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Determination of Dynamic Wind Farm Equivalents using Heuristic Optimization

I. Erlich, Senior Member, IEEE, and F. Shewarega, Member, IEEE, C. Feltes, F. Koch and J. Fortmann, Member, IEEE

Abstract— As a result of the increasing share of wind power the dynamic behavior of power systems will change considerably. To carry out stability studies in the future wind turbine and wind farm dynamic models will be indispensable. Generic models seem to provide the required simplicity and accuracy. But the parameters cannot be derived directly from the mathematical models of the generator and converter system, numerical identification methods are needed. In this paper the authors introduce a new heuristic optimization method called Mean Variance Mapping Optimization (MVMO) which provides excellent performance in terms of the accuracy of the generic model parameters and convergence behavior. The fitness evaluation is performed using time domain simulation in each iteration step. The procedure and the level of accuracy that can be reached are demonstrated using an 18 machine, 90 MW test wind farm consisting of DFIG based wind turbines.

Index Terms-- wind turbine, doubly-fed induction generator, DFIG, dynamic equivalent, heuristic optimization, MVMO

I. INTRODUCTION

THE most promising renewable energy source is the wind energy. All over the world thousands of megawatts of new installed wind turbine capacities are going operational every year and this trend seems to be accelerating. During the initial stage of these developments wind turbines were connected to the existing distribution grid delivering electricity to the consumers. However, with the rapidly increasing size of wind turbines and especially with the installation of wind farms comprising hundreds of megawatts capacity wind power is preferably connected to the high voltage grid. In many countries the focus of new installations has shifted to offshore due to space restrictions, landscape encroachment and better wind resources. In the North Sea off the northern coast of Europe several thousand megawatt offshore wind farms are under consideration and are expected to be built in the next two decades [1]. Since the new wind power plants are usually located in remote areas the grid integration of such huge amount of wind energy requires redesigning the entire high voltage transmission grid to meet the transportation requirements.

Modern multi-megawatt wind turbines are equipped with power electronic components and thus exhibit fast response to grid disturbances. In general the dynamic characteristic of wind turbines differs from that of conventional generation units based on directly connected synchronous generators considerably. In wind turbines the electronics allows fast control of active and reactive power independently of one another. On the other hand the maximum possible short circuit current exceeds the nominal current only slightly.

To investigate the effect of the ongoing changes in power systems due to the increasing share of wind power comprehensive dynamic stability studies are necessary. However, wind turbine control is very complex and corresponding dynamic models are usually not available. Besides, manufacturers are not interested in publishing details of their control systems due to confidentiality. Moreover, the complexity of the system would result in unacceptable computational effort if a large number of wind turbines were to be modeled. Therefore, the only way for large scale stability studies seems to be using generic models which

- are simplified to represent the phenomena affecting the power system stability only
- do not represent specific control schemas or parameters of the wind turbine
- are capable of simulating wind turbines of different manufacturers and types
- allow modeling of whole wind power plants consisting of any realistic number of wind turbines.

The activities concerning generic model development are coordinated in the US by the IEEE Dynamic Performance of Wind Power Generation WG and WECC Renewable Energy Modeling Task Force [2],[3] and on international level at the IEC Working Group on Wind Turbine Generator Modeling (IEC T88 WG27) [4]. The authors of this paper contributed to the development and the design of generic wind turbine models in several publications [5]-[7].

The present paper is intended to address two objectives:

- First the applicability of the proposed generic model to represent the whole wind farm dynamic behavior including the collector grid will be presented.
- The second objective is to introduce a new heuristic optimization algorithm called Mean Variance Mapping Optimization (MVMO) that has been used to calculate the generic model parameters.

In the following chapter some fundamentals of modern wind turbine control and modeling will be discussed. The detailed models can be used to develop the simplified generic model which is valid for both the Doubly-Fed Induction Generator (DFIG) and full converter based wind turbines. The subsequent chapter is devoted to the MVMO algorithm. After that the generic model will be applied to a realistic wind farm

I. Erlich (email: istvan.erlich@uni-due.de) and F. Shewarega (email: fekadu.shewarega@uni-due.de) are with University Duisburg-Essen, 47057 Duisburg, Germany; C. Feltes (email: christen.feltes@rwe.com) and F. Koch (email: friedrich.koch@rwe.com) are with RWE Innogy, Hamburg, Germany, J. Fortmann is with REpower Systems AG, 22768 Osterrönfeld, Germany, (email: j.fortmann@repower.de).

and the corresponding model parameters are estimated by the MVMO algorithm. In the last chapter the results will be presented and discussed.

II. CONTROL AND MODELING OF WIND TURBINES

The DFIG is currently very popular in wind turbine applications due to the low converter ratings which is about 1/3 of the machine rating. It allows variable speed operation by controlling the frequency and magnitude of the voltage injected to the rotor three-phase windings. The main control task is performed through the rotor by the machine side converter (MSC) whereas the line side converter (LSC) controls the power flow through the DC link and thus maintains the DC link voltage. For reactive power and voltage control it is preferable to use the MSC but the LSC can also help when the current limitation under the DC link voltage control allows this. An overview of the DFIG system is shown in Fig. 1

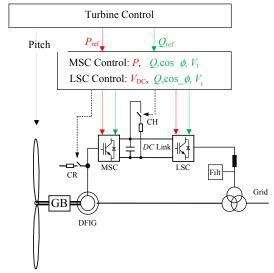


Fig. 1 DFIG-based wind turbine system

In wind turbines based on fully rated converter the entire generated power passes through the converter (Fig. 2).

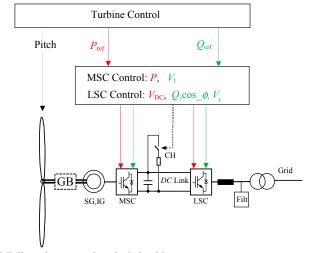


Fig. 2 Full rated converter based wind turbine system

Permanent magnet synchronous generators are very popular but simple squirrel-cage induction generators can also be used. The control task of the MSC is speed control and if necessary to supply the reactive magnetizing power by keeping the terminal voltage within the required range. The grid behavior of this wind turbine is basically determined by the LSC control which is very similar to the LSC control of DFIG based wind turbine systems.

A simplified generic model applicable to both types of wind turbines has been derived in [3]. A voltage source behind an internal impedance (Thevenin model) or alternatively a current source (Norton model) forms an interface to the grid. In this paper the authors opted for the Thevenin representation due to its simplicity and better clarity. The model suggested is shown in Fig. 3.

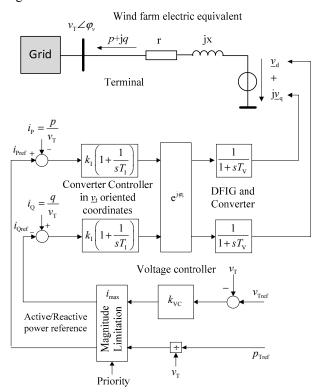


Fig. 3 Wind turbine / wind farm dynamic equivalent

The voltage source is supplied by two delay blocks (one each for the d, and q components) representing the electrical machine (DFIG) and/or the converter delay. This part of the model is in grid synchronous coordinates. The controllers represented by PI blocks operate in terminal voltage oriented coordinates in which the real component of the current corresponds with the active current and the imaginary component with the negative of the reactive current. Consequently, both controllers perform active and reactive current (power) control. For simplicity in this paper the authors assumed that the reference for reactive current is provided by a terminal voltage controller and the active current reference is calculated from the active power which is assumed constant in this example. The last assumption is applicable for 1-2 seconds following the grid disturbance. For

longer simulation durations modeling of the speed controller including the equation of motion may be necessary. The magnitude of the current reference is limited to a maximum allowed for the converter system. As can be seen from the model there is no separate representation of MSC and LSC. Also the parameters do not correspond with any of the real controller parameters, rather characterize the aggregated values.

Therefore, parameter estimation requires identification techniques preferably in the time domain based on measurements or detailed simulation results. Due to the nonlinearities (magnitude limitation, coordinate transformation) and the required time domain simulation in each iteration step the application of heuristic optimization methods is recommended. The parameter identification as an optimization task is illustrated in Fig. 4.

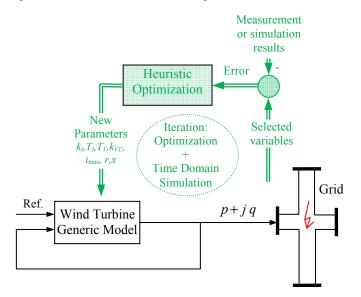


Fig. 4 Identification of generic wind turbine model parameters

The model suggested is not limited to single wind turbines. It can be used to model entire wind farms or even the entire system by shifting the terminal node to the point of common coupling (PCC). In the latter case the model also considers the collector grid including the internal power consumption.

III. MEAN VARIANCE MAPPING OPTIMIZATION

The parameter identification defined in the previous chapter can be solved by several alternative methods In this paper a new heuristic optimization algorithm called Mean Variance Mapping Optimization (MVMO) will be introduced, which is particularly suited for solving this task. The theoretical background of MVMO has been published in [8]. Applications to power systems are shown in [9] and [10]. Based on the application experiences MVMO has been slightly modified recently as will be described next.

The internal search space of all variables in MVMO is restricted to the range [0,1].

Hence, the real min/max boundaries of variables have to be normalized to 0 and 1. During the iteration it is not possible that any component of the solution vector will violate the corresponding boundaries. To achieve this goal, a special mapping function is developed. The input parameters of this function are the mean and variance of the best solutions that MVMO has discovered so far. The mapping function transforms a variable x_i^* varied randomly with unity distribution to another variable x_i which is concentrated around the mean value. The distribution of the new variable x_i doesn't correspond with any of the well-known distribution functions even though there are some similarities to the Gauss function. The transformation $x_i^* \to x_i$ is as follows:

$$x_{i} = h_{x} + (1 - h_{1} + h_{0}) \cdot x_{i}^{*} - h_{0}$$
(1)

where the h-function is defined as

$$h(\bar{x}, s_1, s_2, x) = \bar{x} \cdot (1 - e^{-x \cdot s_1}) + (1 - \bar{x}_i) \cdot e^{-(1 - x) \cdot s_2}$$
 (2)

 h_x , h_1 and h_0 are the outputs of the h-function (2) based on different inputs given by:

$$h_x = h(x = x_1^*), \quad h_0 = h(x = 0), \quad h_1 = h(x = 1)$$
 (3)

Note that the output of (1) is always within the bounds [0,1] for every generated x_i^* .

The shape of the h-function is determined by the mean x and the slope variables s_1 and s_2 . The effect of these parameters on the form of the function is illustrated in Fig. 5.

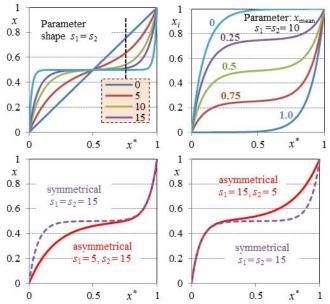


Fig. 5 Effect of parameters on the mapping function

The distinctive property of MVMO is the ability to search around the local best-so-far solution with little chance of being trapped into one of the local optimums. This is shown for two variables in Fig. 6.

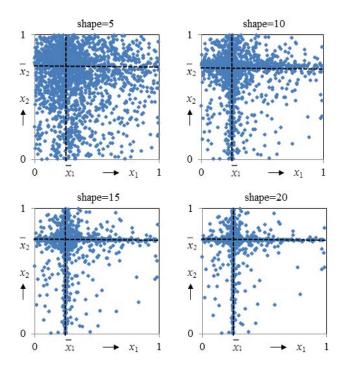


Fig. 6 Search space depending on the shape factor; Number of variables=2, $x_1 = 0.25$, $x_2 = 0.75$, shape= $s_1 = s_2$ for both variables

As can be seen the search is focused around the mean values which are $\bar{x}_1 = 0.25$ and $\bar{x}_2 = 0.75$ in this example. However, there are some samples also outside the mean areas, i.e. the algorithm performs global search but the emphasis is around the means.

Mean and slope variables are calculated from the archive where the n best populations are stored.

$$\bar{x}_{i} = \frac{1}{n} \sum_{i=1}^{n} x_{i}(j) \tag{4}$$

$$s_{i} = -\ln(v_{i}) \cdot f_{s} \tag{5}$$

with the variance

$$v_{i} = \frac{1}{n} \sum_{i=1}^{n} (x_{i}(j) - \bar{x}_{i})^{2}$$
 (6)

The variance is calculated only for different variables in the archive. The factor f_s can be used to change the slope of the function e.g. when the accuracy needs to be improved (increase $f_s > 1$) or more global search is required (decrease $f_s < 1$).

In contrast to the previous publication [8] the slopes s_{i1} and s_{i2} of variable x_i are not calculated directly from (5) but using the following algorithm:

$$\begin{split} s_{i1} &= s_{i2} = s_i \\ &\text{if } s_i > 0 \text{ then} \\ &\text{if } s_i > d_i \\ &d_i = d_i \cdot \Delta d \text{ ; } s_{i1} = s_i \text{ ; } s_{i2} = d_i \\ &\text{else} \\ &d_i = d_i / \Delta d \text{ ; } s_{i1} = d_i \text{ ; } s_{i2} = s_i \\ &\text{end} \\ &\text{end} \end{split}$$

The initial values of d_i are set for all variables at the beginning of the optimization. Experience so far shows that values around 1-5 are suitable to guarantee good initial performance. With the suggested modifications the robustness of the algorithm and the zero variance handling are improved. Zero variance can occur when all variables of x_i in the archive are identical. In this case the previous non-zero value is used further. Sometimes the variance can oscillate over a wide range. By using the factor d_i instead of s_i which is a function of variance a smoothing effect is achieved. Furthermore, the asymmetrical properties of the mapping functions are utilized. The mean and variance are not calculated before the archive is filled up completely. In this stage searching is performed with $s_{i1}=s_{i2}=0$ which corresponds with a straight line between zero and one as the mapping function. Usually an archive size of 2-5 is sufficient. A larger archive size will result in a rather conservative searching with orientation on the saved best populations. The flowchart of the MVMO algorithm is shown in Fig. 7

As parent of the new population the best population saved in the archive (first position) is used. Then a few variables are selected and reflected on the mapping function. Alternative selection methods are described in [8].

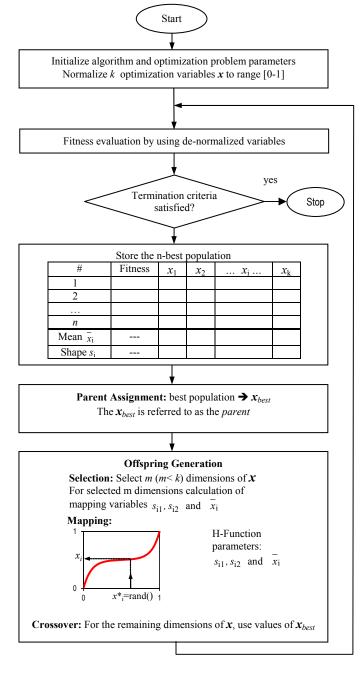


Fig. 7 Flowchart of the MVMO algorithm

MVMO shows excellent convergence behavior in comparison to other heuristic methods. Especially at the beginning of the iteration it outperforms all other methods. In Fig. 8 the convergence behavior of the classical optimal power flow task (OPF) with loss minimization is shown for the IEEE 57 node test system. Different Particle Swarm and Differential Evolution algorithms (PSO and DE) have been used for comparison. The MVMO is varied with respect to the initial values of d_i and Δd (see (7)). For a fair comparison the same constraint handling is implemented (simple penalty function) in all algorithms.

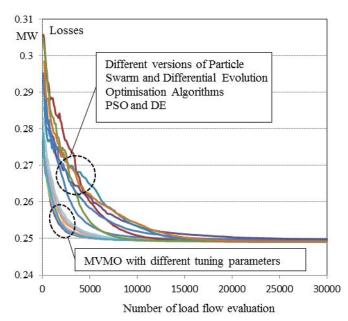


Fig. 8 Performance of MVMO in comparison to different heuristic optimization methods. Task: transmission loss minimization in the IEEE 57 node test system, 25 optimization variables

IV. CALCULATION OF WIND FARM EQUIVALENT The wind farm used in this paper is shown in Fig. 9.

18x5MW DFIG Wind Turbines

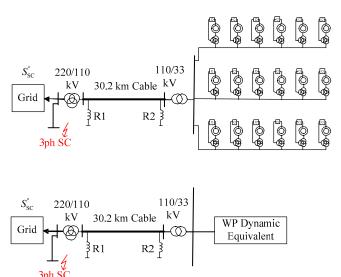


Fig. 9 Wind farm test system and definition of the equivalencing task

The wind farm consists of 18 wind turbines each with 5 MW nominal power. The wind turbines and the corresponding control system including speed and pitch control are described using detailed models. The maximum allowed integration time step is 1 ms. The simulation time by considering all 18 turbines is still tolerable due to the fact that the grid is represented by a simple infinite bus. However, if the model is integrated into a large grid and all wind turbines are modeled in detail the simulation effort would increase to an unacceptable level. Therefore, the whole wind farm should be replaced by the generic model shown in Fig. 3 which includes

a much smaller number of state variables and permits the use of at least 5 ms integration step. For the identification of parameters four short circuits have been simulated using the detailed model, and the active and reactive power, P(t) and Q(t) supplied at the 33 kV busbar as well as the busbar voltage V(t) have been stored as reference signals. The fitness for the heuristic optimization is defined with physical quantities as:

$$F = \Delta t \cdot \sum_{t=0}^{tend} \left(P(t) + Q(t) + V(t) \right) \tag{8}$$

Due to the similarity of the range of values in MW, Mvar and kV all components are weighted equally. However, different weighting may sometimes be appropriate. The simulated short circuits differ in the value of fault impedance used to simulate the short circuit. The identification process is carried out for each fault separately and also for all four faults simultaneously. In the latter case the partial objectives are combined to one overall objective. Thus the identification result is the aggregation over all fault scenarios. Table I shows the identified model parameters.

TABLE I: RESULTS OF PARAMETER IDENTIFICATION

Para- meter	Fault 1	Fault 2	Fault 3	Fault 4	All Faults
$R(\Omega)$	0.500	1.401	2.096	1.711	1.126
$X(\Omega)$	3.228	3.259	3.641	3.551	3.317
$k_{\rm I}$ (pu)	13.003	12.416	13.876	12.321	10.516
$T_{\rm I}\left({ m s}\right)$	0.100	0.045	0.048	0.040	0.038
$T_{\rm V}\left({ m s}\right)$	0.477	0.333	0.389	0.369	0.393
i_{max} (pu)	1.078	1.059	1.062	1.108	1.061
$k_{\rm VC}$ (pu)	1.952	2.127	2.225	2.214	2.183

In case the identification is performed using a single fault scenario the parameters may move to partly unrealistic ranges. Therefore, it is recommended to identify the generic model parameter for several faults simultaneously.

The convergence behavior of optimization variables and the objective is shown for simultaneous optimization in Fig. 10.

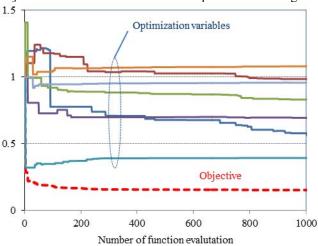
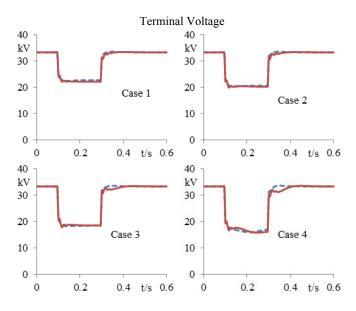
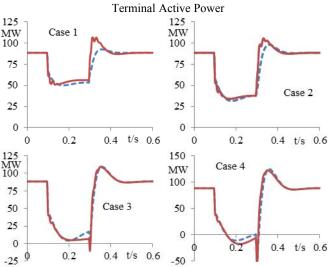


Fig. 10 Convergence of simultaneous parameter optimization; variables and objective are normalized to the initial values

For comparison with the original simulation results all faults have been calculated with the generic model and parameters received from the simultaneous optimization. The results are shown in Fig. 11.





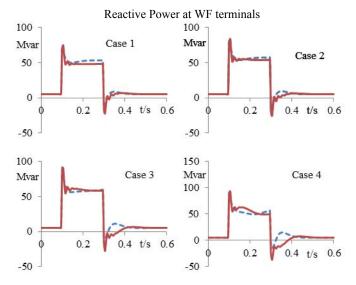


Fig. 11 Comparison of time responses to three phase short circuits calculated with detailed and equivalent models; detailed model: red solid line, generic model: blue dotted line

The simulation time to carry out the optimization including the underlying time domain simulations for all four scenarios is about 2-3 minutes on a standard windows notebook with P8700 processor.

V. CONCLUSIONS

With the increasing share of wind energy the dynamic behavior of power systems will be affected considerably. This fact calls for comprehensive stability studies taking into consideration wind turbines and the corresponding control systems. However, the large number of wind turbines and the complexity of controllers make this task difficult. Moreover, manufacturers usually choose to treat details of the control systems of their turbines as confidential information. The solution seems to be using generic models which are characterized by much lower complexity and contain only aggregated parameters not revealing the real-world parameter setting.

In this paper the authors propose a generic wind turbine model that is not only simple and accurate enough for power system stability studies but is also applicable to any modern wind turbine types and entire wind farms as well. However, the model parameters cannot be calculated directly but need identification methods based on measurements or detailed simulation results. To perform this task a heuristic optimization based new algorithm called MVMO has been introduced. The excellent convergence behavior of MVMO is demonstrated in the 57 node IEEE test system by solving the optimum power flow problem. The application of generic wind farm model is shown for a realistic 18 machine, 90 MW test system. The model parameters are calculated for four fault scenarios simultaneously where four time domain simulation runs are executed in each iteration step. Despite the apparent enormity of the computational effort the simulation time for calculating the generic model parameters is only about 2-3 minutes. The good accuracy of the generic model is verified by comparing the results with those obtained using the detailed model.

The application of the MVMO to calculate wind farm generic model has yet again demonstrated the advantages of heuristic optimization algorithms to solve practical problems fast and without extensive analytical formulations.

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VI. REFERENCES

- [1] http://www.offshorewind2011.info/fileadmin/eow2011_documents/hom epage/EWEA_PR.pdf
- [2] "Generic Type-3 Wind Turbine-Generator Model for Grid Studies," WECC Wind Generator Modeling Group, Version 1.1, Sept. 14, 2006.
- [3] M. Behnke, A. Ellis Y. Kazachkov, A. Muljadi, W. Price, and J. Sanchez-Gasca, "Development and Validation of WECC Variable Speed Wind Turbine Dynamic Models for Grid Integration Studies," *AWEA* 2007 Wind power Conference, Los Angeles, June 4-7,2007.
- [4] Mohamed Asmine, Jacques Brochu, Jens Fortmann, Richard Gagnon, Yuriy Kazachkov, Charles-Eric Langlois, Christian Larose, Eduard Muljadi, Jason MacDowell, Pouyan Pourbeik, Slavomir Seman, KevinWiens, "Model Validation for Wind Turbine Generator Models," ", 201 IEEE Power and Energy Society General Meeting, Detroit, 2011.

- [5] I. Erlich, J. Kretschmann, J. Fortmann, S. Müller-Engelhardt, H. Wrede, "Modeling of Wind Turbines Based on Doubly-Fed Induction Generators for Power System Stability Studies," *IEEE Transactions on Power Systems*, Volume 22, Issue 3, Aug. 2007, Page(s) 909 – 919. and assessment of power quality characteristics of grid connected wind turbines"
- [6] J. Fortmann, S. Engelhardt, J. Kretschmann, M. Janßen, T. Neumann, and I. Erlich, "Generic Simulation Model for DFG and Full Size Converter based Wind Turbines," 9th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Farms, Quebec City, 2010.
- [7] J. Fortmann, "New Generic Aerodynamic Model for RMS Simulation of variable speed Wind Turbines," 9th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Farms, Quebec City, 2010.
- [8] I. Erlich, G. K. Venayagamoorthy, and W. Nakawiro, "A mean-variance optimization algorithm," in WCCI IEEE World Congress on Computational Intelligence Barcelona, Spain, 2010.
- [9] Nakawiro, W.; Rueda, J. L. & Erlich, I. "A Novel Optimization Algorithm for Optimal Reactive Power Dispatch: A Comparative Study," 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, Weihai, Shandong, China, July 2011.
- [10] I. Érlich, W. Nakawiro, and M. Martinez, "Optimal Dispatch of Reactive Sources in Wind Farms," in *IEEE PES General Meeting* Detroit, USA, 2011.

VII. BIOGRAPHIES



István Erlich (1953) received his Dipl.-Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden

respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he has been Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen/Germany. His major scientific interest is focused on power system stability and control, modeling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and senior member of IEEE.



Fekadu Shewarega (1956) received his Dipl.-Ing. Degree in electrical engineering from the Technical University of Dresden, Germany in 1985. From 1985 to 1988 he pursued his postgraduate studies in the same university and obtained his PhD degree in 1988. After graduation, he joined the Addis Ababa University, Ethiopia as an associate professor where he served in various teaching and administrative capacities. Currently he is a member of the research staff at the University Duisburg – Essen. His research interests are

focused on power system analysis and renewable energy technologies. He is a member of IEEE and other professional associations.



Christian Feltes (1979) received his Dipl.-Ing. degree in electrical engineering from University of Duisburg-Essen/Germany in 2005. From January 2006 to February 2011 he worked in the research staff of the Department of Electrical Power Systems at the same University. Since March 2011 he is working as grid integration engineer in the Offshore Wind Engineering department at RWE Innogy GmbH in Hamburg.

His research interests are focused on wind energy

generation, control, integration and dynamic interaction with electrical grid.



Friedrich W. Koch (1969) received his Dipl.-Ing. degree in electrical engineering from the University of Siegen, Germany in 1998. From 1998 to 2000 and 2005 to 2006 he worked as engineer, project manager and finally as head of group in the field of industrial and power plants for the SAG GmbH. In between from 2000 to 2005 he worked on his PhD in the Department of Electrical Power Systems at the University of Duisburg - Essen, Germany. From 2006 to 2009 he was with REpower Systems AG, Germany as head of

the group "Grid Integration / Simulation". Since 2009 he is with RWE Innogy GmbH as head of the Offshore Wind Engineering department.



Jens Fortmann (1966) received his Dipl.-Ing. degree in electrical engineering from the Technical University Berlin, Germany, in 1996. From 1995 to 2002 he worked on the simulation of the electrical system and the control design of variable speed wind turbines at the German wind turbine manufacturers Suedwind and Nordex Energy. Since 2002 he is with REpower Systems AG, Germany as project manager for the simulation and implementation of new technologies for improved grid compatibility of wind turbines like

voltage control and ride-through of grid faults. He is member of IEEE.