of electricity into hydro-thermal unit commitment.

Solution algorithms to stochastic integer programs are treated in many works ([10],[6], [7]). Stochastic programs can get very huge due to their special characteristics with random parameters, so that decomposition might be needed to solve the problem by parts. Special emphasis is given to decomposition algorithms in the thesis of [11] and in [12] a new decomposition framework is elaborated for stochastic optimization of unit commitment. [13] proposes another decomposition methods to solve this kind of problem.

Due to the big size and the quite complex nature of a stochastic programm in comparison to a deterministic one, it is interesting and important to quantify the advantage of using a stochastic optimization program in contrast to solving a series of deterministic optimization programs fixing in each one the random parameter. This can be done with two measures: the Expected Value of Perfect Information (EVPI) and the Value of Stochastic Solution (VSS).

EVPI indicates how much perfect information about the future would be worth. Since decision makers would benefit greatly from having exact future data EVPI expresses their willingness to pay. It is calculated taking into account on the one hand the so-called wait-and-see solution (solving each scenario with a deterministic optimization problem, WS) and on the other hand the solution to the recourse problem (the stochastic optimization problem, RP). The wait-and-see solution is the weighted average of all deterministic optimization problems. These are calculated taking in each deterministic problem one particular realization of the random parameter.

$$WS = E_\xi[min_x z(x,\xi)] \tag{1}$$

E_ξ is the probability of the random parameter which is multiplied with the outcome of the deterministic problem. The recourse problem corresponds to the stochastic problem. EVPI results from the difference $RP - WS$.

The Value of Stochastic Solution can be described as the cost of taking into account random parameters as certain although they comprise uncertainty. It can be determined by the difference of the Expected result of using the Expected Value solution (EEV) with the recourse problem. The expected value solution is simply the deterministic optimization solution using the weighted average of the random parameter. EEV uses this solution to fix the first-stage decisions x in the stochastic problem, that are those variables whose outcome does not depend on the scenario. Furtheron the stochastic problem is only deciding on the other stages. This is expressed in equation 2.

$$EEV = E_\xi[z(\bar{x}^{\bar{\xi}},\xi)] \tag{2}$$

Finally VSS is obtained by subtracting RP from EEV.

B. Optimization of operation with wind production

In the last years the wind prediction and the wind problematic in power systems has attracted the attention of various authors.

Some authors concentrate on changes in generation scheduling in a system with high wind power production. [14], [15] and [16] look at changes in generation scheduling. [17] and [18] model different market environments and analyse the influence of stochastic wind input using a multi-stage stochastic optimization. The case of some countries in Europe and USA is treated in [19]. Other authors work furthermore on the impacts of wind power on security. These issues in systems with significant power generation are canvassed in [20]. Strategies for unit commitment and dispatch for a wind park are examined in [21].

Some authors have dedicated their work to examine how the use of hydro plants can absorb wind over- or underproduction. [22] apply a two-stage optimization model to cope with uncertain electricity production from wind and uncertain market prices. Here, pumped storage units are used to produce in case wind energy is lower than the energy offered in the market. [23] analyse the optimization of the daily operation of a wind-hydro power plant.

A literature review of wind forecasting technology can be found in [24].

III. The modeling approach

Unit Commitment problems try to determine the minimum cost scheduling for power plants to meet the system demand in the short term and to satisfy further restrictions in the power system. Results are startup and shutdown decisions for each generation plant in each hour. Unit commitment problems have received much research since poor management of power resources can turn out very costly.

In the planned optimization problem operational cost are to be minimized taking into account the demand balance constraint, up- and down reserve, minimum and maximum generation capacities, ramping constraints and the logic sequence for the startup and shutdown decisions.

The approach follows the structure of a two-stage stochastic problem. The unit commitment is resolved for each day over a period of one week (see figure 1). This problem could be applied to decisions for the day-ahead market. Unit commitment decisions have to be reached in advance (in Spain until 14 -38 hours in advance), while exact production of generation units is determined later on.

First-stage decisions are the startup and shutdown decisions, arr and par respectively, and thus as well the unit commitment ac. For the second stage three scenarios are considered with the probability $Prob$. Production output over production minimum, $prodt$, of each generation plant and non-served energy pns is determined for a 24-hour timeframe. Depending on the scenario these variables might have different values. Instead of continuing the next day with each of the possible outputs, in this approach, the outcome is sorted randomly. Thus, only one of the possible production outputs (the one marked in figure 1 with a darker rectangle) will be taken

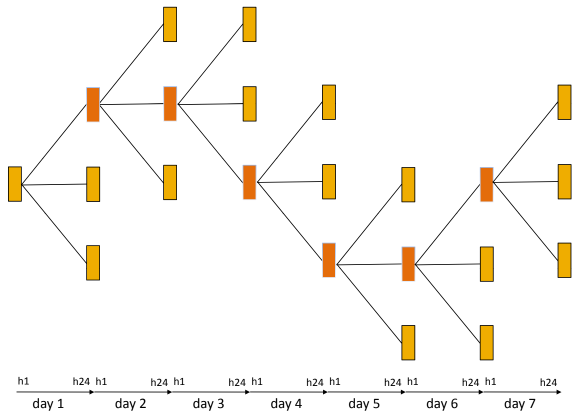

Fig. 1. Scenario tree for the two-stage model

into account as output of previous hours when starting the unit commitment problem for the next day. In the objective function (equation 3) operational cost of the whole power system, $costeop$, is minimized.

$$\begin{aligned} costeop = \textstyle\sum_{p,t}[CosteTF^t ac_p^t \\ +CosteTV^t ProdTMin_p^t ac_p^t \\ +\textstyle\sum_s Prob_s[CosteTV^t prodt_{p,s}^t \\ +CosteArr^t arr_p^t + CostePar^t par_p^t \\ +CostePNSpns_{p,s}]] \end{aligned} \tag{3}$$

In the former equation p considers time periods, t thermal generators and s scenarios. First-stage decisions unit commitment ac, startup decisions arr and shutdown decision par are multiplied with the corresponding cost, namely fixed cost, $CosteTF$, startup costs, $CosteArr$, and shutdown costs, $CostePar$. In the second stage the term including minimum production is active when the generation unit is committed in this period. Then minimum production $ProdTMin$ and production output over minimum $prodt$ are multiplied with variable cost $CosteTV$ for all possible hours and scenarios. Each unit of non-served energy pns will cost $CostePNS$ in each period and scenario.

Constraints are shown in equations 4 to 10:

$$\begin{aligned} Dem_p - ProdI_{p,s} - pns_{p,s} = \\ \textstyle\sum_t ProdTMin_p^t ac_p^t + prodt_{p,s}^t \end{aligned} \tag{4}$$

$$\begin{aligned} \textstyle\sum_t (ProdTMax_p^t - ProdTMin_p^t) ac_p^t - \\ prodt_{p,s}^t \geq RsSub_p \end{aligned} \tag{5}$$

$$\textstyle\sum_t -prodt_{p,s}^t \geq RsBaj_p \tag{6}$$

$$prodt_{p,s}^t \leq (ProdTMax_p^t - ProdTMin_p^t) ac_p^t \tag{7}$$

$$prodt_{p,s}^t - prodt_{p-1,s}^t \leq ProdTSub^t \tag{8}$$

$$prodt_{p-1,s}^t - prodt_{p,s}^t \leq ProdTBaj^t \tag{9}$$

$$ac_p^t - \left\{ \begin{array}{ll} Acp^t & \text{, for p} = 1 \\ ac_{p-1}^t & \text{, for p} \geq 1 \end{array} \right\} = arr_p^t - par_p^t \tag{10}$$

Equation 4 assures that demand is balanced all the time. Demand Dem_p and intermittent wind production $ProdI_{p,s}$ are given parameters. Up- and down-reserve ($RsSub_p$ and $RsBaj_p$) constraints (equations 5 and 6) make sure that a reliability margin is guaranteed for the case of failure of one of the generation plants, errors in wind or demand prevision. In equation 7 maximum generation output of a generation plant $ProdTMax$ limits production over the production minimum $prodt$. Equations 8 and 9 take into account the maximum variation of production output in two consecutive hours. Ramps are decribed with $ProdTSub$ and $ProdTBaj$ for each generation unit. Unit commitment (eq. 10) takes into account the state of each generator in the preceding hour. While unit commitment variables are binary, startup and shutdown decisions can be continuous since equation 10 forces them to take binary values.

Plug-in electric cars might be considered in two senses in this approach: as an additional consumption since they are plugged into the grid to charge their battery. On the other hand they could be used under certain limitations as well as electricity storage to supply a part of the demand in system peaks. Including these considerations into the problem statement means adding two extra terms in the demand balance regarding the consumption and production of an electric car in an hour. As the electricity is stored in the battery an extra balance for the electric car has to be added. This balance must take into account the battery charge level, electricity consumption on the road, electricity consumption to recharge the battery and electricity generation injecting into the grid. Furthermore maximum charge and discharge rate have to be defined similar to the ramping rates in conventional thermal plants and the daily consumption of electric energy during the use of the car.

A. Deterministic Equivalent Problem

To compare the stochastic problem, where uncertainty is taken into account, to the case where future is known with certainty, the deterministic problem formulation has to be considered. Using this formulation the Value of the Stochastic Solution and the Expected Value of Perfect Information mentioned in chapter II on 2 can be determined.

The objective function of the deterministic two-stage problem would be formulated as follows.

$$\begin{aligned} costeop = \textstyle\sum_{p,t}[CosteTF^t ac_p^t + \\ CosteTV^t ProdTMin_p^t ac_p^t + CosteTV^t prodt_p^t + \\ CosteArr^t arr_p^t + CostePar^t par_p^t + \\ CostePNSpns_p] \end{aligned} \tag{11}$$

Production outcome $prodt_p^t$ and non-served energy pns_p will not depend on the scenario.

$$\begin{aligned} Dem_p - ProdI_p - pns_p = \\ \textstyle\sum_t ProdTMin_p^t ac_p^t + prodt_p^t \end{aligned} \tag{12}$$

The demand constraint, equation 12 assumes the given parameters wind production $ProdI_p$ to be scenario-independent.

The rest of constraints stays the same as in equations 5 to 10 but neglecting the scenario dependence of the two decision parameters $prodt_p^t$ and pns_p.

The deterministic problem can assume each of the scenario-dependent parameters as given and certain to calculate the wait-and-see solution, mentioned earlier. In this case three different deterministic problems can be solved, one for each scenario, alternatively an average scenario can be calculated with the average data of the input parameters.

IV. Case Study in Gran Canaria

Gran Canaria is a small island in Spanish territory. It has been chosen as case example since it has a small power system and must cope with demand coverage on its own as it is not interconnected with other grids. Being an island and thus in costal area wind production is becoming an important influencing factor in the generation mix. Over- or underproduction caused by wind cannot be smoothed by importing or exporting electricity, but has to be compensated by local power generation (or demand). Gran Canaria does not have on its disposal a hydro plant which could react to wind production variability as proposed by some authors mentioned in subsection II-B. Since demand management schemes are not yet implemented to a sufficient level, the effects of uncertain wind production on the power system will be examined in this paper. It will be analysed which generation technologies will be replaced by wind.

A. Data and scenarios

Gran Canarias has two generation plants consisting of a total of 20 units. There are four types of generation technology: Combined Cycle, Gas Turbine, Fueloil and Gasoil. Generation cost for these units were taken from [25]. Hourly demand and wind data is based on historic series and scaled down considering the currently installed conventional and wind generation in Gran Canaria. Reserves in the base case make up 3% of demand in each hour. Stochasticity lies in the wind prevision errors. These are deduced from historic prevision errors and taken into account in three different scenarios. Wind prediction errors are usually the bigger the further the prediction reaches into the future. In a 24 hour time frame this error in wind forecasting may grow to as much as 20% [24]. Scenarios with possible wind error correct the wind production in each hour.

In the first scenario prevision errors were high in a negative sense, that means that wind production was foreseen to be higher as it actually was. The second scenario represents variations in a positive sense and the last scenario shows little variations in general.

scenario	wind prediction error	probability
1	–	0.3
2	++	0.4
3	+-	0.3

TABLE I
Scenarios and their probability

A sensitivity analysis is realized changing the installed wind generation going down to the one installed this year , 7% of total generation, to the triple of the installed wind power of today. The calculations to compare stochastic and deterministic approaches are determined with 140 MW of installed wind capacity.

Figure 2 shows the original demand and the demand after substracting wind production (including wind prediction error) for the three possible installed wind capacities and the three wind error scenarios.

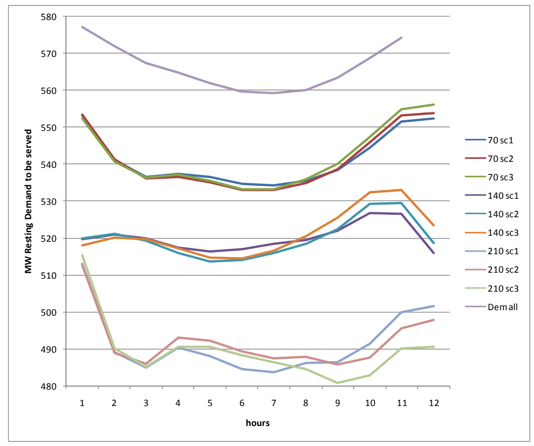

Fig. 2. Resting demand to be supplied in different wind scenarios in hours 1 to 12

In a last calculation consumption and generation of electric cars is considered. Herefore electric cars are to be assumed to amount less than 10% of the current vehicle park. Different uses are assumed (commuters and others), thus the distance travelled per day (average of 35 km), the time of use (different hours during the day) and the electricity consumption during this use is approximated. Battery capacity is assumed to amount between 10-15 kWh and electricity needed for travelling is estimated to be an average of around 25 kWh/100km. Maximum charge and discharge rates are determined. Data is based mainly on [26],[27],[28], [29] and [30].

Taking into account that in the case of Gran Canarias 24 time periods p, 3 scenarios s and 20 generation units t, the two-stage stochastic model has to cope with 6456 constraints, 2472 continuous and 480 binary variables.

B. Results and discussion

The stochastic unit commitment is determined for each day of the week. Some days out of the spectrum of this week are analyzed more in detail.

1) Comparison stochastic versus deterministic approach : In the stochastic approach unit commitment decisions are unique while in the deterministic equivalent these decisions can adapt depending on the wind situation given in each scenario. As in the stochastic approach each scenario is taken into account with its probability unit commitments might differ especially in peak hours with very different wind scenarios.

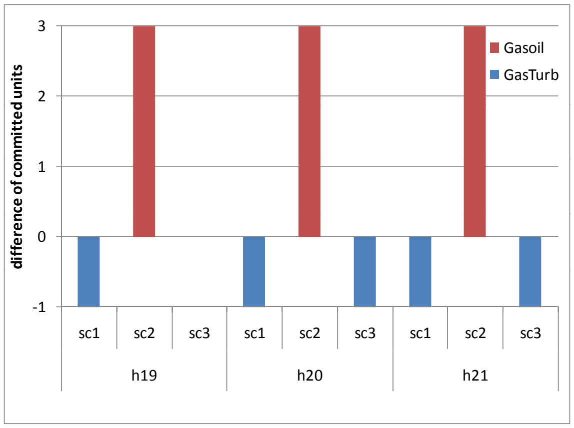

Fig. 3. Difference of units committed between stochastic and deterministic approach in hours 19 to 21

Figure 3 shows the difference of gasoil and gas turbine unit commitments between the stochastic and the deterministic approach during the evening peak from 19 to 21 o´clock of a friday. The combined cycle and the fueloil plant don´t show differences, since they are coping with the base load in contrast to gasoil and gas turbines which work mainly in peak hours and thus change their commitment status more frequently.

As can bee seen from the figure 3 the deterministic approach commits one unit more of gas turbines in scenario 1 and in two hours as well in scenario 3. These are the two scenarios which have a negative or very small wind prediction error (see table below). In contrast the stochastic approach commits three units more of gasoil compared to the second scenario with very high positive wind prediction errors. That means for the deterministic model that more wind generation is available and thus three gasoil plants can be turned down, while the stochastic approach takes into account all scenarios at once and results in the use of gasoil to be the most economic. This results in an Expected Value of Perfect information (see page 2 of around 34.000 Euro in one day, which is a cost advantage of 3% of the stochastic approach. That would be the value of knowing the uncertain future with certainty.

	Demand [MW]	Wind prevision [MW]	Wind error [MW] Scen. 1	Scen. 2	Scen. 3
h19	586	50	-8	37	2
h20	588	52	-9	37	-1
h21	587	54	-10	33	-2

TABLE II
DEMAND, WIND AND WIND ERRORS FOR 19-21 O´CLOCK

The difference of technologies applied in the peak between the two approaches is mainly due to the variable, fixed and start-up cost considered. These are regulated costs based on real plants (see subsection IV-A). The gasoil plants which mark the difference between the two approaches in the considered hours in this discussion have higher variable costs than the two considered gas turbines, but lower fixed and start-up cost. As the stochastic approach is considering all scenarios at the same time and as it has been decided to be more economic to switch off these two gas turbines during this day, the cost-minimization determines the two turned-on gas turbines to supply peak demand. The deterministic case sees only one scenario at once and thus the gas turbines are switched off in scenario 2 with high wind input and turned on in the other two scenarios with normal and low wind production.

2) Scenario analysis of different installed wind capcities : A scenario analysis has been conducted changing the installed wind capacity from 70 MW installed nowadays to double and triple of this capacity. This high capacity might be realistic in the long term as renewable support in Spain is given and offshore wind capacity is supposed to rise in the coming years.

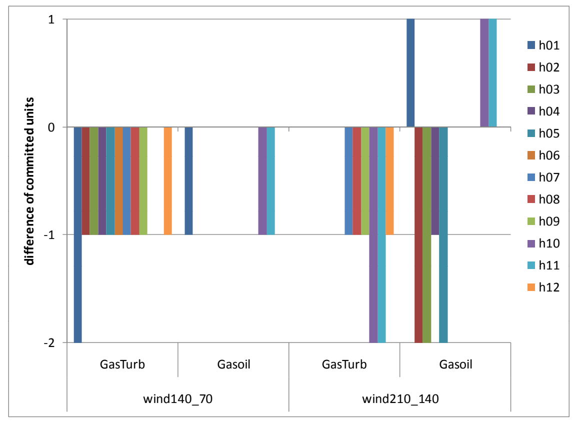

Fig. 4. Difference of units committed between 140 and 70 MW installed wind capacity in hours h1 to h12

Figure 4 indicates on the left hand side the difference of unit commitment from the 140 MW to the 70 MW installed wind capacity case. In almost all shown hours of a saturday one to two gas turbines less will be committed. In some hours additional gasoil unit reduction can be observed. Thus additional wind generation saves thermal production of these two technologies.

On the right hand side the difference between the 210 MW to the 140 MW installed wind capacity case is shown. In less hours than in the 140-70 comparison gas turbine production can be saved. The hours where one to two gas turbines less are needed are the hours closer to the morning production peak. Gasoil technologies are more ambiguous to interprete: in three hours one more unit needs to be committed in other four hours one to two units less are needed in the 210 MW case. In the 210 MW wind scenario, the additional gasoil plant is producing its minimum production of 5 MW while other two gasoil plants are reduced to minimum stable load. In contrast in the 140 MW case where one gasoil plant is turned off while the other two are running at higher production levels. Since the model is optimizing over 24h it takes into account the wind production and the resting demand to serve in all hours. In the case of the 210 MW wind production wind error scenarios result in resting demands that are more widespread than in the 140 MW case (see figure 2). In one case (210 MW) it is more economic not to turn off one gasoil unit and let it work at its minimum while in the other case (140 MW) turning off is the best solution. These results indicate that higher wind production not always means less need of conventional thermal capacity. In contrary it may be that some conventional plants have to run on its minimum stable load to avoid extra start-up cost to cope with variable stochastic wind input in upcoming hours.

3) Including electric cars: Electric cars are included to see how extra consumption affects the system. Additionally electric car generation might lower system peaks.

In the following tables the generation mix and the parts of consumption are shown for one day. Electricity consumption by cars assumes around 6.5% of total consumption. For the considered system of Gran Canaria this rise can be supplied with the current generation without problems. Apart from the minimal capacity which needs to be available and the times of use of the electric cars the model takes into account the system state when letting electric cars consume. That means whenever possible, the electric car will be charged in offpeak hours mainly during the night, in peak hours extra electricity consumption by cars is minimized. When wind production during the night is high consumption by electric cars are kept and charge more in very high hours.

Comb.Cycle	GasTurb.	CarGen	Wind	Gasoil	Fueloil
31.97%	4.51%	0.03%	9.31%	8.63%	45.55%

TABLE III
GENERATION IN A DAY

NSE	Demand	CarCons
0.00%	93.59%	6.41%

TABLE IV
TOTAL CONSUMPTION IN A DAY

Generation by electric cars is limited in some ways. Cars need to have always a minimum battery level, furthermore depending on the type of use and thus the hour and distance of use the battery has to have a certain level. This is to ensure that driving is not limited by electricty production by cars. Thus generation of electric energy by cars will always be significantly lower than the consumption. In the considered case generation by cars appears during some peak hours, but is very small. Demand peaks can be reduced by car generation only very little.

Plug-in electric cars do have an influence on the system operation. At current generation capacities and demand levels this extra consumption is notable but not worrisome. Extra generation by electric cars is quite limited and further storage facilities should be considered. The impact of these cars should be analyzed as well with higher number of cars and higher installed wind capacity during low wind production scenarios, which is out of the scope of this paper.

V. Conclusions

Wind energy causes already today alterations in generation scheduling. It has been shown that wind replaces expensive gas plants in scenarios with high wind production, but when wind production is low more expensive generation plants have to be committed due to their fast reaction ability. Furthermore it has been observed that very high wind input might lead to problems of thermal generation reserve. Taking into account various wind scenarios in stochastic optimization instead of looking at simulations with deterministic optimization, brings advantages as it has been demonstrated with the Expected Value of Perfect Information. A certain degree of plug-in electric cars as to be expected in the upcoming years can be handled by the system without problems, although peak reduction due to extra generation by electric cars is modest. Future research primarily in new storage possibilities and its implementation into stochastic modelling used for operation and planning is indispensable to cope with volatility in wind production.

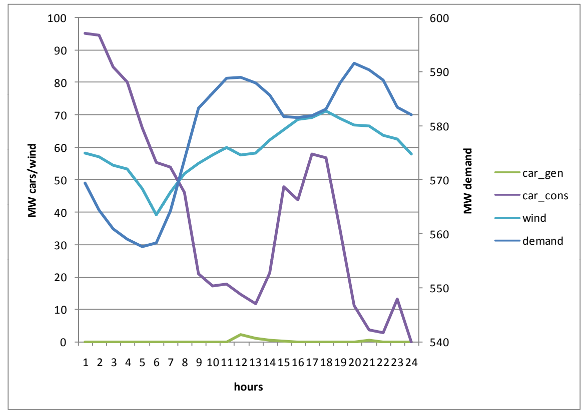

Fig. 5. Different consumption and generation profiles in one day

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