Identification of Gaussian Mixture Model using Mean Variance Mapping Optimization: Venezuelan Case

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Abstract— **The characterization of random load behavior has been largely attempted through statistics-based model fitting. Remarkably, the use of Gaussian mixture model (GMM) has proven to be adequate to tackle the heterogeneity and variability of the statistical distribution of loads. In this paper, an application of the Mean-Variance Mapping Optimization (MVMO) algorithm to the identification of the parameters of GMMs, is presented. The feasibility of the proposed identification approach is demonstrated using historical data records from the Venezuelan transmission system portion that covers the Paraguaná Peninsula.**

Index Terms-- **Gaussian mixture model, load profile, mean-variance mapping optimization, probability distribution function.**

I. Introduction

THE modeling of power system loads is a complex task due to the heterogeneity and random nature of the electricity consumption. Such a task would become more challenging in the context of future power system operational policies, which should deal with large scale integration of distributed energy resources and accommodation of demand side participation.

Accurate models reflecting the variability of system loads are essential for transmission and distribution planning and operational studies. This issue is of greater concern if these models are considered in the development of robust monitoring and control schemes, with the aim of continuous efficient asset utilization through modern management systems (i.e. smart grid concept).

There have been significant research efforts devoted to probabilistic modeling of loads through different probabilistic distribution functions (PDFs), such as Gaussian, log-normal, beta, exponential, and Rayleigh [1], being the Gaussian the most commonly used due to its simplicity (i.e. it can be completely described by its mean and variance parameters). Nevertheless, it has been demonstrated that the aforesaid PDFs may not properly fit the statistical properties of load variations [2].

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Recently, motivated by the wide application of Gaussian mixture models (GMMs) in other fields (e.g. physics and applied mathematics), interest has focused on their use for estimation of the PDFs associated to different variables in power system stochastic analysis. At of this writing, interesting applications for probabilistic modeling of power quality parameters and reliability indexes have been presented in [3] and [4], respectively. GMMs have been also used for statistical representation of load duration curve in the Tunisian power system [5] as well as of distribution system loads in a UK generic distribution system [2]. Furthermore, it has been emphasized that GMMs can be employed to model pseudo measurements for state estimation [6], and smart metering purposes [7].

The expectation maximization (EM) algorithm [8] has been commonly used as general technique for determining the parameters of the GMM components. However, despite of its conceptual simplicity, the EM algorithm may have difficulties in handling problems with high dimensionality since it is sensitive to initialization and only converges to the local maxima [7]. Moreover, the problem of obtaining various mixture components (i.e. number, weight, mean, and variance) can be formulated as an identification problem, where optimization methods provide an efficient solution. Thus, based on the success gained in previous applications to different complex power system optimization problems, this paper presents an application of the Mean-Variance Mapping Optimization (MVMO) algorithm to the identification of the parameters of GMMs that best fit the statistical attributes of power system loads.

MVMO is a novel heuristic optimization algorithm which was originally proposed in [9]. Its most salient feature is that it uses a special mapping function applied for mutating the offspring on the basis of the statistics of the n-best population attained so far. Besides, thanks to the well-designed balance between search diversification and intensification, MVMO exhibits a fast convergence performance so that it can find the optimum solution quickly with minimum risk of premature convergence [10].

The remaining of the paper is organized as follows: Section II introduces the GMM model. Section III describes problem formulation and the adaptation of MVMO to tackle the identification task. Section IV presents results using load samples from the Venezuelan grid. Finally, conclusions are given in Section V.

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II. Gaussian Mixture Model

A Gaussian Mixture Model (GMM) is a parametric PDF represented as a weighted sum of Gaussian probabilistic densities [11]. The GMM is a weighted sum of N_C component Gaussian densities as given by the equation:

$$p\left(\mathbf{x}\middle|\lambda\right)=\sum_{i=1}^{N_C} w_i g\left(\mathbf{x}\middle|\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i\right) \tag{1}$$

where $\mathbf{x}$ is a D-dimensional continuous-valued data vector (i.e. measurement or features), w_i, $i = 1,\ldots ,N_C$, are the mixture weights, and $g(\mathbf{x}|\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i)$, $i = 1,\ldots,N_C$, are the component Gaussian densities. Each component density is a D-variate Gaussian function of the form:

$$g\left(\mathbf{x}\middle|\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i\right)=\frac{1}{(2\pi)^{\frac{D}{2}}\left|\boldsymbol{\Sigma}_i\right|^{\frac{1}{2}}}\mathrm{e}^{\left\{-\frac{1}{2}(x-\mu_i)'\boldsymbol{\Sigma}_i^2(x-\mu_i)\right\}} \tag{2}$$

with mean vector $\boldsymbol{\mu}_i$ and covariance matrix $\boldsymbol{\Sigma}_i$. The mixture weights satisfy the constraint that sum of all the weights must equal to one.

$$\sum_{i=1}^{N_C} w_i = 1 \tag{3}$$

This condition is because a PDF must be nonnegative and the integral of a PDF over the sample space of the random quantity it represents must evaluate to unity.

The advantage of GMM approach is that different types of load distributions can be fairly represented as a convex combination of several normal distributions with respective means and standard deviation [2].

III. Proposed MVMO-Based Identification of GMM

A. Problem statement

The GMM parameter estimation approach presented in this paper, based on the chi-square goodness-of-fit test, is defined as follows:

Minimize

$$\chi^2=\sum_{i=1}^{n}\frac{\left(O_i-E_i\right)^2}{E_i} \tag{4}$$

subject to

$$h=0 \tag{5}$$

where χ^2 stands for Pearson's cumulative test statistic, which asymptotically approaches a χ^2 distribution. O_i and E_i denote observed frequency and the expected frequency (asserted by the null hypothesis), respectively; h is a binary variable that indicates whether the null hypothesis can (h=1) or cannot (h=0) be rejected at the 5% significance level.

B. Solution through MVMO

The theoretical background of MVMO has been published in [9], [10]. MVMO operates on a single solution rather than a set of solutions like in many evolutionary algorithms. It aims at performing prompt and accurate optimization with a minimum amount of objective function evaluations.

The internal searching space of all variables in MVMO is restricted in [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 inputs of this function are mean and variance of the best solutions that MVMO has discovered so far. The output of this mapping function is always inside the range [0, 1]. This means that violation of the variable limits during the search process cannot occur. The shape and location of the mapping curve are adjusted according to the progress of the search process, and MVMO updates the candidate solution around the best solution in every iteration step. Hence, MVMO is able to search around the local best-so-far solution with a small chance of being trapped into one of the local optimums. This feature is enhanced with a strategy for handling the zero-variance [12]. So far, MVMO has successfully been applied for the solution of different power system optimization problems such as optimal reactive power dispatch [10], identification of dynamic equivalents [12], optimal location and coordinated tuning of damping controllers [13], and optimal control in wind farms [14], [15].

The procedure of MVMO for solving the GMM identification problem with D parameters to be identified is schematically illustrated in Fig. 1.

Fitness evaluation and constraint handling: For each individual (defined by number of GMM components and their weight, mean, and variance parameters), the chi-square goodness-of-fit test is performed, the feasibility of the solution is checked and a fitness value is assigned. It is considered that an individual is better if the fitness is smaller. The static penalty scheme is used in this paper to handle constraints. Since the control variables are self-restricted, all dependent variables are constrained by applying the integrated fitness function as follows:

$$\min f'=f+\sum_{i=1}^{n}\upsilon_i \max\left[0,g_i\right]^{\beta} \tag{6}$$

The where f is the original objective function, n is the number of constraints, β is the order of the penalty term (e.g. 1 or 2), υ_i is the penalty coefficient of the i-th constraint and g stands for inequality constraint. It is worth mentioning that other constraint handling techniques are also applicable to MVMO [10].

Termination criteria: In this paper, the MVMO search process is terminated based on completion of a pre-specified number of fitness evaluations.

Solution archive: The solution archive constitutes the knowledge base of the algorithm for guiding the searching direction. Hence, the n best individuals that MVMO has found so far are saved in the archive. Fitness of each individual is also stored. The following rules are set up to compare the individual generated at each iteration and existing archived solutions in order to avoid losing good solutions [9]: (i) Any feasible solution is preferred to any infeasible solution, (ii)

Between two feasible solutions, the one having better objective value is preferred, (iii) Between two infeasible solutions, the one having smaller fitness value (i.e. smaller constraint violation) is preferred.

An update takes place only if the new individual is better than those in the archive. The archive size is fixed for the entire process. The archived individuals are dynamically sorted so that the first ranked individual is always the best. Feasible solutions are placed in the upper part of the archive. Among these solutions, they are sorted based on their fitness values. Infeasible solutions are sorted according to their fitness and placed on the lower part of the archive. Once the archive is filled up by n feasible solutions, any infeasible candidate solution does not have chance to be saved in the archive.

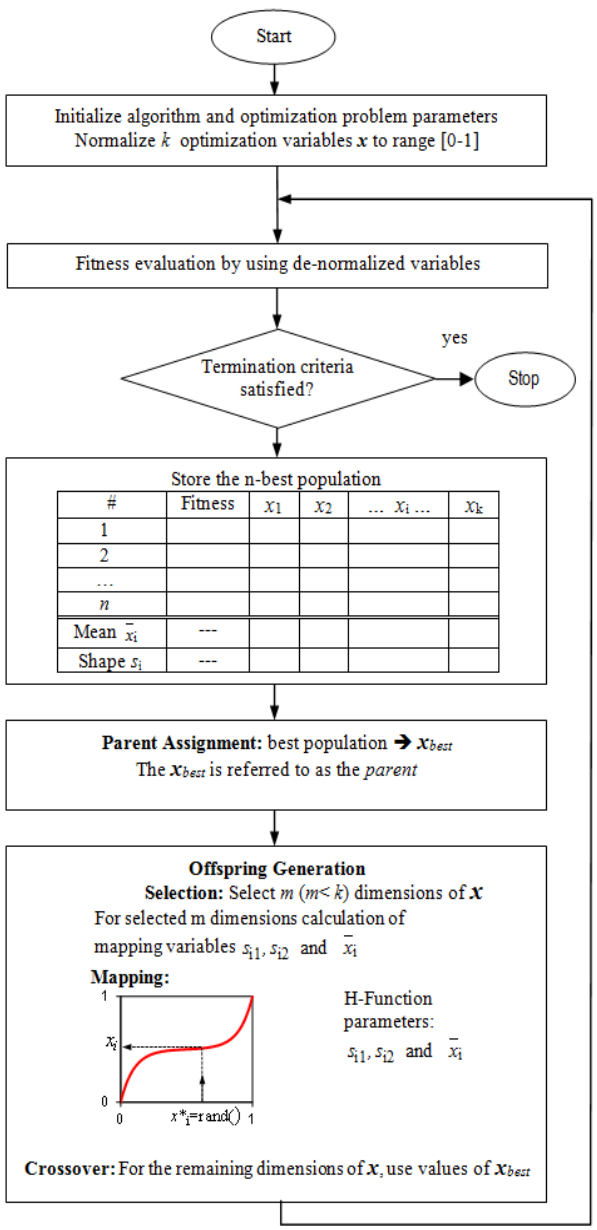

Fig. 1. MVMO implementation procedure for identification of GMM parameters.

Parent assignment: The first ranked (best-so-far) solution, denoted as $\mathbf{x_{best}}$, is assigned as the parent.

Variable selection: The MVMO searches around the mean saved in the archive for the better solution only in *m* selected directions. This means that only these dimensions of the offspring will be updated while the remaining D-*m* dimensions take the corresponding values from $\mathbf{x_{best}}$. In this paper, a random sequential selection strategy was implemented.

Mutation: For each of the *m*-selected dimension, mutation is used to assign a new value for that variable. The procedure is as follows: Given a uniform random number $x_i' \in [0,1]$, the new value of the i-th variable x_i is determined by:

$$x_i = h_x + (1 - h_1 + h_0)\, x_i' - h_0 \tag{7}$$

where h_x, h_1 and h_0 are the outputs of the transformation mapping function based on different inputs given by:

$$h_x = h(u_i = x_i'), \quad h_0 = h(u_i = 0), \quad h_1 = h(u_i = 1) \tag{8}$$

The mapping function is parameterized as follows

$$h(\bar{x}_i, s_{i1}, s_{i2}, u_i) = \bar{x}_i\left(1 - e^{-u_i s_{i1}}\right) + (1 - \bar{x}_i)\, e^{-(1-u_i) s_{i2}} \tag{9}$$

where s_{i1} and s_{i2} are shape factors allowing asymmetrical slopes of the mapping function. The slope is calculated by

$$s_i = -\ln(v_i)\, f_s \tag{10}$$

where f_s is a scaling factor, which enables the control of the search process during iteration. Interested readers are referred to [12] for further details on how to set the two different shape factors and the scaling factor as well.

IV. Results

A. Venezuelan test case

Venezuela's power system is an integrated vertical power company, called Corporación Electrica Nacional (Corpoelec) which covers most of the country. Its transmission grid comprises about 11,747 kilometers of 765-kV, 400-kV, and 230-kV transmission lines. It is expected that the first wind power plant (with a total capacity of 100MW), which is currently under construction in the Paraguaná Peninsula, come into operation by the end of 2012 [16].

The Paraguaná Peninsula network is fed from a single circuit (230 kV) transmission line of San Isidro substation as part of the Venezuelan power pool. Its average demand is 280 MW whereas average imports through San Isidro tie line are around 187 MW. Fig 2 depicts the single line diagram of the Paraguaná's network, including transmission lines, static reactive compensators, and generators [16]. Parameters of system elements are not provided due to confidentiality. For illustrative purposes, the rated capacity of each generator is also depicted with red text in the figure in order to highlight the importance of the contribution from the wind power plant to the overall regional energy supply. Indeed, preliminary studies have shown that the variability of wind power plant output may led to considerable changes in Paraguaná Peninsula transmission network power flows resulting in major operational challenges due to higher congestion and dynamic reactive power support issues [16], [17]. Hence, the development of new monitoring and control infrastructures in the near future, which includes the introduction of smart metering, is being planned. This task also involves proper modeling of load variability, specially, if predictive control, considering load probabilistic models as pseudo measurements, is to be performed.

Since Punto Fijo and Judibana substations supply an important amount of the total demand of the Paraguaná network, they are selected for testing the proposed approach. For this purpose, real data measurements collected during two years are used. Initially, several tests were performed to the data in an attempt to fit a unique PDF to the measurement statistics. Results are shown in Fig. 3 and Fig. 4. Note that a single PDF would not entail a good fit to explain the variation of the measured load active power at those substations.

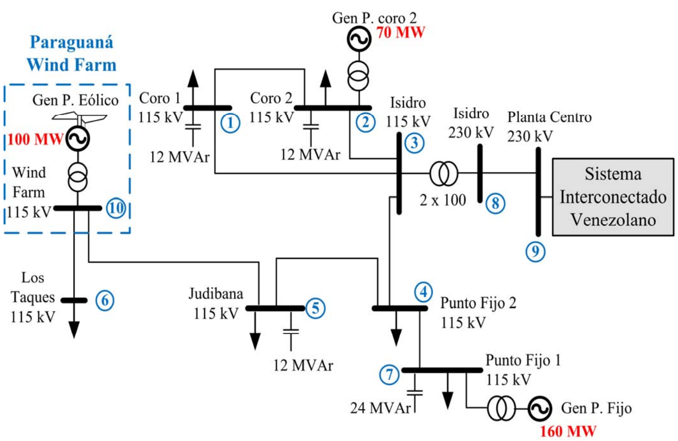

Fig. 2. Layout of the Paraguaná Península network.

A. Identification of GMMs

For illustrative purposes, the convergence performances of the objective function and the number of mixture components (needed to define the best GMM fit describing the variability of the loads at Punto Fijo Subestation), averaged from 100 independent trials of the MVMO-based identification, are shown in Fig. 5. Note that MVMO is very fast in the global search capability because the lowest χ^2 has been found after 750 objective function evaluations. These results further demonstrate the fast convergence performance of MVMO.

In contrast to Fig. 3 and Fig. 4, Fig. 6 and Fig. 7 show that the full component merging of the identified weighted mixture components provides good approximation to the variation of the data collected at two substations of the Paraguaná network. The parameters of each GMM component are summarized in Table I and Table II. Note that in both cases, the GMM components have similar weights, which indicates the importance of considering all of them together without incurring in overlapping between the respective PDFs. This observation matches with one of the findings reported in [2], which pointed out that GMM components exhibiting comparable weights and low overlap should be kept. Therefore, these results suggest that any load PDF, irrespective of its distribution, can be estimated with a high degree of confidence using GMMs.

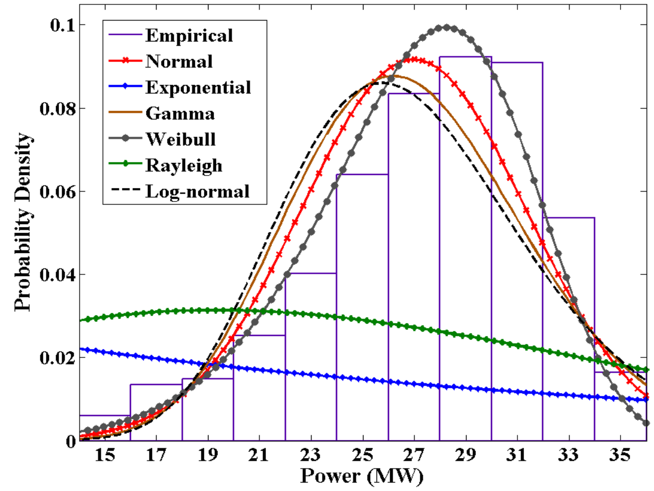

Fig. 3. Single PDF approximation for load at Punto Fijo substation.

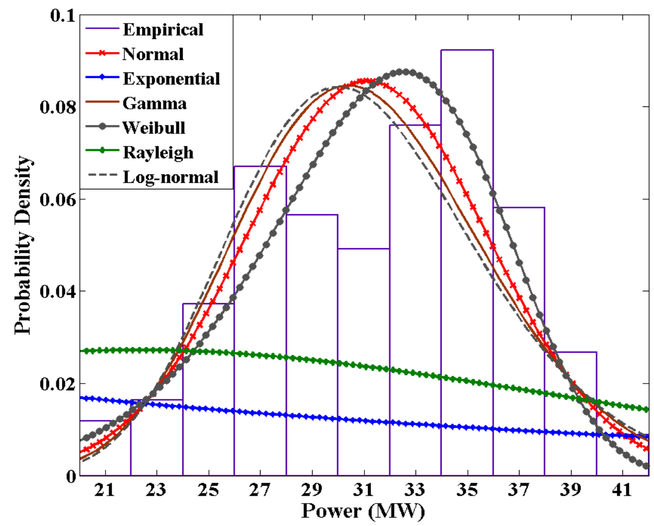

Fig. 4. Single PDF approximation for load at Judibana substation.

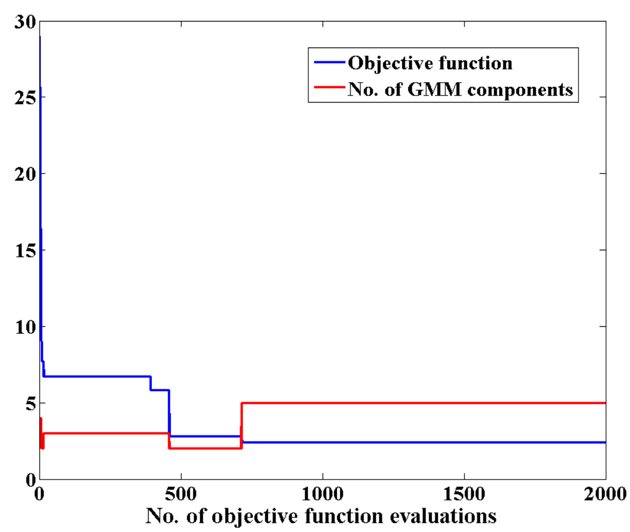

Fig. 5. Convergence behavior of the MVMO-based identification of GMM.

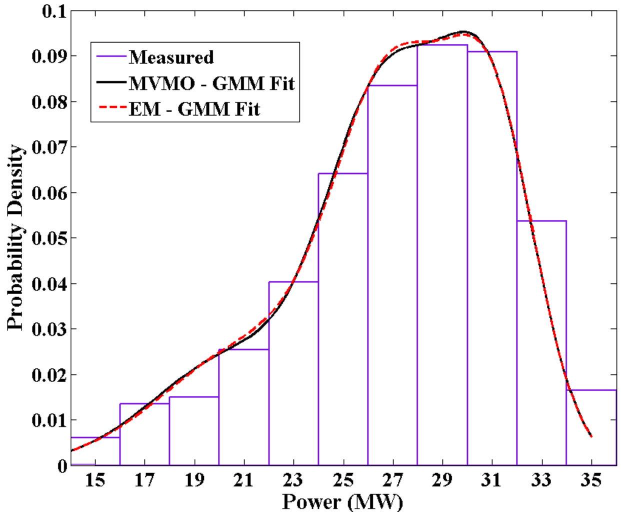

Fig. 6. GMM approximation of the load PDF at Punto Fijo Subestation.

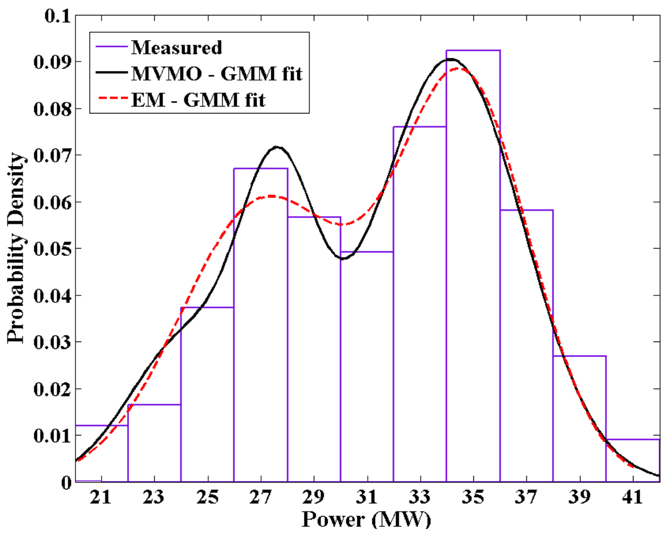

Fig. 7. GMM approximation of the load PDF at Judibana Subestation

In addition, it can be seen that the GMM fits obtained through the expectation maximization (EM) algorithm were also included in Fig. 6 and Fig.7, in order to validate the results obtained via MVMO-based identification. The EM-based identification can be easily performed in Matlab [18] using the *gmdistribution.fit* command. Note the closeness between the models identified using both MVMO and EM, especially for the estimation of GMM at Punto Fijo substation, which indeed highlights the accuracy that can be achieved with the proposed approach. Since the closeness for the estimation of GMM at Judibana substation is not so tight, Chi-square goodness-of-fit tests were performed (using the *chi2gof* Matlab function) for GMM estimates from MVMO and EM. Results were 11.35 and 22.12, respectively. Despite of the small difference, it can be concluded that the MVMO estimate provides better estimation accuracy, since a smaller value of the Chi-square goodness-of-fit indicates a better fit.

V. Conclusions

In this paper, the problem of obtaining various components (along with their weight, mean, and standard deviation) of GMMs was formulated as a problem of identification, which was solved using the MVMO algorithm. The adoption of this algorithm to deal with the optimization task has further confirmed its outstanding performance both in terms of convergence and the minimum reached. Numerical comparisons with results from single PDF fitting and identification of GMM through the EM algorithm demonstrated the effectiveness of the proposed approach. In addition, it is worth to mention that, unlike to the EM-based identification, the proposed approach does not need pre-specification of the number of GMM components. Future research work is being directed towards development of a real-time reactive power predictive control using GMMs as pseudo measurements. The application of GMMs to model the statistical properties of several power system performance indexes is also being pursued.

Table I. Results of GMM approximation of the load pdf at Punto Fijo Subestation.

Gaussian PDF No.	*Weight (p.u.)*	*Mean (MW)*	*Std (MW)*
1	0.1790	32.4068	9.2641
2	0.1956	27.6210	2.0460
3	0.4649	34.4864	6.8014
4	0.1605	24.1748	4.5416

Table II. GMM 2: Results of GMM approximation of the load pdf at Judibana Subestation.

Gaussian PDF No.	*Weight (p.u.)*	*Mean (MW)*	*Std (MW)*
1	0.1665	29.0589	4.8444
2	0.1936	20.6211	10.7520
3	0.1939	26.1117	4.5117
4	0.1922	26.8740	6.3281
5	0.2539	31.1581	3.1041

VI. References

[1] EPRI, "Selected Statistical Methods for Analysis of Load Research Data," EPRI EA-3467, May 1984.

[2] R. Singh, B. C. Pal, and R. A. Jabr, "Statistical Representation of Distribution System Loads Using Gaussian Mixture Model," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 29 - 37, Feb. 2010.

[3] J. Meyer, and P. Schegner, "Characterization of power quality in low voltage networks based on modeling by mixture distributions," in *Proc. Probabilistic Methods Applied to Power Systems*, pp. 1-6, Stockholm, Sweden, June 2006.

[4] O.A. Mousavi, G.B. Gharehpetian, and M.S. Naderi, "Estimating risk of cascading blackout using probabilistic methods," in *Proc. International Conference on Electric Power and Energy Conversion Systems*, pp. pp.1-4, Nov. 2009.

[5] M.O.M. Mahmoud, M. Jaidane-Saidane, J. Souissi, and N. Hizaoui, "The mixture of generalized gaussian model for modeling of the load duration curve: Case of the Tunisian power system," in *Proc. 14th IEEE Mediterranean Electrotechnical Conference*, pp. 774-779, May 2008.

[6] E. Manitsas, R. Singh, B. C. Pal, G. Strbac, "Distribution System State Estimation Using an Artificial Neural Network Approach for Pseudo Measurement Modeling," *IEEE Transactions on Power Systems*, 2012.

[7] S. Wang, L. Cui, J. Que, D.H. Choi, X. Jiang, S. Cheng, and L. Xie, "A Randomized Response Model for Privacy Preserving Smart Metering," *IEEE Transactions on Smart Grid*, 2012.

[8] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the Royal Statistical Society*, vol. 39, no. 1, pp. 1-38, 1997.

[9] I. Erlich, G. K. Venayagamoorthy, and W. Nakawiro, " A mean-variance optimization algorithm," in *Proc. 2010 IEEE World Congress on Computational Intelligence, Barcelona, Spain*.

[10] W. Nakawiro, I. Erlich, and J.L. Rueda, "A novel optimization algorithm for optimal reactive power dispatch: A comparative study," in *Proc. 4th International Conference on Electric Utility Deregulation and*

Restructuring and Power Technologies, Weihai, Shandong, China, July 2011.

[11] G. McLachlan and D. Peel Finite Mixture Models. New York: John Wiley and Sons, 2000.

[12] J.C. Cepeda, J.L. Rueda, and I. Erlich, "Identification of Dynamic Equivalents based on Heuristic Optimization for Smart Grid Applications," in *Proc. 2012 IEEE World Congress on Computational Intelligence*, Brisbane, Australia, June 2012.

[13] J.L. Rueda, J.C. Cepeda, and I. Erlich, "Estimation of Location and Coordinated Tuning of PSS based on Mean-Variance Mapping Optimization," in *Proc. 2012 IEEE Power & Energy Society General Meeting*, San Diego, USA, July 2012.

[14] I. Erlich, W. Nakawiro, and M. Martinez, "Optimal dispatch of reactive sources in wind farms," in *Proc. 2011 IEEE Power and Energy Society General Meeting,* pp. 1-7, July 2011.

[15] P. Chakravarty and G.K.Venayagamoorthy, "Development of optimal controllers for a DFIG based wind farm in a smart grid under variable wind speed conditions," in *Proc. 2011 IEEE International Electric Machines & Drives Conference*, pp. 723 – 728, Niagara Falls, Canada..

[16] F. Gonzalez-Longatt, J. Orldan, J. Rueda, C. Charalambous, "Evaluation of Power Flow Variability on the Paraguaná Transmission System due to Integration of the First Venezuelan Wind Farm," in *Proc. 2012 IEEE Power & Energy Society General Meeting*, San Diego, USA, July 2012.

[17] F. Gonzalez-Longatt, V. Zapata, O. Ravelo, and P.M. De Oliveira-Jesús, " Evaluación de Alternativas de Compensación Dinámica de Potencia Reactiva: Caso Parque Eólico Paraguaná," in *Proc. III CICGRE Congreso Venezolano de Redes y Energía Eléctrica*, Caracas, Venezuela, March 2012.

[18] MATLAB, version 7.12.0.635 (R2011a 64-bit) Natick, Massachusetts: The MathWorks Inc., 2011

VII. Biographies

Francisco M. Gonzalez-Longatt (S'01, M'03, SM' 2009) was born in Cagua, Venezuela, on July 30, 1972. is currently a Lecturer in Electrical Engineering in the Faculty of Engineering and Computing, University of Coventry and he is Vice-President of Venezuelan Wind Energy Association. His academic qualifications include first Class Electrical Engineering of Instituto Universitario Politécnico de la Fuerza Armada Nacional, Venezuela (1994), Master of Business Administration (Honors) of Universidad Bicentenaria de Aragua, Venezuela (1999) and PhD in Electrical Power Engineering from the Universidad Central de Venezuela (2008). He is former associate professor on Electrical engineering Department of Universidad Nacional Politécnico de la Fuerza Armada Nacional, Venezuela (1995-2009). He was formerly with the School of Electrical and Electronic Engineering, The University of Manchester as Postdoctoral Research Associate (2009-2011). His main area of interest is integration of intermittent renewable energy resources into future power system and smart grids.

José L. Rueda (M'07) was born in Santa Rosa, Ecuador, on March 26, 1980. He received the Electrical Engineer diploma from the Escuela Politécnica Nacional, Quito, Ecuador, in 2004, and the Ph.D. degree in electrical engineering from the Universidad Nacional de San Juan, San Juan, Argentina, in 2009. From September 2003 till February 2005, he worked in Ecuador, in the fields of industrial control systems and electrical distribution networks operation and planning. Currently, he is a research associate at the Institute of Electrical Power Systems, University of Duisburg-Essen. His current research interests include power system stability and control, system identification, power system planning, probabilistic and artificial intelligence methods, heuristic optimization, FACTS devices and wind power.

István Erlich (SM'08) was born in 1953. He received the Dipl.-Ing. degree in electrical engineering and the Ph.D. degree from the University of Dresden, Dresden, Germany, in 1976 and 1983, respectively. From 1979 to 1991, he was with the Department of Electrical Power Systems of the University of Dresden. In the period of 1991 to 1998, he worked with the consulting company EAB, Berlin, Germany, and the Fraunhofer Institute IITB Dresden. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he has been a Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen, Duisburg. Germany. His major scientific interest comprises power system stability and control, modeling, and simulation of power system dynamics, including intelligent system applications. Dr. Erlich is a member of VDE and the chairman of the IFAC (International Federation of Automatic Control) Technical Committee on Power Plants and Power Systems.

Dimitar Bogdanov was born in Sofia, Bulgaria, on June 11, 1974. He graduated from the Technical University - Sofia, and received Master degree from the same university in 1998. He has received a PhD degree from Technical University - Sofia in 2009 in Electrical Power Engineering. His field of interest includes electrical relay protections and automation, electrical networks, nuclear power plants (electrical and technological aspects), renewable energy sources (electrical aspects). Currently he is assistant professor in the Faculty of Electrical Engineering of the Technical University – Sofia. He works on studies related to improvement of the protection schemes for connection of renewable sources of energy to the grid.

Walter M. Villa (GSM'12) was born in Medellín, Colombia, on November 19, 1979. He is Electrical Engineer, graduated from the University of Antioquia in 2006. Currently, he is pursuing the Ph.D. degree at Instituto de Energía Eléctrica, Universidad Nacional de San Juan, San Juan, Argentina, as part of a scholarship financed by the German Academy Exchange Service (DAAD). From 2006 to 2009, he worked in Colombia, as research associate in the Group of Efficient Energy Management (GIMEL). His current research interest areas are: electromagnetic compatibility, grounding systems, power system voltage stability and artificial intelligence.