

Online Estimation of Equivalent Model for Cluster of Induction Generators: A MVMO-based Approach

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Abstract— This paper presents an approach based on the hybrid variant of the mean-variance mapping optimization algorithm (MVMO-SH) for the estimation of an Equivalent Model for a cluster of induction generators (IGs) from the on-line system response to a system frequency disturbance. Numerical results, obtained by using a small-size test system, demonstrate the viewpoint and effectiveness of the proposed approach.

Index Terms—Induction generator, equivalent model, parameter estimation, Variable Metric Method.

I. INTRODUCTION

The *induction generator* (IG) is widely used in many applications due to its simplicity and ease of operation. Typical applications involve: *split-shaft micro-turbines* (SSMT) [1], *mini-hydro* (MH) [2], and *fixed speed wind turbines* (FSWT) [3]. The accurate knowledge of the machine parameters is especially important in order to establish the performance of the IG as well as to directly affect its operational and control characteristics [4].

A range of techniques have been used to estimate the parameters of an induction machine model. These include: non-linear least squares, Kalman Filters [5], genetic algorithms (GA) [6]-[8], local search algorithms (LSA), simulated annealing (SA), differential evolution and various forms of particle swarm optimization (PSO) [9]-[12]. Most of these techniques are applied to data gathered during the start-up of the machine [7], [13], [10], [11]. Some approaches compare the results of the estimated model to data gathered by applying mechanical tests to the machine [12], [14].

The problem of IG parameter estimation results specially complicated to solve when a cluster of IGs is interconnected to create of *virtual power plant* (VPP). The VPP concept enables the aggregation of distributed generation, controllable loads and storage devices supported on information and communication system [15]. It is desirable to have an effective method to estimate the parameters of an equivalent model for a cluster of IG (which does not require detailed definition of the power plant structure and parameters) by using novel digital measurement equipment such as *phasor*

measurement units (PMU) in transmission and distribution networks.

Most of the parameter estimation schemes found in literature deal exclusively with the response of an IG to a change in voltage. By contrast, the approach introduced in this paper uses the on-line measured response of an IG to system frequency disturbance and considering potential impact of voltage changes. Consideration of both voltage and frequency changes allows covering all relevant phenomena related to the fundamental frequency of electromechanical dynamic. The response of the IGs is viewed in terms of the active and reactive power flow associated with the IG. Parameter estimation based on the IGs response to a change in frequency is feasible as both the generated active power and consumed reactive power are dependent on the frequency of the system that the IG is connected to. The approach presented in this paper also constitutes an improvement in the performance of the parameter estimation, since the fast convergence property of the hybrid variant of the *mean-variance mapping optimization* (MVMO-SH) provides an important benefit to on-line applications dependent on accurate representations of power system components, e.g. intelligent controlled islanding or stability assessment. The paper is organized as follows: Section II briefly overviews the assumptions underlying the modelling of the dynamic equivalent for a cluster of IGs. In Section III, the proposed MVMO-SH based identification approach is presented. Section IV discusses the numerical results obtained by using a small-size test system, including comparisons with two recently developed evolutionary optimization algorithms. Finally, concluding remarks and outlook for future work are given in Section V.

II. EQUIVALENT MODEL FOR A CLUSTER OF IG

In this paper, the concept of a cluster of IG is defined by several IGs connected to the electrical power network through a *collector system*. This system starts from the step-up transformer connected to each induction generator and includes power cables, power-factor compensation devices and the main substation. Finally, the cluster of IGs is connected to the power network at the so-called *point common*

coupling (PCC). The structure assumed here for a cluster of IG can be easily found on a wind farm based on fixed speed wind turbines but also under the approach of micro grid. A typical micro-grid includes a set of generation and demand together connected using a PCC to a larger AC grid, if the dynamic (voltage and frequency) related to the load is neglected then the topology previously described take validity. Fig. 1 shows the typical layout of an IG cluster. Representative examples of the cluster of IGs concept include VPP based on SSMT and wind farm based on FSWT.

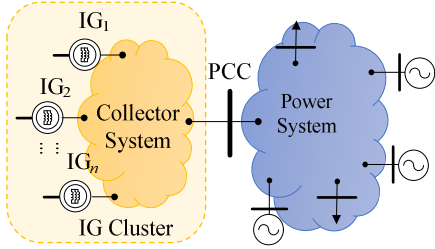


Figure 1. Layout of a grid-connected cluster of IG.

In order to develop an equivalent model for a cluster of IG valid for system disturbances and suitable for on-line response the following aspects have been assumed: (i) the dynamic of prime-mover of each IG unit is neglected. The mechanical power (P_m) on the shaft of each IG is considered constant and equal to the value previous to occurrence of the disturbance. This assumption is valid for very small time scales (seconds) in most of IG applications, i.e. the cluster of IG represents the equivalent model of a wind farm. (ii) The electromechanical model of the IG is included. The electrical model of the IG is represented by a 4th order state-space model and the mechanical part by a 2nd order system. This model has been successfully used in other publications related to the parameter estimation of IM [11], [15]. (iii) Equivalent series impedance is used to model the collector system. This assumption is motivated by the fact that capacitive effects are considerable lower than inductive effects in overhead transmission lines that span over short distances. Also, considering that changes in the system frequency are small, the collector system can be considered as a linear system (e.g. RLC electrical network). Thus, thevenin equivalent impedance is used to model the collector system in per unit values.

III. PROPOSED APPROACH

A cost-effective solution to improve grid planning, operation, maintenance, and energy trading in large power systems is the use of *wide area monitoring, protection, and control scheme* (WAMPAC) [16]. It enables the development of several applications such as estimation of parameters of network components' models, which can be used for other real-time applications. In this paper, the identification of an equivalent model for a cluster of IGs, called **EqMCIG App**, based on measurement data is tackled. The general concept of EqMCIG App, which includes a parameter identification

module based on MVMO-SH, is depicted in Fig. 2. EqMCIG App receives voltage and current phasor measurements from PMU device at PCC, which are used to derive P and Q at PCC to compared them with those obtained by simulating the dynamic response of the equivalent model, such that the embedded optimization process attempts to identify the parameters of the equivalent model that entails the minimum difference. A fast and effective optimization solver is crucial to perform reliable parameter identification for real-time application. The identification performed by EqMCIG App is focused exclusively on electromechanical transients.

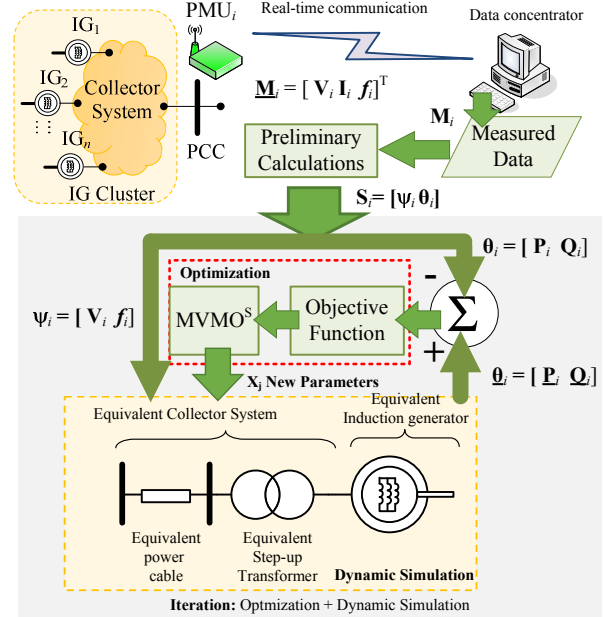


Figure 2. Schematic representation of EqMCIG application.

Basically, it is assumed that there is a phasor measurement unit (PMU_i) installed at the PCC of the cluster of IGs (bus i). The PMU provides a data set (\mathbf{M}_i) which represents accurate time-stamped measurement data suitable for observing power system dynamics. Measurements of voltages (\mathbf{V}_i) and currents (\mathbf{I}_i), and frequency (\mathbf{f}_i) compose the data set \mathbf{M}_i , which is transmitted to the *data concentrator* (DC). When a system frequency disturbance occurs, the DC sends the measurement raw data to the EqMCIG application. For the purpose of the study presented in this paper, it is assumed that the data set is preprocessed such that noise and outlier related issues are properly overcome, so reliable measurements of voltage and current are used to compute the active and reactive power at PCC, $\theta_i = [\mathbf{P}_i \ \mathbf{Q}_i]$.

A. Model of the EqMCIG

The EqMCIG is defined by a set of electrical and mechanical parameters included in the vector \mathbf{X} . The model proposed in this paper has a flexible structure, so several levels of details (beyond the scope of this paper) can be easily added.

The most simple model is defined by eight parameters: $\mathbf{X} = [R_{eq} L_{eq} R_s X_{ls} R_r X_{lr} X_m H]$, where R_{eq} and L_{eq} are the electrical parameters of an equivalent series element that represent the Thevenin equivalent model for the collector system and the remaining parameters correspond to the equivalent IG model. The EqMCIG in this simple case is represented in Fig. 3.

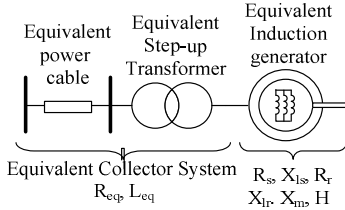


Figure 3. Simplest representation of a cluster of IG.

More detailed models consider several other effects: compensation devices, cable capacitances, and active power losses associated to the magnetizing current in the transformers, etc. Under these situations the procedure used for identifying the EqMCIG is in essence the same, the only differences are the number of parameters in the vector \mathbf{X} and its impact on the computing time required to reach a near-optimal solution.

The vector \mathbf{X} is represented in per unit quantities in order to take advantages of several properties of this system: all quantities are referred to one side of the transformer (PCC), the results are independent of the three phase connections used in transformers, the per unit quantities varies in narrow band as consequence errors are easily detected. A convenient selection of the base values is needed, thus, in this method, the active power immediately before the system frequency disturbance and the rated voltage at PCC are used as base values.

An important issue of the EqMCIG application is the incorporation of a suitable strategy to perform reliable parameter estimation with a small computing effort. Different types of approaches can be adopted to accomplish this task, namely, artificial intelligence (AI) methods [17], classical optimization methods [18], and hybrid methods [14]. Motivated by successful application to other optimization problems in power system field and fast convergence capability [19], the MVMO-SH is adopted in this paper.

B. Statement of the parameter identification problem

Generally speaking, the problem of parameter identification concerns the reconstruction of an unknown function appearing as parameters. The main idea behind parameter estimation is the comparison of the response of the real system and the response of the equivalent model with the estimated aggregated parameters to the same input. Based on this comparison, the parameter vector \mathbf{X} , which defines the model variables, is then adjusted to minimize a predefined error function ε .

For the non-linear model used on the simplest representation of a cluster of IG, there are eight state

variables that cannot be measured directly; therefore, the parameter vector contains eight unknown parameters that must be estimated:

$$\mathbf{X} = [R_{eq}, X_{eq}, H, R_s, X_{ls}, R_r, X_{lr}, X_m]^T \quad (1)$$

The initial values of the states (\mathbf{X}_0) of the cluster of IG are obtained by solving the model with respect to the initial (pre-disturbance) frequency. Parameter estimation can be transformed into an optimization problem, where the task is formulated as a curve fitting problem. The goodness of fit is used to summarize the discrepancy between observed values and the values expected under the model. Mean square error is used as cost function to determine goodness of fit, and the following objective function is minimized:

$$\min \varepsilon(\boldsymbol{\theta}) = \min \frac{\|\boldsymbol{\theta} - \boldsymbol{\theta}_0\|^2}{N_s} \quad (2)$$

where, N_s is the number of samples simultaneously processed in the estimation process, and $\|\cdot\|$ indicates the 2-norm of a vector.

It is known that IG parameters vary only in a certain range of values, as consequence the following inequality constraints should also be satisfied during this optimization:

$$\begin{aligned} 4 < H < 10 \text{ [s]} \\ 0.02 < R_s < 0.08 \text{ [p.u.]} \\ 0.04 < X_s < 0.12 \text{ [p.u.]} \\ 0.009 < R_r < 0.03 \text{ [p.u.]} \\ 0.06 < X_r < 0.15 \text{ [p.u.]} \end{aligned} \quad (3)$$

These ranges can also expand or use other parameters, if needed. No penalty scheme is needed since (2)-(3) constitute a bound constrained optimization problem, and the adopted optimization approach does not require any penalty action due to the adoption of a normalized search space, i.e. it is always guaranteed that the optimization variables are within their boundaries.

C. MVMO-SH

The Mean-variance mapping optimization (MVMO) constitutes an emerging optimization algorithm, which possesses two salient features: Firstly, the evolution procedure is performed considering normalized range of the search space for all optimization variables within $[0, 1]$. This ensures that new values generated for optimization variables in offspring creation stage are always within their bounds. The optimization variables are de-normalized only for every fitness evaluation. Secondly, MVMO exploits the statistical attributes of search dynamics by using a special mapping function for mutation operation on the basis of the mean and variance of the n -best solutions attained so far and saved in a continually-updated archive [20].

The original MVMO represents a single particle approach, which has shown a great potential for solving different optimization problems. Recently, a new variant of MVMO, termed as MVMO-SH has been introduced, which is conceived as a population based scheme and incorporates a multi-parent crossover strategy to increase the search diversity

while striving for a balance between exploration and exploitation. Broadly speaking, MVMO-SH performs as follows [21]:

Step 1: Define N_p , the initial and final values ($f_{s_min}^*$ and $f_{s_final}^*$) for scaling factor f_s , solution archive size, dynamic shape factor Δd , the initial and final proportion of good particles ($g_{p_min}^*$ and $g_{p_final}^*$), and the initial and final number of dimensions (m_{min}^* and m_{final}^*) to be selected for mutation operation. Next, generate an initial random population of N_p particles within the search boundaries and normalize the sampled optimization variables by considering the range of search within [0, 1].

Step 2: De-normalize each particle from [0, 1] range to their original [min, max] boundaries and evaluate its fitness.

Step 3: Fill/update the solution archive associated to each particle. The archive stores the n -best child solutions achieved so far in a descending order of fitness. The archive size is fixed for the entire process. For each particle, an update of its archive takes place only if the new solution is better than those in the archive.

Step 4: The first ranked solutions (i.e. local bests) of all solution archives are classified into two groups: A set of GP “good particles”, and the set of remaining N_p -GP “bad particles”. Local best-based parent assignment is adopted for each particle classified as good, whereas for each bad particle \mathbf{x}_p , the parent $\mathbf{x}_p^{\text{parent}}$ is synthesized by using the following multi-parent criteria.

$$\mathbf{x}_p^{\text{parent}} = \mathbf{x}_k + \beta(\mathbf{x}_i - \mathbf{x}_j) \quad (4)$$

where \mathbf{x}_i , \mathbf{x}_j , and \mathbf{x}_k represent the first (global best), the last, and a randomly selected intermediate particle in the group of good particles, respectively. The factor β is a random number, which is drawn according to:

$$\beta = 0.5 - 0.25 \cdot \alpha, \quad \alpha = i / i_{\text{max}} \quad (5)$$

where i denotes fitness evaluation number, and r_n is a random number with uniform distribution in [0,1]. An element of $\mathbf{x}_p^{\text{parent}}$ is set to 1 or 0 if it is outside the range [0, 1].

Step 5: Create a child vector \mathbf{x}^{new} for each particle by combining a subset of $N_{\text{var}} \cdot m^*$ directly inherited dimensions from $\mathbf{x}_p^{\text{parent}}$ and m^* selected dimensions (via roulette wheel tournament selection) that undergo mutation operation through mapping function based on the means and variances calculated from the particle’s solution archive. m^* is progressively decreased as follows:

$$m^* = \text{round}\left(m_{\text{final}} + \text{rand}\left(m^\dagger - m_{\text{final}}\right)\right) \quad (6)$$

$$m^\dagger = \text{round}\left(m_{\text{ini}} - \alpha(m_{\text{ini}} - m_{\text{final}})\right) \quad (7)$$

Step 6: The new value of each selected dimension x_r of \mathbf{x}^{new} is determined by:

$$x_r = h_x + (1 - h_1 + h_0) \cdot x_r^* - h_0 \quad (8)$$

where x_r^* is a randomly generated number with uniform distribution between [0, 1], and the term h represents the transformation mapping function defined as follows:

$$h(\bar{x}, s_1, s_2, x) = \bar{x} \cdot (1 - e^{-x \cdot s_1}) + (1 - \bar{x}) \cdot e^{-(1-x) \cdot s_2} \quad (9)$$

h_x , h_1 and h_0 are the outputs of the mapping function calculated for

$$h_x = h(x = x_r^*), \quad h_0 = h(x = 0), \quad h_1 = h(x = 1) \quad (10)$$

The shape factors s_{r1} and s_{r2} of the variable x_r are assigned by using a sequential scheme which accounts for mean and variance of x_r , quadratic decrement of f_s from $f_{s_min}^*$ to $f_{s_final}^*$, and Δd in order to exploit the asymmetry of h [20].

Step 7: Stop if the termination criterion is met; else go to Step 2.

IV. RESULTS

Numerical experiments were performed on a computer with Intel® Core™ i7-4600 CPU, 2.7 GHz and 8 GB RAM, under Windows 7 Enterprise, 64 bit OS. The proposed approach was implemented by interfacing a routine written in Matlab® for MVMOS with the functionalities of DIgSILENT PowerFactory©, namely, DIgSILENT Simulation Language (DSL) and DIgSILENT Programming Language (DPL), which were used to model the dynamic equivalent and to perform automatically dynamic simulation-based evaluations of the fitness, respectively. A single run of the proposed identification approach entails approximately 10 min.

A. Test system and identification of EqMCIG

A cluster of IGs, which comprises 9×500 kW generators is considered to evaluate the effectiveness and robustness of the identification approach proposed in this paper for EqMCIG. The parameters used for these machines are summarized in Table A.1 in the Appendix. Fig. 4 shows the topology which is considered for the collector system. Each IM has a step-up transformer (0.75 MVA, 0.69/11kV, $x_{tr}=2\%$) and it is connected to the 11kV by a power cables ($r_{\text{line}}=0.253 \Omega/\text{km}$, $x_{\text{line}}=0.103672 \Omega/\text{km}$) of different lengths. The active power produced by the cluster of IGs is 4.4 MW, and each machine is operating between 96.4 to 98.8% of rated power, before an active power step at PCC occurs.

Fig. 5 illustrates the best (green dashed line), worst (red solid line), and average (blue solid line) convergence performance of the MVMO-SH based approach for identification of the parameters of EqMCIG, which was obtained after 100 optimization runs, each one terminated upon completion of 1000 function evaluations. MVMO-SH was executed to evolve only a single candidate solution (i.e. single parent-offspring approach) and by considering the parameters given in [20]. The difference in performance is attributed to the stochastic factors involved in the random initialization and evolutionary operations of the algorithmic procedure of MVMO-SH. Although not shown in the figure, the worst convergence performance needed 700 additional function evaluations to achieve the same fitness value achieved in the best convergence performance case in 1000 function evaluations. It is worth highlighting that the difference in performance could be considerable narrowed

down by properly tuning the parameters of MVMO-SH. From Fig. 5, it can also be noticed that a near-to-optimal solution can be reached after approximately 600 function evaluations.

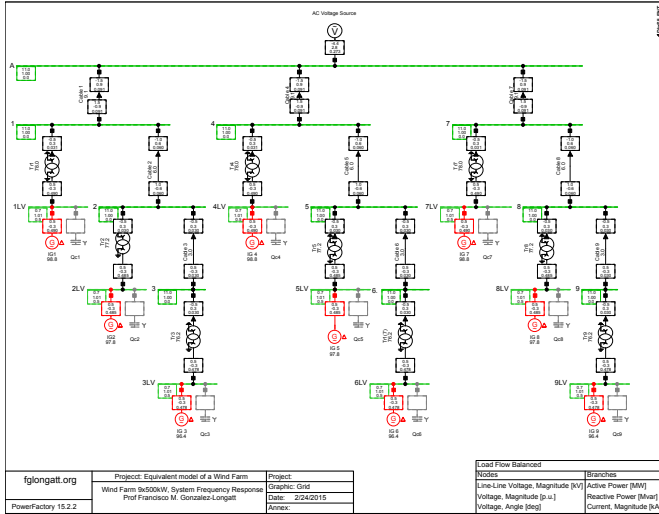


Figure 4. Test System: Layout of the studied cluster of IGs.

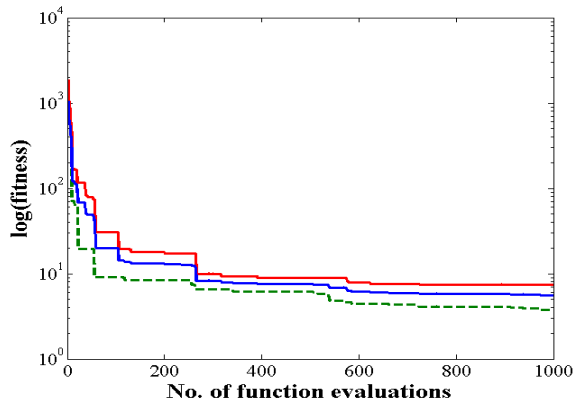


Figure 5. Convergence of MVMO-SH based approach: Worst performance (red solid line), best performance (green dashed line), and averaged convergence over 100 optimization repetitions (blue solid line).

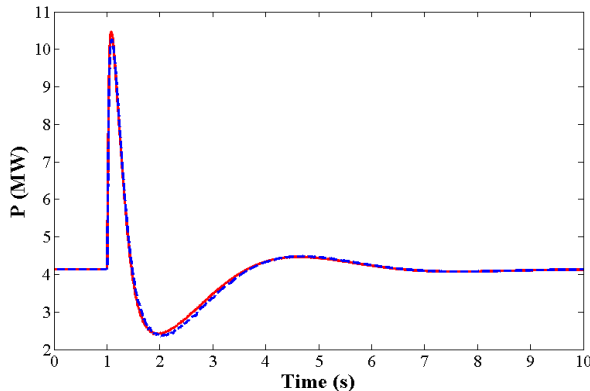


Figure 6. Comparison of active power responses at PCC: detailed model of the cluster of IGs (red solid line) and EqMCIG (blue dotted line).

For the best convergence performance case, Figs. 6 and 7 demonstrate the suitability of the identified EqMCIG to recreate the dynamic response of the detailed model of the

cluster of IGs for the disturbance considered in the identification task. Despite of the difference in performance under optimization repetition, the fitness obtained in 1000 function evaluations in the worst convergence performance case does not entail a considerable difference with respect to the responses shown in Figs. 6 and 7.

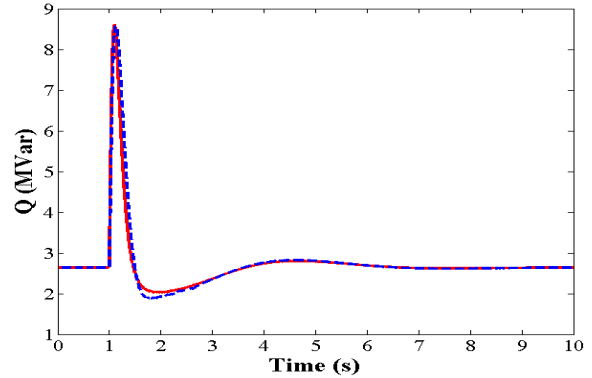


Figure 7. Comparison of reactive power responses at PCC: detailed model of the cluster of IGs (red solid line) and EqMCIG (blue dotted line).

B. Comparison with other evolutionary algorithms

Basic numerical comparisons are performed considering the possibility of using other emerging evolutionary algorithms instead of MVMO-SH for the identification of EqMCIG. Among the compared algorithms are the covariance matrix adaptation evolution strategy (CMA-ES) [22], and the linearized biogeography-based optimization (LBBO) [23]. Similarly to the case of MVMO-SH, the recommended parameters given in [22] and [23] were used for testing these algorithms. The main difference between these algorithms and MVMO-SH resides in the way the evolution operations are performed.

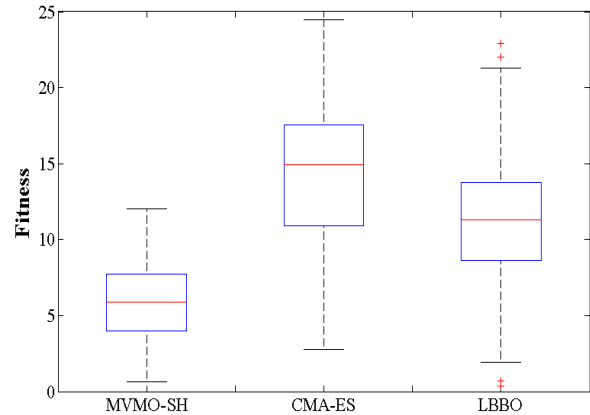


Figure 8. Comparison of obtained fitness value after 1000 function evaluations and 100 optimization runs by using different evolutionary algorithms.

The box plot in Fig. 8 shows the difference in the obtained fitness value after 1000 function evaluations and over 100 optimization runs for each algorithm. In contrast to the case when MVMO-SH is used for identification of EqMCIG, it can be seen that there could be a possibility of obtaining

higher fitness values if the recommended parameters for CMA-ES and LBBO are used. Nevertheless, it is worth pointing out that the outcomes of this basic comparison are not conclusive, since a more exhaustive analysis by using an optimal set of parameters for each algorithm must be carried out. This is however beyond the scope of this paper.

V. CONCLUSIONS

Motivated by increasing deployment synchrophasor measurement devices, this paper introduces a simple approach for parameter identification of an equivalent model for a cluster of IGs. The identification is formulated as a curve fitting optimization problem, which pursues minimization of the mean square error between the measured response of the cluster of IGs at the point of common coupling, e.g. active and reactive power, and the response obtained via simulation by using EqMCIG (dynamic equivalent). The optimization problem is tackled by using MVMO-SH algorithm, which was set to perform by following a single-parent-offspring approach. Numerical results demonstrate the feasibility and effectiveness of MVMO-SH to provide estimated parameters that entail high dynamic response resemblance of the identified EqMCIG. Basic comparison with other emerging evolutionary algorithms evidence the potential of these tools for solving optimization problems concerning the dynamic performance of electrical power systems. However, broader evaluations and comparisons by using optimal set of parameters for each of these tools is needed to ascertain their robustness with respect to the stochastic factors involved in the different stages of the algorithms. Further research effort is also needed to properly tackle noise or lack of data in the measurements used for the identification of EqMCIG. Future development includes the use of PI model for the collector system and assessment of massively distributed IG on weakly meshed or radial networks.

VI. APPENDIX

TABLE A.1
PARAMETERS OF THE INDIVIDUAL IG

Parameter	Variable	Value
Stator resistance	R_s [p.u]	0.00599
Rotor resistance	R_r [p.u]	0.01691
Stator inductance	L_s [p.u]	0.08213
Rotor inductance	L_r [p.u]	0.10723
Magnetizing reactance	L_m [p.u]	2.55619
Inertia	J [kgm ²]	145.00

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