AN INTEGRAL ENERGY MANAGEMENT FOR DECENTRALIZED POWER SYSTEMS

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SUMMARY

Decentralized power systems with a high portion of energy generated from renewable energy sources and cogeneration units (CHP) are emerging worldwide. Optimising the energy usage of such systems is a difficult task as the stochastic fluctuations of generation from renewable sources, the coupling of electrical and thermal power generation by CHP and the time dependence of necessary storage devices require new approaches. Conventional optimisation algorithms observe many difficulties handling it. Methods for an integral energy management that optimises the use of electrical and thermal power as well as storage devices are introduced in this paper. The management is based on modified hybrid evolutionary algorithms.

INTRODUCTION

Decentralized power systems are emerging worldwide. In developing countries where no grid exists they are built to supply small communities. Because of the liberalization of the energy market and the politically forced raise in the usage of renewable sources their number increases in industrial countries, too. Decentralized systems can be integrated into existing grids but they can also be operated as islanded networks.

In most cases decentralized systems are characterized by a high portion of energy from renewable sources like sun and wind. Power generation by these sources depends on the availability of the natural resources. In contradiction to most water resources sun and wind are characterised by a highly stochastic behaviour and large power fluctuations occurring in short time spans. For an autonomous operation of the system or to minimise the energy exchange with the connected grid storage devices are needed. They introduce a dependence of the operation over time.

Using cogeneration leads to a coupling between electrical and thermal energy. Because of time constants there exists a delay in the reaction on operational commands in the thermal system.

An energy management system optimises the use of energy of defined system structures. Observing all technical, economical and ecological restrictions the system covers the demand by the generation units available handling the possibilities of export or import contracts and storage devices.

Such a system consists of three modules (Figure 1):

- prediction module
- optimisation module
- controlling module

Based on predictions of the loads and the generation of units with renewable energy sources optimised schedules for generation units, the storage devices and the contracts are generated that minimize defined optimisation criteria, normally with a time horizon of 24 hours.

In case of any deviations from the planned energy values the controlling module performs an optimised energy reallocation based on the results of the energy commitment. A 1 min supervision interval is sufficient for this task. Additional required real-time SCADA functionality has to be provided by separate systems.
To meet the requirements of a changing market with distributed generation and an increased share of renewable generation Siemens has developed the decentralised energy management system DEMS [1]. With this the usability and profitability of energy management systems could be proven in several projects in Germany. Independent of that, driven by the same reasons, parallel research takes place at Dresden University of Technology to analyse and optimise methods that are required for such an innovative energy management system. The results of these investigations on the prediction and in more detail of the optimisation module are presented in the paper.

PREDICTION MODULE

Based on weather forecasts, historical load data, information regarding time (time in the day, day in the week, type of the day, season...) the prediction module uses artificial neural networks to generate forecasts of the consumed power as well as the power generated by the renewable sources. Limited by the possibility to predict weather situation and customer load for longer time periods in sufficient quality a prediction period of 24 hours was selected with 96 intervals of 15 min. For each interval an average value for expected customer load and by renewable sources generated power is estimated. As the prediction accuracy is limited by the quality of the used input data and by the stability of the weather situation the accuracy of the forecast is also delivered. So, for each source or load group two values are created in each interval: the expected power and its standard deviation (Figure 2). It could be shown, that the values of the actual power follow a normal distribution around the predicted value [2].

OPTIMISATION MODULE

The optimisation task is special in decentralized power systems. The high portion of generation by renewable sources introduces another group (besides the load) of units in the system that show a highly stochastic behaviour. As there are only few units in the system no levelling effects appear that can be observed in wind or sun powered plant that cover a large area. Each cloud and each wind drop will have a considerable effect on the generated power. Hence in islanded systems large storage devices have to be included in the system and a sophisticated storage management is required. Adequate risk and reserve strategies have to be developed in case of reduced storage capacity. Because of the small number each consumer does not have a negligible effect on the power balance. Compared to conventional large power systems in decentralized systems the power fluctuation is much more dynamic and the portion of stochastic power is much higher.

On the other hand there is a limited number of units in decentralized systems. The usually high degree of combined heat and power plants opens the possibility to optimise simultaneously electrical and thermal power, operation of storage devices, and control of schedulable load. Therewith the effects that rise by the combination of cogeneration and storages can be exploited much better than in conventional systems.

Several optimisation criteria are possible, for instance:

- minimal costs
- minimal emissions
- maximal use of renewable sources.

The following examples use minimal costs as the optimisation criterion. The cost to operate a given power system for a given time span is minimized. All the characterizations of the power system have now to be expressed in the form of costs. Total costs consist of

- cost of operation (e.g. fuel costs)
- cost of use (e.g. starting costs of thermal power plants)
- penalty costs.

Penalty costs are charged if a soft restriction is violated, e.g. minimum running time of a thermal power plant. They allow such violations if the realised gain is greater than the additional wear of the equipment.

The cost function then is the objective function of the optimisation task. It is non-linear, discontinuous, and of high dimension. The storage devices introduce an
inseparability in time. The balances of thermal and electrical power as the main constraints are coupled in power and displaced in time.

Conventional algorithms have strong problems handling such objective functions and constraints. In most of the cases they are unable to solve optimisation tasks of this type at all (e.g. linear optimisation methods). If the models of the units have to be simplified too much, the algorithm might converge to solutions that are not optimal in the real system. Other algorithms (such as dynamic programming) can solve these problems but their computation time requirements are very high, much higher than the optimisation interval.

Evolutionary algorithms that realise ideas of evolutionary strategies and genetic algorithms [3,4] can optimise objective functions of nearly arbitrary form. The only restriction is that at every point of the solution space the objective function must either be defined or it must be determined that it is not defined.

Evolutionary algorithms (Figure 3) use the principles of erroneous replication and cumulative selection that can be observed in biological evolution processes, too. Very often recombination is included in the optimisation process. Using these quite simple principles the algorithm is able to explore difficult, large and high dimensional solution spaces. It will converge to the optimal solution in most of the cases quite, compared to other types of optimisation algorithms.

To work with evolutionary algorithms the schedules of all components of the given energy system for the given optimisation period has somehow to be coded as a vector or matrix. Depending on the chosen coding scheme the algorithm behaves quite different. The computing time to reach the optimal solution might vary considerably [5].

There is a variety of parameters (more than 15) that can be set in the algorithm. Some have a greater influence on the convergence speed than others. With quite extensive investigations it could be shown that the product of number of replicators and number of calculated generations has the most important influence on the quality of the solution but the calculation is proportional to this number, too. Slow or none convergence is achieved in case of a bad selection of the mutation rate. Variation around the successful value of about one mutation of a single element of the vector of the replicator per replication process does not have a considerable influence on the convergence speed. If there are reasonable values chosen for mutation rate, selection pressure (for recombination as well as selection for the following generation), number of crossover points and the other parameters the algorithm will find appropriate solutions in reasonable time in most of the cases. Because many steps in the algorithm are controlled by stochastic operations (e.g. selecting randomly chosen replicators, adding normal distributed random numbers in the mutation process) the algorithms might not converge to exactly the same solution when run several times with the same parameter set. If there is only one global optimum the solutions will gather around it.

Several variations to realise the crossover were investigated. They also depend on the chosen coding scheme. It could be found that using both recombination with “vector-crossover” (Figure 5) and “matrix-crossover” (Figure 6) with the same frequency but in a random sequence will lead to the best results for solutions coded in “natural coding” [5](Figure 4).

![Initial Population](initial_population.png)

**Figure 3: Principle of evolutionary algorithm**

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![Individual in “natural coding”](individual_natural_coding.png)

**Figure 4: Individual in “natural coding”**

![Recombination with “Vector crossover”](recombination_vector_crossover.png)

**Figure 5: Recombination with “Vector crossover”**

Although a pure evolutionary algorithm will converge to a solution the convergence speed can be greatly enhanced by extending it to a hybrid algorithm (Figure 7). Grouping the replicators of the first generation in suggestive regions of
the solution space by an intelligent initialisation algorithm and repairing bad solutions by introducing a Lamarckian repair algorithm makes the optimisation converge fast to good optima.

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**Figure 6:** Recombination with “Matrix crossover”

The intelligent initialisation is realised by a rule-based algorithm. This algorithm is designed to be as universal as possible for use in power systems of very different structure but also to lead to results that will be near the global optimum with high probability. So many rule of common sense are realised although in very special cases they might not lead to the best results. For example energy from renewable sources is used as available although this might require additional shut downs of thermal plants. These plants are used to cover large and continuous blocks of load. Water power plants a load equal to the water inflow is allocated. Many other rules are implemented. Their relationship is quite complex and partly depends on the actual form of the power system under consideration.

The main reason of the Lamarckian repair algorithm is to avoid wasting computing time on exploring solutions that contain large power deficits. Such solutions might be useful as intermediary results to be able to move between two promising areas of the solution space in order to approach the global optimum.

But in many cases they only consume computing time to evaluate and to deselect them. Therefore with a certain probability solutions showing a large power deficit are modified in order to remove the deficit. According to Lamarckism the chromosome of the individual is been modified [5]. The repair algorithm is also based on heuristic rules. According to a ranking the power allocation to sources is increased until the balance in this interval is balanced.

**RESULTS**

The algorithm was tested using data of several existing energy systems of different structure. To optimise the energy usage in a power system with 10 different types of units for a time horizon of 24 hours divided in 96 intervals of 15 min each the required computation time is in the range of 30 min. Longer computation further minimally increases the quality of the results.

The optimisation results of two examples based on data from power systems in southern Germany are shown in following part of the paper. In the first power system under consideration there exists a large wind power plant. In Figure 8 one can clearly appreciate the large, fast, and stochastic fluctuations of the generation. Because it is difficult to predict local wind speed a longer time ahead the standard deviation will become quite high at the end of the day.

![Forecasting result of a wind power plant](image)

In the morning most of the fluctuations are compensated by the storage devices in the system. Because of the waning wind in the afternoon the backup generator has to be switched on to supply the load. In Figure 9 for clarity only the expected values are shown.

![Hybrid evolutionary algorithm](image)
In the second power system electrical and thermal sources and loads are combined by a cogeneration power plant. From the combined electrolyser fuel cell power plant the excessive heat from the fuel cell process can also be used. There are large and fast fluctuations in the load, the generation by the wind power plant and the photovoltaic power plant (Figure 10). Because the rated power of the photovoltaic power plant is small compared to the system power its fluctuations can be neglected. The rated power of the wind power plant is in the range of the maximum system load. So its fluctuations have to be predicted to know when to switch on the cogeneration unit. Excessive energy in the night is used to charge the storage devices. This strategy allows to switch off the cogeneration unit for several hours through noonday (Figure 11). In these hours no thermal energy can be extracted from the cogeneration unit. Therefore the boiler has to be used to charge the heat storage device to bridge the early afternoon time and to allow for an interruption of the boiler operation.

CONCLUSION

Based on weather information, historical load data and other input information the developed energy management system is able to predict customer load as well as generation of renewable sources like sun and wind for a time span of about 24 hours. The optimisation module will propose switching schemes of sufficient quality even in difficult power systems containing many storage devices with different characteristics and a coupling between the electrical and thermal energy balances.

REFERENCES


