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A Genetic Algorithm Solution to the Governor-Turbine Dynamic Model Identification in Multi-Machine Power Systems

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Abstract— **Speed governors are key elements in the dynamic performance of electric power systems. Therefore, accurate governor models are of great importance in simulating and investigating the power system transient phenomena. Model parameters of such devices are, however, usually unavailable or inaccurate, especially when old generators are involved. Most methods for speed governor parameter estimation are based on measurements of frequency and active power variations during transient operation. This paper proposes a genetic algorithm based optimization technique for parameter estimation, which makes use of such measurements. The proposed methodology uses a real-coded genetic algorithm. The paper estimates the parameters of all system generators simultaneously, instead of every machine independently, which is fully in line with the interest to treat the electric power system as a whole and study its comprehensive behaviour. Moreover, the methodology is not model-dependent and, therefore, it is readily applicable to a variety of model types and for many different test procedures. The proposed methodology is applied to the electric power system of Crete and the results demonstrate the feasibility and practicality of this approach.**

I. INTRODUCTION

POWER system simulation results depend greatly on the accuracy of system model parameters. This is especially true for synchronous generators and their control subsystems, such as governors, exciters, limiters and stabilizers. Dynamic data of generating units are, however, usually inaccurate, incomplete, or even unavailable, especially when old generators are involved. Therefore, typical parameters are frequently used, leading to results of reduced credibility. Thus, the estimation and verification of these parameters are necessary for acquiring accurate system models.

Most techniques employed for the estimation of the unknown parameters are based on processing suitable actual measurements of the system dynamic behavior, recorded during appropriate tests [1-11]. These measurements are used as input to an identification procedure to estimate the model parameters. However, as noticed in literature [1], many of the existing methods may not be adequate. For example, several methods are based on linear system techniques (like transfer function identification), therefore, have limited applicability when nonlinearities are present [4,10]. Many methods require cumbersome symbolic manipulations of dynamic models and therefore may be limited mainly to simpler models [10]. Furthermore, several of the existing approaches are model-specific [11].

This paper presents a methodology for estimating the dynamic data of generating units that is based on genetic algorithms and makes use of measurements of transient system response. It should be emphasized that the methodology is not model-dependent and, therefore, it is readily applicable to a variety of model types and different test procedures. The work presented in the paper estimates the governor and the electromechanical dynamic parameters of a generating unit; however the methodology can be easily expanded to any dynamic model, provided that appropriate measurements are available.

Evolutionary computation techniques and particularly genetic algorithms (GAs) are computational-intelligence-based optimization methods. They are used in several scientific fields, mainly in hard, large-scale optimization problems, where other classical analytical optimization techniques may prove inadequate. In the power engineering area, such problems include operation optimization (unit commitment [12], economic dispatch [13], optimal power flow, optimal allocation of reactive resources [15]) [12-15], parameter estimation [8-9], etc. A comprehensive literature survey on such applications is presented in [16].

The paper investigates the parameter identification problem from a power system point of view, rather than from the electric machinery side. This means that the identification procedure is not applied to every machine independently, but it attempts the simultaneous parameter estimation of all system generators. This is because it is of interest to study the comprehensive behaviour of the system as a whole, rather than of a single machine. It should be noted that the methodology can be readily applied in a machine-oriented approach, if appropriate measurements are available.

The paper is organized as follows. Section II presents a general overview of the parameter estimation framework.

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Section III describes the genetic-algorithm-based identification procedure of generator parameters. Section IV presents results from the application of the proposed methodology to a single-machine test system. Section V describes the application of the proposed methodology to the electric power system of Crete. Section VI concludes the paper.

II. Estimation Framework

The proposed identification procedure is a simulation-based process that uses a genetic algorithm as optimization tool, as presented in Fig. 1. The physical system and the mathematical model of the system are excited by the same input. The output of the physical system, which is the set of available measurements, is compared to the simulated output of the model. The error between the two outputs is used as input to a genetic algorithm optimization module, which updates the model parameters in such a way that this error is minimized.

The output $\hat{\vec{y}}(t)$ of the system model is a function of the system state, the input and the model parameters, as described by the set of differential-algebraic equations (1):

$$\begin{aligned} \dot{\vec{x}}(t) &= f\left(\vec{x}(t), \vec{z}(t), \vec{u}(t), \vec{a}\right), \\ 0 &= h\left(\vec{x}(t), \vec{z}(t), \vec{u}(t), \vec{a}\right), \\ \hat{\vec{y}}(t) &= g\left(\vec{x}(t), \vec{z}(t), \vec{a}\right), \\ \vec{X}(t_0) &= \vec{X}_0, \end{aligned} \tag{1}$$

where $\hat{\vec{y}}$ is the vector of the system model outputs, $\vec{x}$ is the vector of the dynamical states of the system, $\vec{z}$ is the vector of the algebraic states, $\vec{u}$ is the vector of the system inputs, and $\vec{a}$ is the vector of the model parameters. The global state vector is denoted by $\vec{X}(t) = \left[\vec{x}(t)^T \quad \vec{z}(t)^T\right]^T$ and $\vec{X}_0$ denotes the initial condition vector.

The identification procedure estimates the unknown vector of model parameters, $\vec{a}$, so that the deviation between the model and the real system responses to the same input $\vec{u}$ is minimized. The error to be minimized is the square error between the measured and the simulated output waveforms defined as (assuming discrete-time signals):

$$e(\vec{a}) = \sum_{k=1}^{T} \sum_{i=1}^{N} \left(y_i(t_k) - \hat{y}_i(t_k, \vec{a})\right)^2 , \tag{2}$$

where $y(t_k)$ and $\hat{y}(t_k, \vec{a})$ are the measured and simulated values of the outputs at time instant t_k, respectively; t_k is the time sample $(k = 1,...,T)$, given that T discrete observations are made on the real system, and i is the output index $(i = 1,...,N)$, N being the number of outputs. The vector of the unknown, constant, system parameters is denoted by $\vec{a}$. The values of these parameters are constrained in some specific intervals.

A key feature of the approach is that the estimation process is not model-specific and it is therefore straightforward to switch between a large variety of models. This advantage results from the fact that the simulation-based optimization method uses only the model output. It does not require any knowledge of the specific model structure. The use of GAs as optimization tool enhances this feature, since one of the main attributes of genetic algorithms is that they do not require any auxiliary knowledge on the objective function, such as gradient information. Therefore, the proposed method is, in fact, a black-box identification method, which automatically adjusts the parameters of the model until the model output matches the measurements.

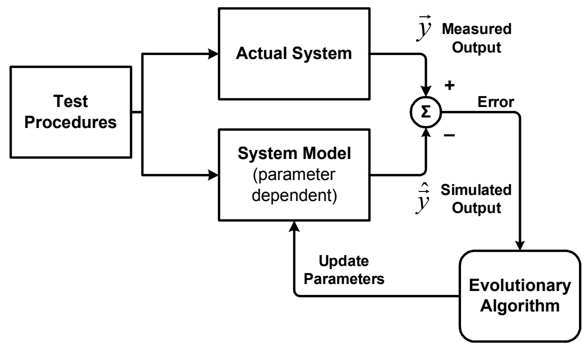

Fig. 1. Block diagram of estimation procedure.

III. Genetic Algorithm For Generator Parameter Identification

A. Fundamentals of Genetic Algorithms

Genetic algorithms are optimization methods inspired by natural genetics and biological evolution. They manipulate strings of data, each of which represents a possible problem solution. These strings can be binary strings, floating-point strings, or integer strings, depending on the way the problem parameters are coded into chromosomes. The strength of each chromosome is measured using fitness values, which depend only on the value of the problem objective function for the possible solution represented by the chromosome. The stronger strings are retained in the population and recombined with other strong strings to produce offspring. Weaker ones are gradually discarded from the population. The processing of strings and the evolution of the population of candidate solutions are performed based on probabilistic rules. References [17-19] provide a comprehensive description of genetic algorithms.

B. Chromosome Representation

Two types of representations have been investigated in this work, binary and real (floating-point).

C. Creation of Initial Population

The initial population of candidate solutions is created randomly.

D. Evaluation of Candidate Solutions

Each candidate solution represents a parameter vector, $\vec{a}$.

The evaluation of each candidate solution is based on the objective function value, $e(\vec{a})$. Note that the objective function value is obtained after system simulation. The purpose of the process is to solve a minimization problem, or equivalently, a maximization problem that maximizes a transformed objective function. In this paper, the objective function to be maximized is defined as

$$F(\vec{a}) = \frac{1}{e(\vec{a}) + K}, \tag{3}$$

where K is a small positive real number used as scaling coefficient, in order to avoid problems that may arise as $e(\vec{a})$ approaches zero, and to control problems like premature convergence.

E. Reproduction

Reproduction refers to the process of selecting the best individuals of the population and copying them into a "mating pool." These individuals form an intermediate population. Three types of the reproduction process are implemented in this work:

1) *Roulette-wheel selection,*
2) *Tournament selection* with user-defined window,
3) *Deterministic sampling* based on the fitness-proportionate selection scheme.

No significant differences in the results were observed between the different types of reproduction in this problem. The reported results are obtained using deterministic sampling, i.e. each individual is assigned an expected number of appearances in the "mating pool," according to its calculated fitness. Subsequently, the individuals in the "mating pool" are randomly grouped in pairs, each of which produces two offspring.

F. Crossover Operation

In binary representation the following four types of crossover are used:

1) *1-point crossover*,
2) *2-point crossover*,
3) *Uniform crossover*, which is a crossover operator that swaps only single bits between the two parent binary strings.
4) *Multi-point crossover*, in which one crossover point is selected, randomly, for each parameter represented in the chromosome, and, thereafter, 1-point crossover is performed in each parameter.

In floating-point representation the crossover types used are:

1) *1-point* crossover,
2) *2-point crossover*,
3) *Uniform crossover*,
4) *Arithmetical crossover.*

The arithmetical crossover operator creates offspring with new parameters values, defined as a linear combination of the two parents. If s_u and s_w are to be crossed, the resulting offspring are $s'_u = a \cdot s_w + (1-a) \cdot s_u$ and $s'_w = a \cdot s_u + (1-a) \cdot s_w$, where a is a random number of the interval [0, 1] [18].

G. Mutation Operation

When binary coding is used, the genetic algorithm mutation simply changes a bit from "0" to "1" or vice versa. The bits that undergo mutation are chosen based on a probability test. The probability of mutation is generally set to a small value, about 0.001 to 0.01.

In real representation, two mutation operators are implemented: uniform and non-uniform mutation.

1) *Uniform mutation:* This operator is analogous to the binary operator, but it applies to real values instead of binary bits; it randomly replaces the parameter value with another one from the appropriate interval;

2) *Non-Uniform mutation:* This mutation type is described in [18] and it is responsible for the fine-tuning capabilities of the real-coded GA. If a parameter k of value u_k of a candidate solution is selected for mutation, its value is changed to u'_k, where

$$u'_k = \begin{cases} u_k + \Delta(t, UB - u_k) \\ u_k - \Delta(t, u_k - LB) \end{cases} \tag{4}$$

depending on whether a random binary digit is 0 or 1. LB and UB are the lower and upper bounds of the interval parameter k belongs to. The function $\Delta(t, y)$ returns a value in the range $[0, y]$ such that the probability of $\Delta(t, y)$ being close to 0 increases as the current generation number, t, increases. This property causes this operator to uniformly search the space at initial stages, when t is small, and very locally at later stages. The function used is

$$\Delta(t, y) = y \cdot (1 - r^{(1-\frac{t}{T})^b}), \tag{5}$$

where r is a random number in [0, 1], T is the maximal generation number, and b is a parameter determining the degree of non-uniformity [18].

In real representation, since parameters do not change during crossover, but are just recombined differently (except for the arithmetical crossover), the only way of affecting their values is by the mutation operator. So, the mutation probabilities used are greater than the ones in binary representation and may reach up to 5%.

H. Creation of the Next Generation

After mutation is completed, the children population is created and the previous population is replaced by the new generation. Children are evaluated and the fitness function for each individual is calculated. The procedure is repeated until the termination criterion is met, defined by a maximum number of generations.

As an option, an elitist operator is also used. If this option is selected, the new population is not the children population, but is created by the best N individuals from the children and the previous population, where N is the population size. The aim of this elitist strategy is to eliminate the possibility of destruction of good solutions that may appear in early generations and to aid in achieving good solutions quite fast and to subsequently be able to fine-tune them. Additionally, it is expected that the best individuals will provide the best offspring after crossover. The risk of premature convergence to a sub-optimal solution is increased with this operation, but this can be controlled with the parameter K of the fitness function and with a slightly increased mutation probability.

IV. Test Cases

A. Problem Formulation

The identification procedure was tested using a single-machine test-system, to investigate the feasibility of the approach and to configure the genetic algorithm parameters for the specific problem. The model used for the governor-turbine subsystem representation is shown in Fig. 2.

The following values are assumed for the five parameters of the model that are to be estimated:

$R = 0.05$, $TG = 0.2s$, $T_t = 0.7s$, $M = 10s$, $D = 0$

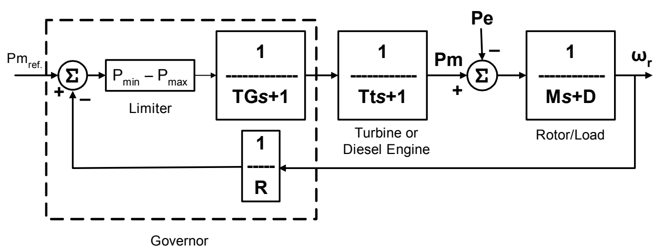

Fig. 2. Unit speed control and turbine (engine) dynamic model.

A step input ΔP_e of 0.2 per unit (p.u.), i.e. 20% change of the pre-disturbance power demand, is applied at $t = 0s$, representing a load increase. The system is simulated in the time interval from -2s to 10s. The frequency variation (in Hz) and the mechanical power deviation (in p.u.) are calculated every 0.05s, and these results are assumed to represent the measured input data for the identification procedure. This way the estimated parameters obtained can be directly compared with the actual ones.

The optimization problem is defined as

$$Minimize \quad e(\vec{a}) = \sum_{k=1}^{T} \left(\vec{y}(t_k) - \hat{\vec{y}}(t_k, \vec{a}) \right)^2, \tag{6}$$

$$subject\ to: \begin{array}{l} 0.01 \le R \le 0.2, \ \ 0.05 \le TG \le 0.5s, \\ 0.6 \le Tt \le 2s, \\ 0.01 \le M \le 10s, \ \ 0 \le D \le 2, \end{array} \tag{7}$$

where $\vec{y}(t) = [\Delta f(t) \quad \Delta P_m(t)]^T$ is the assumed system measured output, $\hat{\vec{y}}(t)$ is the simulated output, $u(t) = \Delta P_e(t)$ is the system scalar input, and $\vec{a} = [R \quad TG \quad Tt \quad M \quad D]^T$ is the unknown parameter vector.

B. Numerical Experiment Results

A number of numerical experiments were conducted on this problem, testing the effect of the various parameters of the genetic algorithm on the results. Results, using binary and real representation, are presented in Tables I and II. They reveal the fact that the proposed methodology for model identification can provide satisfactorily accurate results. Furthermore, by comparing Tables I and II, it is concluded that real-coded GA performs better than the binary-coded GA

TABLE I
TYPICAL RESULTS OF BINARY CODING

Binary coding with 20 bits per parameter
Population size: 200, Number of generations: 1000
Uniform crossover with probability 0.6
$p_m = 0.05$, K = 0.01, Elitist operator: On
Mean error of final population = 9.21e-4, Best solution error = 9.21e-4

	Real Values	Estimated Values	% Error
R	0.05	0.0499	0.20%
TG	0.20	0.1806	9.70%
Tt	0.70	0.7313	4.47%
M	10.00	9.8237	1.76%
D	0.00	0.0000	-

TABLE II
TYPICAL RESULTS OF FLOATING-POINT CODING

Population size: 200, Number of generations: 1000
Uniform crossover with probability 0.6
Non-uniform mutation (b=4) $p_m = 0.05$, K = 0.01, Elitist operator: On
Mean error of final population = 7.16e-4, Best solution error = 7.16e-4

	Real Values	Estimated Values	% Error
R	0.05	0.0501	0.20%
TG	0.20	0.1948	2.60%
Tt	0.70	0.7081	1.16%
M	10.00	9.8940	1.06%
D	0.00	0.0587	-

C. Determination of Method Parameters

Results obtained using floating-point coding were repeatedly much closer to the optimal solution compared to binary coding. Furthermore, the floating-point representation was faster and more consistent from run to run.

A population size of one to two hundred, and about one thousand generations proved to be sufficient for this problem, providing very good or even excellent results. Uniform and two point crossover provided better results compared to other crossover types and the use of the non-uniform mutation operator proved to be an important factor when floating-point representation was used. Finally, results obtained using the elitist operator were superior compared to cases where no elitism was used.

The described floating-point configuration provides results with an error less than 3% for every parameter. The largest errors appear in the estimation of the time constants, especially the governor time constant, while the other parameters are estimated with a much higher precision. However, simulation tests proved that simulation results are much less sensitive to the values of the time constants compared to the droop values, therefore, less accuracy for these parameters can be tolerated.

D. Effects of Measurement Noise

The work presented so far tested the capability of the GA based estimation methodology in an ideal situation, where the mathematical model was able to describe precisely the actual system. This is not the case, when actual field measurements are used. In a realistic situation the model output cannot match precisely the actual system output, especially if simplified models are used to facilitate calculations. Moreover, field measurements may be severely corrupted by noise, or unmodeled dynamics may be present, having similar effects as noise.

In order to investigate the behavior of the methodology under such conditions, numerical experiments were carried out assuming the presence of random noise in the measurements. The assumed noise was zero-mean, uniformly or normally distributed.

Results obtained from a case with noise uniformly distributed in $(-0.15, 0.15)$ for the frequency and in $(-0.04, 0.04)$ for the power deviation are presented in Fig. 3 and Table III, assuming the same real-coded GA configuration as in Table II. The "measured" waveform in Fig. 3 refers to the simulated results that are assumed to represent the measurements as described in section IV.A

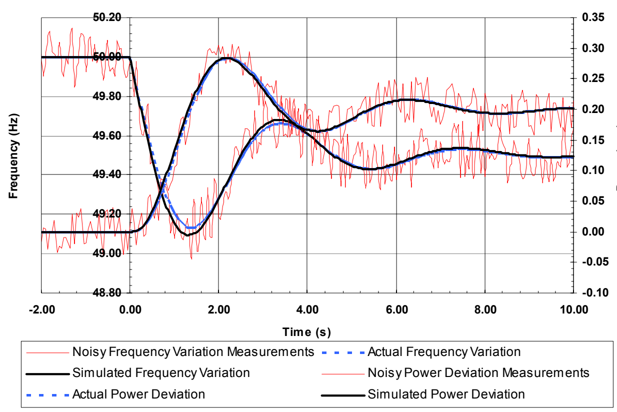

Fig. 3. Comparison of "measured" and simulated waveforms (using estimation results), with additive stochastic noise in the measurements.

TABLE III
TYPICAL RESULTS USING MEASUREMENTS WITH STOCHASTIC NOISE

	Real Values	Estimated Values	% Error
R	0.05	0.0495	1.00%
TG	0.20	0.1715	14.25%
Tt	0.70	0.7643	9.19%
M	10.00	9.1287	8.71%
D	0.00	0.0001	-

These numerical experiments reveal that, even with heavily corrupted measurements from random noise, the methodology provides results of satisfactory accuracy. Furthermore, the maximum errors appear in the parameters that least affect the outputs of the model, therefore, the error in simulation studies using these parameter values is minimal.

In several cases, the measurement noise may not be completely random, but it may follow some deterministic pattern. Such a situation may arise if unmodeled dynamics are present. To investigate this condition, numerical experiments were carried out assuming the presence of additive deterministic noise in the measurements of the form of one or two sinusoidal signals. The total amplitude of the disturbance was up to 0.15 Hz for the frequency and 0.02 p.u. for the power deviation. The numerical test showed that the GA could filter out the deterministic noise almost perfectly. Results from a test with a 2 Hz sinusoidal noise are presented in Table IV and in Fig. 4, assuming the same real-coded GA configuration as in Tables II and III.

TABLE IV
TYPICAL RESULTS USING MEASUREMENTS WITH DETERMINISTIC NOISE

	Real Values	Estimated Values	% Error
R	0.05	0.0502	0.40%
TG	0.20	0.1931	3.45%
Tt	0.70	0.7096	1.37%
M	10.00	9.8791	1.21%
D	0.00	0.0406	-

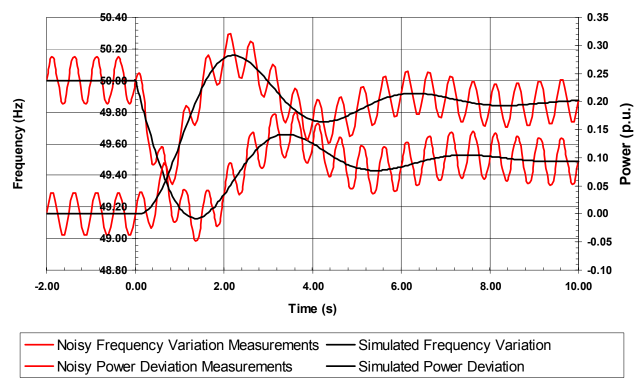

Fig. 4. Comparison of "measured" and simulated waveforms (using estimation results), with additive deterministic noise in the measurements.

V. CRETE SYSTEM TEST CASE AND ESTIMATION RESULTS

A. Test-Case System of Crete

The estimation methodology was applied to the autonomous power system of the Greek island of Crete. The power system of Crete is a relatively large, isolated system consisting mainly of oil-fired generators. It consists of 52 buses, 66 branches and 18 thermal units. Six of them are steam units, four are diesel engines, seven are gas turbines and there is a combined cycle plant. The total installed capacity is about 400MW, while the system peak load is approximately 360MW. The Greek public power corporation has conducted real time measurements of frequency and unit active power variations during intentional machine trip tests; these data were used for the identification of the governor and the unit electromechanical dynamic model parameters of each conventional generating unit.

B. Transient-Response Measurements

Field tests involved a conventional machine rejection under different operating conditions. Two outages were performed of 10 MW and 19 MW, at a total load of 159 MW and 208 MW, respectively. The transient behavior of the system was recorded in computers equipped with A/D converter cards. The sampling rate was 20 Hz. Recordings involved the active power response of the remaining thermal units and the system frequency deviation, which was measured at four points in the system. The total duration of each recording was 3min, including some pre-disturbance time. Data up to 10s after the disturbance were used for estimation procedure, since the dynamics of interest had reached steady state after 10s. Some typical recording are shown in Fig. 5 and 6.

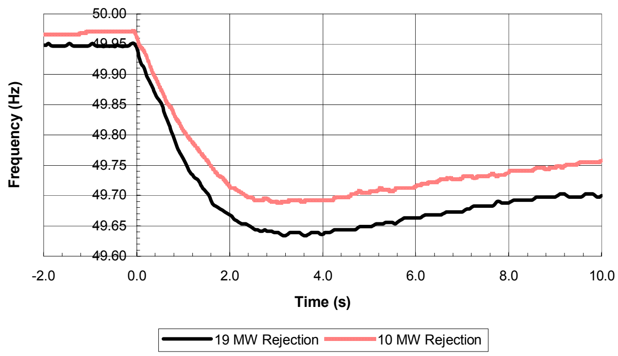

Fig. 5. Recordings of frequency variations of the system for the three disturbances.

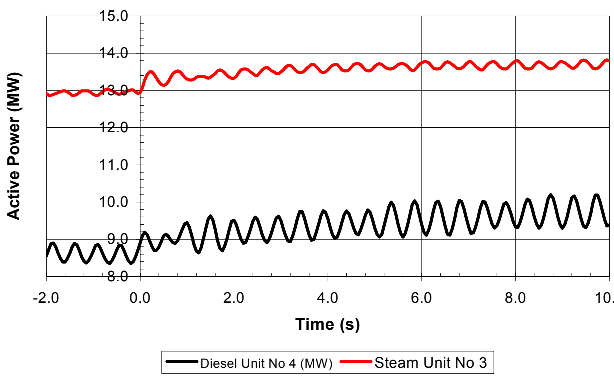

Fig. 6. Recordings of active power variations for a steam and a diesel unit (19 MW rejection test).

It is of interest to observe the active power oscillations in Fig. 6. Such oscillations of frequency around 5 Hz were observed in the output of all the diesel and steam units, even in steady-state operation. They exist because the mechanical system of the diesel units produces a pulsating torque on their shaft. The steam units are physically installed on the same power plant as the diesel units, and, therefore, they also produce a pulsating active power to compensate for the oscillations of the diesel units. Fig. 6 shows that the diesel and steam unit oscillations are in fact in opposite phase.

Since modeling such oscillations would not provide any additional information for the governor-model estimation procedure, these oscillations are considered unmodeled dynamics and are treated as noise. However, based on the discussion on measurement noise, in section IV, the GA is expected to be able to filter out the noise very adequately. This was, indeed, observed in the estimation procedure results.

C. Estimation Results

The identification procedure is applied to both sets of available measurements performing two independent estimation procedures, for the different disturbances and under different loading conditions.

The power system of Crete was modeled in the EUROSTAG dynamic simulation program. Static network data and pre-disturbance operating conditions were provided by electric utility, along with any available generator dynamic data. These data allowed a three-winding representation of the synchronous generators [20]. A standard IEEE Type 1 voltage regulator-exciter model was used for all units [20]. The three parameter governor-turbine model shown in Fig. 2 was used. Governor limits were set based on the utility provided values of minimum and maximum power output for each unit. The parameters to be identified were constrained as follows:

$$0.01 \le R_i \le 0.2\,,\ 0.05 \le TG_i \le 0.5s\,,$$
$$1 \le Tt_{steam(j)} \le 3s\,, \qquad (8)$$
$$1 \le TD_k \le 2s\,,\ 0.5 \le Tt_{gas(m)} \le 1.5s\,,$$

where R_i is the droop of each unit, TG_i the governor time constant of each unit, $Tt_{steam(j)}$ the turbine time constant of each steam unit, TD_k the mechanical time constant of each diesel engine, and $Tt_{gas(m)}$ the turbine time constant of each gas turbine.

Comparative graphs of the measured transients and the simulated dynamic responses using the estimated parameters are presented in Fig. 7 through 9. The results show a considerably good agreement between the measured response and the simulated waveforms using the estimated model parameters.

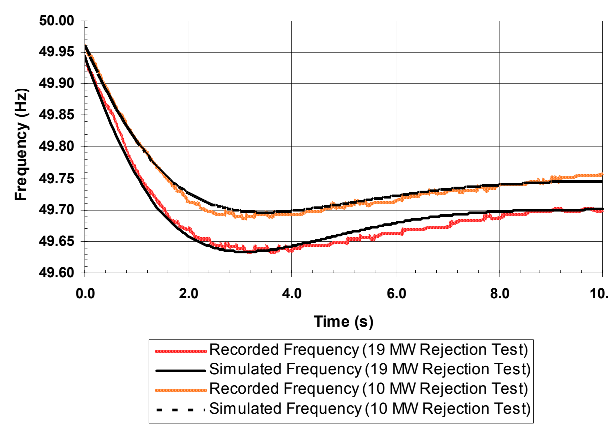

Fig. 7. Measured and simulated system frequency for the 10 MW and 19 MW rejection tests.

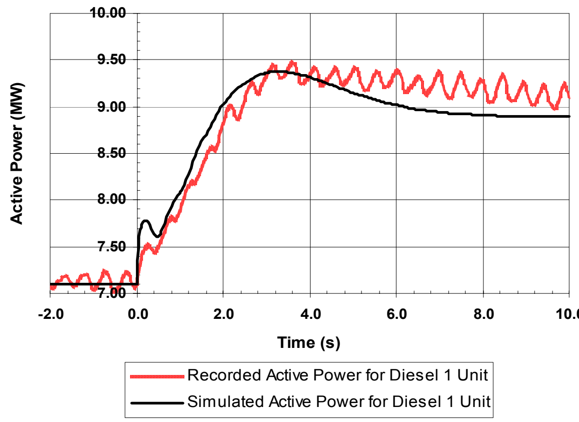

Fig. 8. Measured and simulated power output for diesel unit 1, for the 19 MW rejection test.

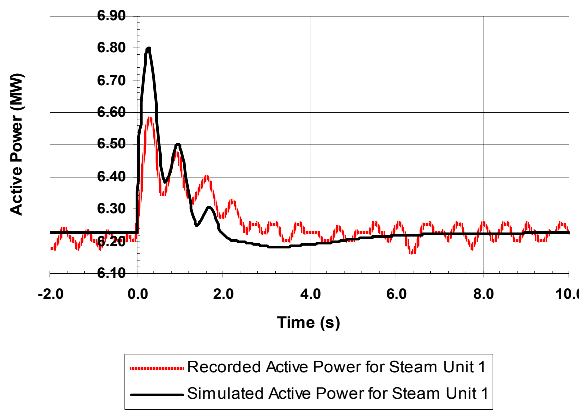

Fig. 9. Measured and simulated power output for steam unit 1, for the 19 MW rejection test.

VI. Conclusion

This paper investigates the application of genetic algorithms for the identification of dynamic models of generating units in power systems. The paper proposes the use of a real-coded genetic algorithm as optimization tool for the estimation procedure. The main advantages of the proposed methodology are the few input data required, its flexibility, and the simplicity of its mechanism.

The methodology proved to be able to provide accurate results, even in the presence of measurement noise or unmodeled dynamics. It is shown that the simulated system response using the estimated parameter values can correctly represent measurements, even if they are significantly corrupted by noise. It was also shown that the simulated system response using the estimated parameter values can correctly capture the main features of the measurement even with some deviation present in the parameter values.

The proposed method has been successfully applied to the simultaneous identification of the turbine–governor models of the units of the medium size, isolated power system of Crete. The obtained results demonstrate the feasibility and practicality of the proposed GA approach.

References

[1] M. Shen, V. Venkatasubramanian, N. Abi-Samra, and D. Sobajic, "A new framework for estimation of generator dynamic parameters," *IEEE Trans. Power Systems*, vol. 15, no 2, pp. 756–763, May 2000.

[2] T. Inoue, H. Taniguchi, Y. Ikeguchi, and K. Yoshida, "Estimation of power system inertia constant and capacity of spinning reserve support generators using measured frequency transients," *IEEE Trans. Power Systems*, vol. 12, no 1, pp. 136–142, February 1997.

[3] D. J. Trudnowski and J. C. Agee, "Identifying a hydraulic–turbine model from measured field data," *IEEE Trans. Energy Conversion*, vol. 10, no 4, pp. 768–773, December 1995.

[4] Z. Zhao, F. Zheng, J. Gao, and L. Xu, "A dynamic on–line parameter identification and full–scale system experimental verification for large synchronous machines," *IEEE Trans. Energy Conversion*, vol. 10, no 3, pp. 392–398, September 1995.

[5] L. N. Hannett and A. H. Khan, "Combustion turbine dynamic model validation from tests," *IEEE Trans. Power Systems*, vol. 8, no 1, pp. 152–158, February 1993.

[6] N. D. Hatziargyriou, E. S. Karapidakis, and D. Hatzifotis, "Frequency stability of power systems in large islands with high wind power penetration," in *Proc. 1998 Int. Conf. Bulk Power System Dynamics and Control IV–Restructuring*, August 24–28, 1998, Santorini, Greece, pp. 699–704.

[7] N. D. Hatziargyriou, G. S. Stavrakakis, E. S. Karapidakis, F. Dimopoulos, and K. Kalaitzakis, "Identification of synchronous machine parameters using constrained optimization," in *Proc. 2001 Power Tech Conf. (PowerTech '01)*, vol. 4, September 10-13, 2001, Porto, Portugal.

[8] P. Pillay, R. Nolan, and T. Haque, "Application of genetic algorithms to motor parameter determination for transient torque calculations," *IEEE Trans. Industry Applications*, vol. 33, no 5, pp. 1273–1282, Sep/Oct 1997.

[9] P. Nangsue, P. Pillay, and S. E. Conry, "Evolutionary algorithms for induction motor parameter determination," *IEEE Trans. Energy Conversion*, vol. 14, no 3, pp. 447–453, September 1999.

[10] J. R. Smith, F. Fatehi, C. S. Woods, J. F. Hauer, D. J. Trudnowski, "Transfer function identification in power system applications," *IEEE Trans. Power Systems*, vol. 8, no 3, pp 1282-1290, Aug, 1993.

[11] J. C. Wang, H. D. Chiang, C. T. Huang, Y. T. Chen, C. L. Chang, C. Y. Huang, "Identification of excitation system models based on on-line digital measurements," *IEEE Trans. Power Systems*, vol. 10, no 3, pp.1286-1293, Aug. 1995.

[12] C. P. Cheng, C. W. Liu, and C. C. Liu, "Unit commitment by lagrangian relaxation and genetic algorithms," *IEEE Trans. Power Systems*, vol. 15, no 2, pp. 756–763, May 2000.

[13] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, "Network-constraint economic dispatch using real-coded genetic algorithm," *IEEE Trans. Power Systems*, vol. 18, no 1, pp. 198–205, February 2003.

[14] E. L. da Silva, H. A. Gil, and J. M. Areiza, "Transmission network expansion planning under an improved genetic algorithm," *Proc. 21st Int. Conf. Power Industry Computer Applications (P.I.C.A.)*, May 16-21, 1999, Santa Clara, CA, U.S.A., pp. 315–321.

[15] M. M. Begovic, B. Radibratovic, and F. C. Lambert, "On multiobjective volt-VAR optimization in power systems," in *Proc. 37th Annual Hawaii Int. Conference on System Sciences*, Hawaii, January 5-8, 2004, pp. 59-64.

[16] D. Srinivasan, F. Wen, C. S. Chang, and A. C. Liew, "A survey of applications of evolutionary computing to power systems," *Proc. Int. Conf. Intelligent Systems Applications to Power Systems (I.S.A.P.)*, January 28-February 2, 1996, Orlando, FL, U.S.A., pp. 35–41.

[17] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

[18] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*. New York: Springer-Verlag, 1996.

[19] Z. Michalewicz and D. B. Fogel, *How to Solve It: Modern Heuristics*. New York: Springer-Verlag, 1999.

[20] P. Kundur, *Power System Stability and Control*. New York: McGraw-Hill, 1994.