INTELLIGENT ENERGY MANAGEMENT OF ELECTRICAL POWER SYSTEMS WITH DISTRIBUTED FEEDING ON THE BASIS OF FORECASTS OF DEMAND AND GENERATION

Chr. Meisenbach	M. Hable	G. Winkler	P. Meier
Dresden University of Technology, Laboratory of Electrical Power Systems	Dresden University of Technology, Laboratory of Electrical Power Systems	Dresden University of Technology, Laboratory of Electrical Power Systems	Allgäuer Überlandwerk GmbH

To guarantee power supply with a required service reliability every time in an economical, ecological and resource saving way utilities have to schedule the energy allocation for the next day. In addition to forecasts of the demand this planning is based on forecasts of the non-schedulable supply by distributed plants using renewable energy resources. Although this portion is difficult to predict renewable energies gain more importance because of political guidelines and social trends in Germany. This prediction task is complicated further by the fact that in deregulated markets the system has to respond to changes in load demand fast and at low cost.

With this background an intelligent management system was developed at Dresden University of Technology which enables short-term energy allocation scheduling at minimum costs based on an optimised forecast of power. The management allows the optimisation of the supply of a wide region as well as of certain parts of it. The system was tested and verified for application using data of power demand and generation as well as meteorological data from the Allgäuer Überlandwerk, a utility in southern Germany.

Artificial neural networks outperform traditional methods of forecasting generated and demanded power in terms of accuracy and simplicity of handling. So far, artificial neural networks are designed on a “trial and error” base using rules of thumb. Efficient use of these forecasting systems requires design rules which make it easy to apply them to very different energy systems. Universal design rules for a neural forecasting system are described in the paper. Theses rules were found with systematic tests of all relevant designs of neural forecasting systems. Results are documented with examples.

In addition to the prediction of the power a second artificial neural network determines the forecast accuracy by calculating the probability distribution of the power. Resultant confidence intervals of the predicted power are derived. This is an important feature because for an efficient energy management it is necessary to know the range of values a certain power will be in with high probability. The size of this range is determined by the limits of power forecasts which are caused by stochastic or unknown influences on the power.

The management system uses evolutionary algorithms considering the predicted probability distributions. In every optimisation interval the optimal power distribution of all components and the required spinning reserve are calculated. By the simultaneous optimisation of generation, storage control, and load control of schedulable loads an economical but nevertheless ecological and an all technical restrictions meeting use of energy is accomplished (Figure 1). In the paper this is proved with selected days in summer and winter.

A main advantage of the developed management system is its portability. It can be adapted to very different energy systems comprising different kinds of components. Optimisation and model description are independent from each other. So, the only limit is set by the fact that calculation time gets high if the models are detailed. In opposition to other optimisation algorithms this energy management system can handle systems with storages that produce a time dependency and systems with non-linearities.

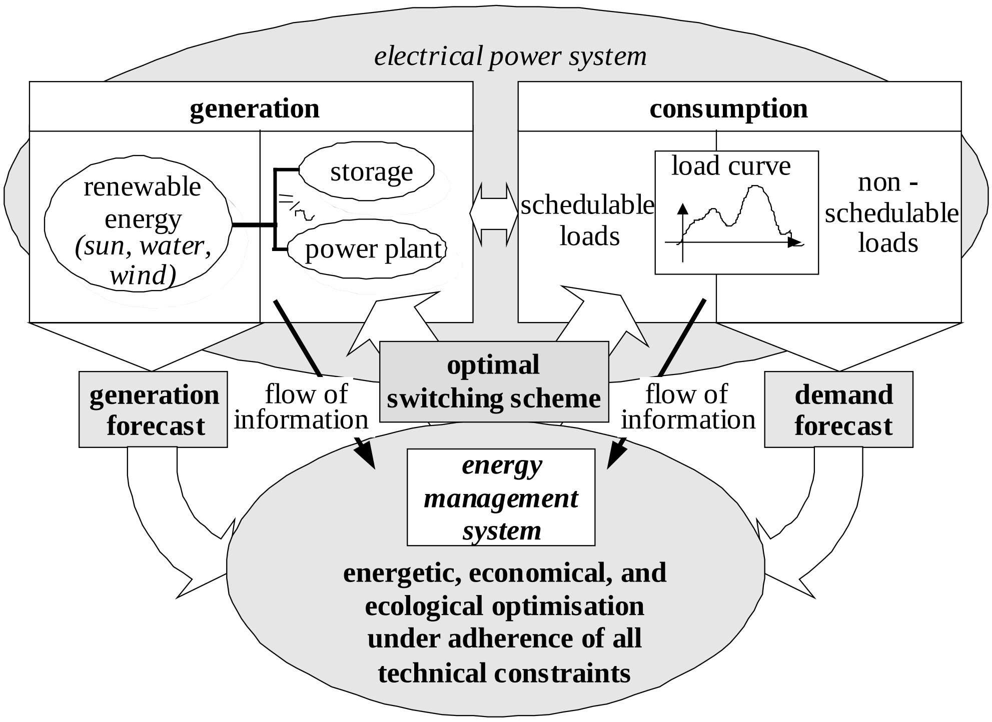

Figure 1. Principle of the energy management

The forecast algorithm and the optimisation algorithm together ensure an optimal operation of all energy systems with distributed feeding for a given period of time.

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G Winkler
Dresden University of Technology
Germany

C Meisenbach
Dresden University of Technology
Germany

M Hable
Dresden University of Technology
Germany

P Meier
Allgäuer Überlandwerk GmbH
Germany

ABSTRACT

The intelligent energy management system described in this paper allows optimum short-term scheduling especially of power systems with distributed feeding considering energetic, ecological and economical criteria. With it the demand of the loads is covered with the required reliability of supply regarding all technical constraints.

The energy management works with evolutionary methods based on forecasts of the probability distribution of the power generated by the regenerative sources of energy as well as the demand of the load. For the prediction task the use of artificial neural networks is recommended. Precise rules for the design of the prediction system, which have been determined by systematic investigations, are presented.

Even though forecasts of renewable energy generation show higher prediction errors than forecasting the load it is possible to include renewable energy sources into power scheduling.

INTRODUCTION

To guarantee power supply with the required service reliability at all times in an economical, ecological and resource saving way utilities have to schedule the energy allocation for the next days. Due to the world wide deregulation of the energy market economic criteria of energy dispatch became more important for the utilities. Therefore, an optimisation is required even in local service areas and power systems with decentralised feeding. Fast reactions to changes in supply and demand at low cost are vitally necessary (Seidel [1]).

With this background an intelligent management system was developed which enables short-term energy allocation scheduling at minimum costs based on forecast of power demand and of generation by renewable energy sources.

ENERGY SYSTEM WITH DISTRIBUTED FEEDING

Distributed power systems establish a reliable and stable basic supply with electrical energy in developing and threshold countries as well as in regions far from existing central systems in industrial countries. Meanwhile distributed feedings also arise in fully developed grids to complement the existing supply structures. According to ecological interests based on political guidelines and social trends these systems contribute to environmental protection and economical use of resources with a high portion of power generation by non-controllable renewable energies. Their power production is varying depending on the weather. Characteristically the proportion of the renewables with regard to the total installed power of distributed systems is high. Whereas their spatial size and therefore the number of different loads is limited. Thus independent of the size of the energy system the demand of the loads has to be covered with the required reliability of supply.

FUNCTION OF THE MANAGEMENT

Up to now in decentralised power systems an instantaneous optimisation is used which optimises the use of the equipment only in the current optimisation interval. The use of storage however requires an optimisation which considers the time integral parts of the load flow, too. Therefore the management has to perform a single or multi day ahead energy scheduling.

The components of the power system can be divided into the categories production, consumption and storage, all providing possibilities for the optimisation of the short term energy allocation. With the management system developed not only the power generation of the shortest term dispatchable conventional plants, but also the storage and the controllable or switchable loads are scheduled (figure 1).

The management determines the mean switching levels of all components of the power system in each time interval of optimisation. These levels describe the mean demand or generation in relation to the maximum power of the components. They are best if the target function becomes minimal, which contains all costs to dispatch the energy system depending on the corresponding switching levels. In addition to the costs of power generation constant costs for violated constraints as well as additional costs are taken into consideration. These costs increase exponentially with increasing probability of power deficiency

To ensure general usability of the management and to handle stochastic inputs but nevertheless guarantee

compliance with all constraints for every component a model was developed where all relevant costs and valid vectors of switching levels are calculated.
Costs and parameters were adapted to the conditions of the Allgäuer Überlandwerk GmbH, a regional utility in southern Germany. The management system was tested and its practical usability was verified using data of load and generated power as well as the corresponding meteorological information. The management system enables the optimisation of a whole service area as well as of individual parts of it. It is simple to transfer the developed optimisation program to different power systems adapting the customised costs and parameters.

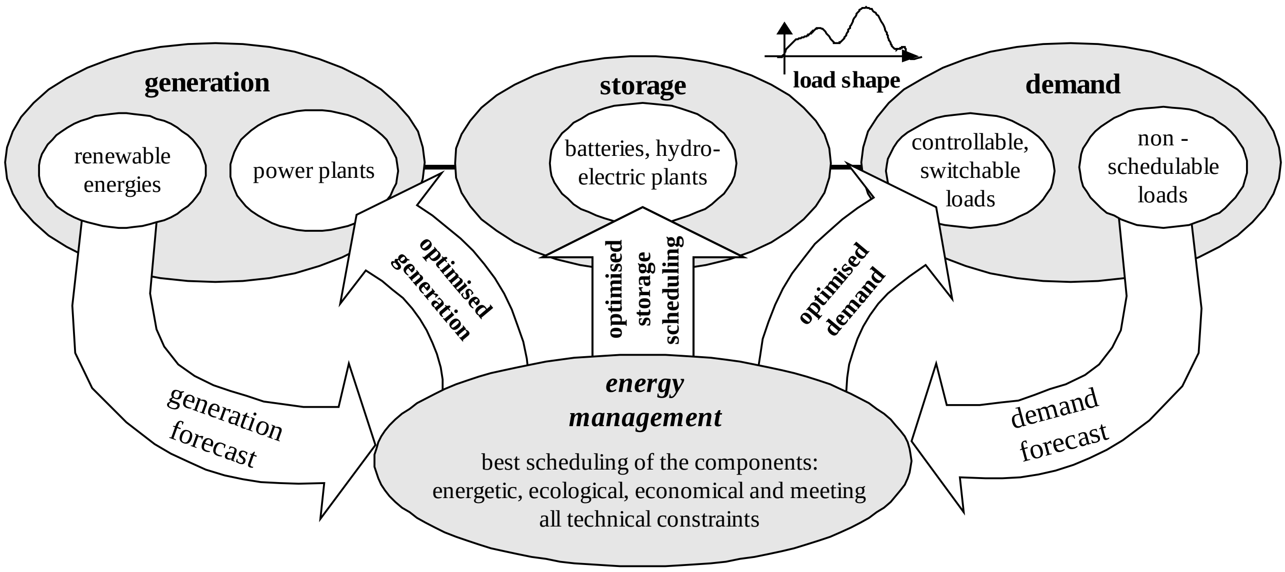

FIGURE 1. Principle of the intelligent energy management system

The example in figure 2 shows results of the scheduling of a part of the service area of the Allgäuer Überlandwerk GmbH on a work day. The non - schedulable and the dispatchable loads demand power from the grid. Photovoltaic, wind and conventional power plants produce electrical power. Altogether power is balanced. In times of high demand storages are discharged and dispatchable loads are switched off.

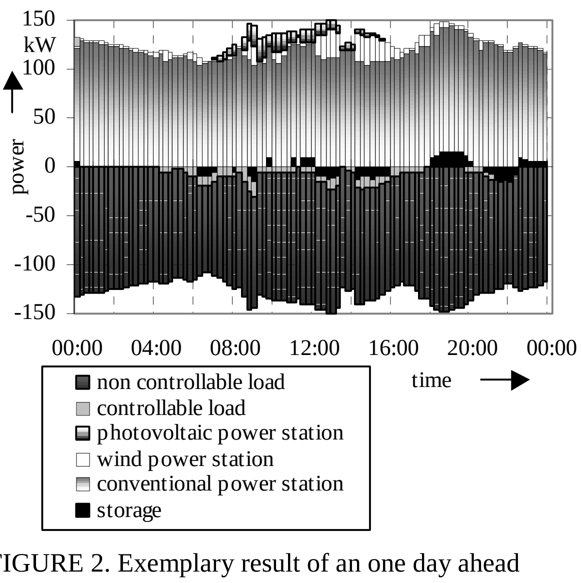

FIGURE 2. Exemplary result of an one day ahead energy scheduling

Evolutionary algorithms proved to be the most suitable optimisation method. They do not require special properties of the target function and will always find the global optimum after sufficient calculation time. Already after few iterations a usable result is available. Extensive investigations showed calculation time and initialisation of the start population, i.e. the initialisation of the switching levels of all components, as main factors for the quality of the achieved result. The overall calculation time requirements can be reduced using an intelligent initialisation strategy. But with short interval steps and a large number of vectors of switching levels they are still in the range of one to several hours. The time required for the optimisation of the next day with 10 components and 1 hour time intervals is reduced to about 25 minutes. Continuing research will further reduce time requirements.

Ecological and economical criteria of the optimisation are fulfilled with

increasing the lifetime of the components by

- avoiding needless operation time
- meeting the technical constraints
- operating the plants at rated power
- minimizing the storage use

and saving of environment and resources by

- operating the plants with optimised efficiency
- maximum usage of renewable generation plants
- minimum usage of conventional power plants
- avoiding losses by needless energy flows
- minimizing the deficit power or surplus energy.

With the help of the intelligent management renewable energy sources can also be included in the power scheduling. The economical benefits of renewable energies increase. Further energy delivery from a central power system can be optimised.

For this purpose the energy management system processes the probability density distributions of the forecasted, in time much fluctuating power supply of the renewable energy sources as well as the stochastic demand of the loads. It has to ensure that the power balance is at least equated at every interval according to the required service reliability β. The requirement for the probability W of total power P_{total} can be deduced

$$W(P_{\text{total}} \geq 0) \geq \beta. \qquad (1)$$

The probability density of the total power determines the spinning reserve that is necessary to guarantee the required service reliability at every optimisation interval if power balance is equated ($P_{\text{total}} = 0$). If there is no spinning reserve provided the management has to plan a power surplus P_{res} at every optimisation interval to establish a supply with the required service reliability (figure 3).

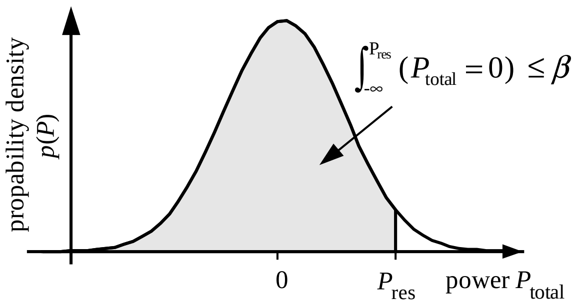

FIGURE 3. Determination of the required spinning reserve

FORECASTING THE POWER

Exact power forecasts in the considered optimisation intervals are substantial prerequisites of a successful energy management, besides technical constraints. Power demand forecasts predict the power consumed by the load. Forecasts of power generation determine the power delivery of the renewable energy power plants. In opposition to centralised energy systems, in which power demand forecasts take place since dozens of years there are usually no forecasts in decentralised power systems. In recent years the use of artificial neural networks (ANN) has been established in centralised power systems for load forecast although precise design rules have been unknown so far. Forecasts of the power generation by renewable energy sources have not been realised in centralised energy systems, too.

Compared to simple statistical methods the use of artificial neural networks showed significant advantages regarding accuracy of forecasts and simplicity of handling. The implications of choice and preprocessing of input data as well as the design of the neural forecasting system onto the forecast results were determined systematically by testing all relevant designs of forecasting procedures with different combinations of parameters.

Simple feed-forward multilayer perceptrons (figure 4) with few hidden neurons in one hidden layer were found to be the most suitable neural network. The number of neurons of the output layer has to be chosen depending on the required time intervals. To predict the energy production per day one neuron is necessary. To predict the mean production per hour respectively per 15 minutes of the next day 24 respectively 96 output neurons are necessary. To predict the power demand previous load values, temperature, calendarical information, and information about the occurrence of special days have to be used. The information about the current week day is presented to the neural network in binary code ‚1 out of 7'. Seasonal inputs, e.g. the day of the year, are realised sinusoidal according to the periodicity of the yearly load shape using a single input neuron. When forecasting the generated power week day information is irrelevant. Albeit all available meteorological data has to be used as input (Meisenbach [2]).

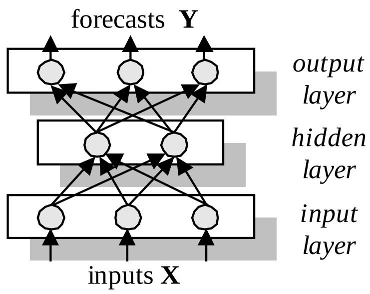

FIGURE 4. Principle of a feed-forward multilayer perceptron

Independently of the kind of power forecast the data has to be normalised. Best prediction results were achieved using a standardisation with a mean of 0 and a standard deviation of 1 for every input and tangent hyperbolicus as activation function. To train the multi-layer perceptron the backpropagation method with adaptive learning rate and momentum term has to be chosen.

The use of network committees allowed to remove uncertainties regarding the right determination of the weights of the artificial neural networks depending on the initialisation at beginning. In this case the output is calculated as the mean of several different neural networks with possibly different configurations. The parameters of the ANN are determined using the same training data set but varying initialisation (figure 5).

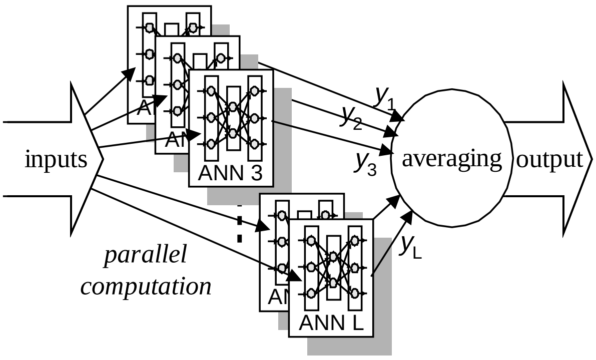

FIGURE 5. Forecasting with network committees

The differences in the outputs of the single ANN increase with growing stochastic portions of the power shape. The overall forecasting accuracy of the network committee exceeds even the best forecasting accuracy of a single network of this network committee.

Limits of the achievable accuracy of the forecast are found in the irrelevant inputs and the non-definable stochastic portions of the power. These limits exist independent of the used forecasting system. Only the portion of power with explicit correlation to the inputs is predictable.

The higher the portion of the predictable power is the better are the results accomplished by a suitable forecast system in comparison to simple mathematical methods. Forecasting the demand with artificial neural networks achieves a mean relative prediction error of less than 2% in respect of the maximum system power. Forecasting the generated power by the renewable energy sources causes prediction errors of up to 20% because of the highly stochastic nature of the influences caused by weather. Nevertheless consideration of probability density permits to integrate the generation from renewable power sources into the scheduling.

Time requirements for forecasting are minimal because of modern computer power. The results are evaluated within seconds with large neural networks or network committees containing up to 500 different networks. Training of the multi-layer perceptrons requires few minutes time. With appropriate software doing the forecasts can be automated easily. Knowledge of the functional correlation between inputs and requested power is not required. Response on short-termed power changes or unexpected incidents can be realised using an automated readjustment of network parameters.

DETERMINATION OF FORECAST PROBABILITY

The highly stochastical and non-definable portions of the power generated by photovoltaic and wind power plants as well as the demanded power of the non-controllable loads in decentralised energy systems require additional information to the forecasting probability to determine the required spinning reserve.

Investigations showed that the forecasting errors follow a normal distribution. Due to this fact stating the parameters expected value μ and standard deviation σ is sufficient to fully describe the probability distribution of the power. The expected value corresponds to the so far considered point forecasts as long as the neural network is trained with a squared error criterion (Bishop [3]). A second, separate artificial neural network with one hidden layer containing maximum 20 hidden neurons computes the standard deviation (figure 6). Again best results are achieved using network committees and standardised data sets.

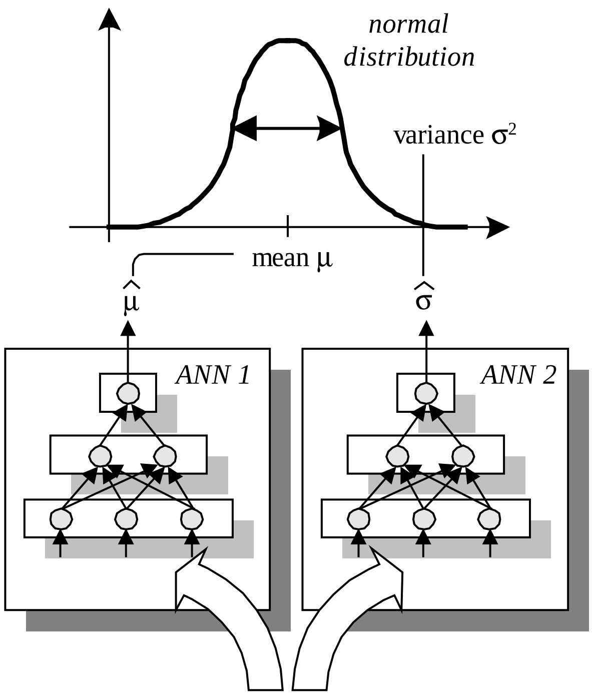

FIGURE 6. Forecast of probability distribution

Probability distribution bands around the expected value predicted limit the range in which the power will lie within with a certain probability. According to the common quantiles the 68%, 95% and 99% confidence intervals are used with the examples in this paper. Figures 7 to 10 show the results of forecasts of the power demand on a work day in winter, a Sunday in summer as well as the power generation of a photovoltaic power plant on a slightly overcast day in summer and of a wind power plant in winter.

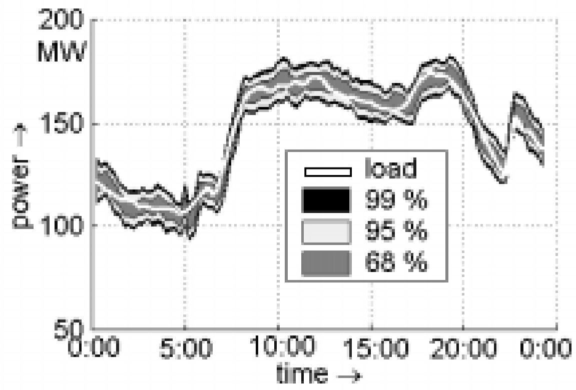

FIGURE 7. Forecasting results for the power demand on a workday in winter

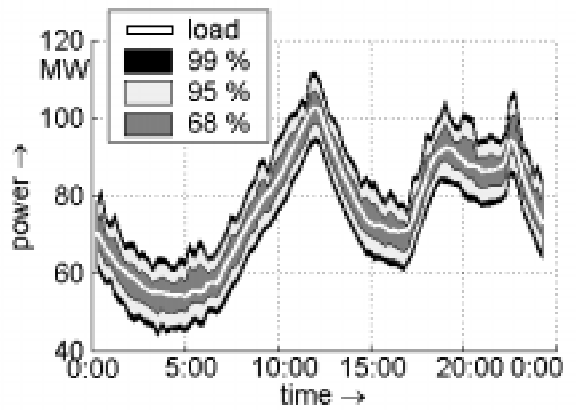

FIGURE 8. Forecasting results for the power demand on a Sunday in summer

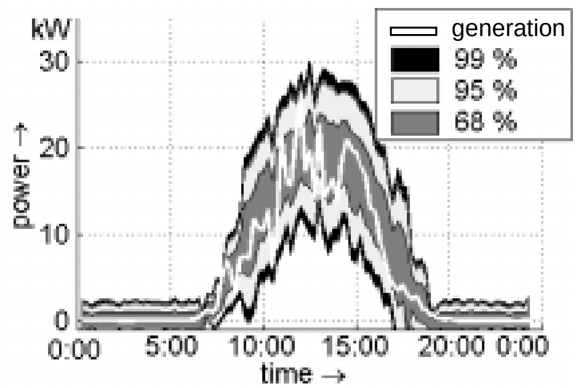

FIGURE 9. Forecasting results for the generation of a photovoltaic power station

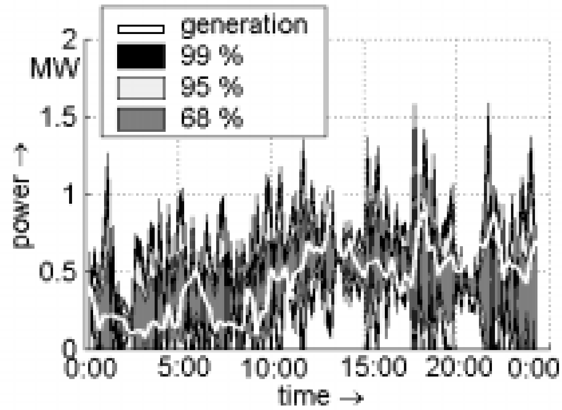

FIGURE 10. Forecasting results for the generation of a wind power station

The higher the stochastical not predictable portion of the power and therefore the less precise the forecasts are the wider the bands of the probability distribution will be.

CONCLUSION

Especially in energy systems with distributed feeding an intelligent energy management is required to ensure the covering of the demand at all times with the required reliability of supply in a energetic, economical and ecological best way. The energy management system presented in this paper combines the utilisation of artificial neural networks and evolutionary algorithms for the forecast of power and the subsequent scheduling of energy use.

The forecasts of the probability distributions of the power demand and the generation by renewable energy sources permit the consideration of certain portions of distributed feeding for energy scheduling. The innovative management does not only optimise generation and storage of electrical energy but also the demand of controllable loads.

LITERATURE

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