

UNIVERSITY OF PLOVDIV "PAISII HILENDARSKI"



FACULTY OF PHYSICS AND TECHNOLOGY DEPARTMENT OF ELECTRONICS, COMMUNICATIONS AND INFORMATION TECHNOLOGIES

Mag. Sezgin Fahri Ismail

PARAMETRIC AND STRUCTURAL OPTIMIZATION OF TELECOMMUNICATION MODELS

ABSTRACT

of a dissertation for a degree of education and science "DOCTOR"

Field of higher education 5. Technical sciences

Professional direction 5.3. Communication and Computer Equipment

Ph.D.:

Automation of areas of non-material sphere (medicine, education, science, administration, etc.)

Supervisor: Assoc. Prof. Dr. Eng. Slavi Yasenov Lyubomirov

Plovdiv, 2023

The dissertation has 183 pages, including 66 figures, 21 tables, organized in an introduction, 4 chapters, general conclusions, scientific and applied contributions, a list of terms and abbreviations used, and a list of the author's publications. The list of cited literature includes 132 titles.

The notations of the formulas, figures and tables in the abstract coincide with those in the thesis.

The dissertation was discussed and directed for defense at a meeting of the Extended Departmental Council of the Department of ELECTRONICS, COMMUNICATIONS AND INFORMATION TECHNOLOGIES at the UNIVERSITY OF PLOVDIV "PAISII HILENDARSKI" on 28.02.2023, Protocol № 48.

The defense of the dissertation will take place on 19.06.2023 at 11:00 in "BI 15", Kostaki Peev 21 str. of PLOVDIV UNIVERSITY "PAISII HILENDARSKI" at a meeting of the scientific jury.

The materials for the doctoral defense are available to those interested in the office of the Faculty of Physics and Technology at the UNIVERSITY OF PLOVDIV "PAISII HILENDARSKI", Kostaki Peev 21, floor 4, cabinet 1.

Scientific Jury:	Prof. Dr. Nevena Stoyanova Mileva									
-	Prof. Dr. Rumen Kostadinov Popov									
	Prof. Dr. Todor Stoyanov Dzhamiykov									
	Assoc. Prof. Dr. Borislav Hristov Milenkov									
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Author: Mag. Sezgin Fahri Ismail Title: PARAMETRIC AND STRUCTURAL OPTIMIZATION OF TELECOMMUNICATION MODELS

Circulation: 30 pcs.

GENERAL CHARACTERISTICS OF THE DISSERTATION Relevance of the problem

The topic of this dissertation deals with a problem that has been very actively worked on worldwide in recent years, it is related to the development of new telecommunication systems and networks and models for them. It is specified on parametric and structural optimization of telecommunication models.

Considering the topicality and importance of the problem, generating the need to search for new methods and approaches related to in-depth experimental research, attention is focused on telecommunication models and the causes affecting the quality performance of telecommunication networks and systems.

This dissertation focuses on the modeling and identification of specific nonlinear systems from telecommunication models. The actual scientific task is the development and evolution of methods to ensure reliable transmission, processing and protection of information in telecommunication networks in order to improve their technical characteristics and increase the efficiency of their functioning.

The overall theoretical and practical research reflected in this dissertation is focused on parametric and structural optimization of telecommunication models. Emphases are focused on current problems in the evaluation of systems with evolutionary algorithms. An analysis is made of the possibilities of applying the genetic algorithm and the particle swarm method.

The development of new versions of stochastic evolutionary algorithms is a current and active direction in modern scientific research worldwide. In the implementation of this type of algorithms there are a number of problems, the main ones are: accuracy, speed, overcoming local optima, etc. The presence of unsolved problems requires the development of new versions of stochastic evolutionary algorithms, which under certain conditions give better results.

The relevance of the topic stems from the increasing complexity of projects and the scale of telecommunication systems, which make us pay attention to the level and quality of work at all stages of the project and not least the level of performance of the design process itself. The conceptual aspect of this task is due to the fact that developing a competent cabling project even in two or three rooms with several dozen ports is a very difficult procedure. In the same situations, when the number of jobs to be served is large enough and there is a backbone subsystem in the composition of the telecommunication system, then obviously the task of optimizing designs to find the most optimal option for their implementation is difficult enough.

Emphasis is placed on the use of artificial intelligence methods and techniques in assessing the condition of components in telecommunication systems.

Aim of the dissertation:

The aim of this dissertation is to investigate the capabilities of genetic algorithm and optimization methods using particle swarm in automating the process of determining the structure and parameters of mathematical models of devices specific to telecommunications.

Tasks to achieve the goal:

1. Investigation and analysis of existing artificial intelligence methods, techniques and tools for estimating the structure and parameters of basic components of communication systems.

- 2. Creation of test simulation models of communication system specific classes of modules and devices approbate specific procedures implementing GA and PSO algorithms.
- 3. Application of numerical experiment and Monte Carlo simulation methods to explore the capabilities of GA and PSO algorithms for automated determination of the parameters and structure of classes of modules and devices specific to telecommunication systems.
- 4. Investigate the significance of the factors affecting the convergence, error and speed performance of the individual algorithms and perform a comparative analysis of the merits of the proposed algorithms.
- 5. Deriving approaches for the application of the studied artificial intelligence methods in practice.

Research methods and tools used:

The research methods used are from the following scientific fields: theory of artificial intelligence techniques and tools for estimating the structure and parameters of basic components of communication systems, computer aided design methods, modeling and simulation analysis.

Implementation and practical applicability

Procedures implementing the Genetic Algorithm and the Particle Swarm Method have been developed and the importance of factors affecting the qualities of the considered algorithms has been investigated and a comparative analysis has been carried out.

Publications on the topic

The main results have been published in: 3 issues in the annual International Conference on Education and New Learning Technologies - Web of Science, 2 issues in the proceedings of the International Conference of Young Scientists, USB – Smolyan (Union of Scientists in Bulgaria). Four of the publications are co-authored with the supervisor and one is independent.

Volume and structure of the dissertation

The dissertation is 183 pages long, including 66 figures, 21 tables, arranged in an introduction, 4 chapters, general conclusions, scientific and applied contributions, list of terms and abbreviations used, list of publications of the author. The list of cited literature includes 165 titles, all in Latin

CONTENT OF THE DISSERTATION

Chapter 1. Analysis of the state of the problem

Chapter one of the thesis presents a study of the main parametric and structural optimization procedures affecting telecommunication models.

It is evident from the review that model prediction can be used in the search for new and attractive ways. The explanatory model can be applied to the study of the internal and external behavior of non-technical systems, especially in cases where experiments cannot be carried out or are very expensive, such as subsystems of telecommunication networks. For process optimization, sometimes the real system is simulated by a dynamic model that can be used in different operating conditions. Dynamic models can also be used for error detection by comparing the studied and measured process with known models. The application of evolutionary algorithms ensures accuracy, speed, convergence and robustness.

It is found that statistical communication theory offers a large number of possibilities for building telecommunication systems. How to choose the most appropriate option from this set under the given conditions? What criteria should be used to make this choice? To what extent is the use of certain new systems and models justified and how can existing ones be improved? The basic solution to these problems ultimately comes down to optimizing communication models and systems according to performance criteria.

The development of new versions of stochastic evolutionary algorithms is a current and active direction in modern scientific research worldwide.

The presence of unsolved problems requires the development of new versions of stochastic evolutionary algorithms that give better results under certain conditions.

Results of the literature research on the topic of the thesis

The following issues can be defined from the literature review:

- 1. The review and analysis of the state of the art of modeling and parametric and structural identification methods provide grounds to conclude that, unlike traditional deterministic methods for searching for optimal solutions, stochastic methods have many unsolved problems related to their application in specific complex systems.
- 2. The application of artificial intelligence methods in the assessment of the current state and quality of operation of telecommunication networks, in addition to the complexity of the systems and their models, is related to the development of new computational procedures, allowing the use of integer, real and complex values of parameters.
- 3. It is necessary to find approaches to train students in the use of artificial intelligence methods and techniques in the assessment of the state of components in telecommunication systems, aiming at acquiring knowledge to apply these methods in practice.

Chapter 2. Research Methodology

In this chapter of the dissertation, a Monte Carlo method for conducting simulation with stochastic models is presented. Emphasis is placed on sensitivity analysis in order to determine the input parameters that affect the uncertainty in the model output. The use of Artificial Intelligence (AI) methods in system identification is justified.

An important place in system identification is occupied by the parameter identification process. A number of technically well-founded methods, such as the least squares method, the instrumental variable method, and the maximum likelihood method, exist for estimating model parameters.

2.3. Artificial Intelligence (AI) methods used in system identification

The self-decision procedures of artificial intelligence systems are implemented through two main approaches, conventional and computational. The conventional approach uses methods based on special formalism and statistical analysis. On this basis, expert systems (Expert System), systems using analogy with previous cases (Case-Based Reasoning), probabilistic (Bayesian) networks (Belief Networks), etc. are built. The computational approach is associated with the use of interactive learning of AI systems based on empirical data and associated "flexible" computations. The main architectures of this type are Neural Networks, Fuzzy Logic systems, Genetic Algorithms, Swarm Intelligence (SI-Swarm Intelligence), etc.

2.4. Genetic algorithm GA.

Genetic Algorithm (GA) is a method for solving both types of optimization problems with and without constraints that are based on natural selection.

2.6. Conclusions

Emphasis is placed on sensitivity analysis to determine the input parameters that affect the uncertainty in the model output. The use of Artificial Intelligence (AI) methods in system identification is justified.

An important place in system identification is occupied by the parameter identification process. A number of technically well-founded methods, such as the least squares method, the instrumental variable method, and the maximum likelihood method, exist for estimating model parameters.

Chapter 3. Compilation of simulation test models of communication devices and procedures applying artificial intelligence methods

This chapter of the dissertation presents the use of artificial intelligence methods and techniques in assessing the state of components in telecommunication systems.

3.1. Parameter estimation of test linear and nonlinear models

3.1.1. Evaluating models of linear systems

In order to be used for performance evaluation of GA and PSO algorithms, various linear dynamical system models have been prepared.

3.1.1.1. Black box type models with linear polynomial structure

The following types of black box type

models with linear polynomial structure canbe distinguished (3.1):

$$A(q) y(t) = \sum_{i=1}^{nu} \frac{B_i(q)}{F_i(q)} u_i(t - nk_i) + \frac{C(q)}{D(q)} e(t), \qquad (3.1)$$

The polynomials A, B_i, C, D , and F_i contain the transition operator q. u_i is the i-th input signal, nu is the total number of input signals, and nk_i is the i-th input delay that characterizes the delay. The white noise variance e(t) is taken to be λ . To estimate polynomial models we need to define the polynomial order as a set of integers that represent the number of coefficients for each polynomial we include in our chosen structure - n_a for A, n_b for B, n_c for C, n_d for D, and n_f for F. We must also determine the number of samples nk corresponding to the input delay time given by the number of samples before the output signal responds to the input signal. The number of coefficients in the number of zeros plus 1. When the dynamics from u(t) to y(t) contains a delay of nk samples, then the first of B's nk coefficients is zero.

3.2. Test models of telecommunication devices to which identification methods based on artificial intelligence techniques will be applied

As test benchmark models in this dissertation the following have been selected:

- test model 1 of a linear system without noise;
- test model 2 of a linear system with noise;
- Test model 3 of a third-order analog bandpass filter with Chebyshev characteristic;
- Test Model 4 of PLL loop with 4th order low pass filter ;
- test model 5 of PLL loop with 3rd order low pass filter;
- test model 6 nonlinear model of cooling system of communication equipment.

3.3.1. Test model 1 of a linear system without noise

A general discrete-time linear polynomial model, IDPOLY ARX (autoregressive with external variables), is used as described in Table 3.1. The noise component in this case is zero.

The response of the model under step input is shown in Figure 3.3.



Fig. 3.3 *Transient response of the 3rd order linear system of test model 1*

The generated input and output signals are represented in the Matlab workspace as a pillar, each of which has 300 elements. The input and output data of model 1 are shown in Fig. 3.4.



3.2.1. Test model 2 of linear system with noise



Fig. 3.5. Test model 2 - graph of input and output signal.

3.2.2. Test model 3 of a third-order analog bandpass filter with Chebyshev characteristic

The general type of the transfer function of this filter is

$$H(s) = \frac{b(s)}{a(s)} = \frac{b(1)s^{n} + b(2)s^{n-1} + \dots + b(n+1)}{a(1)s^{m} + a(2)s^{m-1} + \dots + a(m+1)}$$
(3.14)

The synthesis of a third-order analog band-pass filter with Chebyshev type I characteristic, 3 dB non-uniformity (peak-to-peak) of the amplitude-frequency response and a passband from 200π to 500π rad/s is performed using the Matlab command:

[b,a] = cheby1(3,3,[200 500], 'bandpass', 's');

The transfer function of this filter is:

$$H(s) = \frac{6.766\ 10^6\ s^3}{s^6 + 179.2\ s^5 + 3.836\ 10^5\ s^4 + 4.26\ 10^7\ s^3 + 3.836\ 10^{10}\ s^2 + 1.792\ 10^{12} + 10^{15}}$$
(3.15)

Generating the data

The test input signal fed to the filter input is a pseudo-random sequence of 150 values having a normal distribution law (Fig. 3.7). The filter output signal is shown in Fig. 3.8.



Fig. 3.8. Analog bandpass filter output sequence

Data on the values of the input and output test signals (filter input and output) are stored as reference signals to be used during filter parameter identification procedures. The number of parameters to be estimated in this model is 7. These are the coefficients of the s-transmission function: vector a - 6 values (a0 = 1) and vector b - 1 value (b0 = b1 = b2 = b4 = b5 = b5 = 0).

3.3.4. Building test models of frequency synthesizers with PLL

For the purpose of the present study, two PLL loops were synthesized using different 3rd order and 4th order filters, respectively.



Fig. 3.11. General model of the frequency synthesizer in SIMULINK

3.3.6. Test model 4 of the synthesis of a PLL loop with a 4th order low pass filter

The control loop parameter synthesis methodology is demonstrated on the example of the synthesis of a 4th order low-pass filter.

The open-loop amplitude-frequency response requirements are set and monitored (Fig. 3.13).



Fig. 3.13. Target amplitude-frequency response of the open loop

Perform the contour synthesis and plot the result in Fig. 3.14



Fig. 3.14 . Tuned amplitude frequency response of the open loop

The open-loop Bode diagram is demonstrated in Fig. 3.16, and the zero-pole diagram, amplitude-frequency response, step input response, and impulse response of the system are given in Fig. 3.17.



Fig. 3.16. Bode diagram of the open loop in a 4th order filter



Fig. 3.17. Zero-pole diagram, amplitude-frequency response, response to step input and impulse response of the system at a 4th order filter

3.3.7. Test model 5 of PLL loop with 3rd order low pass filter

The design of the frequency synthesizer using a 3rd order filter is analogous to that of a

4th order filter.

With the loop synthesized in this way, the following values of the frequency error are obtained in the settling process (Fig. 3.18).

Fig. 3.18. Frequency error in the synthesizer settling process using a low-pass 3rd-order filter

The zero-pole diagram, amplitude-frequency response, step input response, and impulse response of the closed-loop synthesizer system using a low-pass 4th-order filter are given in Fig. 3.20.

Fig. 3.20. Zero-pole diagram, amplitude-frequency response, response to step input and impulse response of the system at a 3rd-order filter

3.3.8. Test model 6 of a non-linear model of a cooling system

Model description

This model simulates the process of air heating due to the operation of communication equipment. For this purpose, data obtained during the operation of a Feedback experimental rig type PT 326 is used. The process contained in the PT 326 involves air being drawn from the atmosphere by a centrifugal fan and heated as it passes through a heating grid before being vented to the atmosphere through a duct.

The purpose of the control is to maintain the air temperature at the desired level. The appearance of the bench is shown in Fig. 3.22.

Fig. 3.22. Appearance of the Feedback stand type PT 326

The structural diagram of the mathematical model of this bench (developed in Simulink) is shown in Fig. 3.23, and the transfer function is given by equation (3.21).

$$\frac{ke^{-\alpha}}{\tau s+1} \tag{3.21},$$

where $k = k_1 k_2 k_3$ and

 k_1 is the transmission coefficient of the heating element;

 k_2 is the heat transfer coefficient;

 k_3 is the transmission coefficient of the temperature sensor;

 τ_d is the time of the net delay due to the travel time of the air masses;

 τ is the heating time constant;

Generating the data:

Fig. 3.24 shows the input-output data record under step load variation by pseudo-random law.

Fig. 3.24. Input-output data taken from PT 326 process trainer

The models developed in paragraph 3.3 are used as follows:

- to evaluate the performance of the code implementing the genetic algorithm and particle swarm optimization (test models 1 and 2);
- to conduct Monte Carlo simulations for parameter estimation of linear communication systems (test models 3, 4 and 5);
- to conduct Monte Carlo simulations to estimate the parameters of a nonlinearcommunication system (test model 6);
- to conduct Monte Carlo simulations to evaluate the structure of a linear communication system (test model 1).

3.5.2. GA test results - the procedure

Results from the example using linear system - test model 1 as described in paragraph 3.3.1. The margin of error is err = 0.01, the population size is assumed to be **popsize = 30**, the mutation rate **mutation_r = 0.9** and the number of generations is **n_generations = 30**. Fig. 3.27 graphically represents the correlation between the site and model output.

The average sum of absolute error (AvSAE), by generation, is presented in Figure 3.28. AvSAE shows a value of 0.10216 at the end of the estimation process. This value changes across experiments, although the GA parameters remain the same. The reason for this is that the GA uses a statistical approach to generate the first generation and during the mutation phase.

Fig. 3.27 Test model 1- graph of the object and model output data

Fig. 3.28 AvSAE of test model 1 in GA-based estimation

3.6.2. Results of the PSO test procedure

Results from the example using test model 1 of a linear system as described in paragraph 3.3.1. The margin of error is err = 0.01, the population size is assumed to be swarm_size = 50, correction factor: correction_factor = 2, inertia: inertia = 0.5 and number of iterations = 30. Figure 3.30 graphically represents the output data of the object and the model under estimation with PSO.

Fig. 3.30 Test model 1 - graph of the output data of the object and model in the evaluation with PSO

The average sum of absolute error (AvSAE) is shown in Figure 3.31. The AvSAE shows a value of 3.2515e-6 at the end of the estimation process. This value changes from experiment to experiment, while the PSO parameters remain identical. The reason is that the PSO uses a statistical approach to generate the initial population. This is illustrated in Fig. 3.32, where AvSAE is represented graphically with different test codes without changing the parameters.

Fig. 3.31 The average sum of absolute error (AvSAE) for test model 1 with estimation using PSO

Fig. 3.32 Test model 1 - Evaluation process with PSO in several experiments with the same parameters of the evaluated model

3.7. Conclusions

In this chapter of the thesis, presents the use of artificial intelligence methods and techniques in assessing the state of components in telecommunication systems. For this purpose, the following approach (algorithm) is chosen:

• Creation of test models of basic telecommunication devices in Matlab environment;

• testing the created reference models by simulating and creating input-output data sets to be used in the process of identifying their parameters, as well as determining the main characteristics of the test models;

• creation, in the Matlab environment, of procedures for the implementation of the selected artificial intelligence methods: genetic algorithm (GA) and particle swarm optimization (PSO);

• Testing the established procedures implementing the GA and PSO techniques;

• Selection of significant factors and planning of the numerical experiments using the Monte Carlo simulation method;

 setting up an automated procedure to carry out the planned experiments and systematize the results;

• Performing comparative analysis and quality assessment using GA and PSO of the test system parameters;

evaluation of the rapidity of identification methods and the influence of factors.

The problem of determining the structure of an ARX-model is presented. Test models of telecommunication devices to which the identification methods based on artificial intelligence techniques will be applied are described.

As test benchmark models in this dissertation the following have been selected:

- test model 1 of a linear system without noise;
- test model 2 of a linear system with noise;
- Test model 3 of a third-order analog bandpass filter with Chebyshev characteristic;
- test model 4 of PLL loop with 4th order low pass filter;
- test model 5 of PLL loop with 3rd order low pass filter;
- test model 6 nonlinear model of cooling system of communication equipment.

The GA-based evaluation procedure was written for the purpose of this study.

Results from the example using linear system - test model 1 as described in paragraph 3.3.1. The margin of error is err = 0.01, the population size is assumed to be **popsize = 30**, the mutation rate **mutation_r = 0.9** and the number of generations is **n_generations = 30**. Fig. 3.27 graphically represents the correlation between the site and model output.

The average sum of absolute error (AvSAE), by generation, is presented in Fig. 3.28, which for AvSAE shows a value of 0.10216 at the end of the estimation process.

The average sum of absolute error (AvSAE) is shown in Fig. 3.31. The AvSAE reports a value of 3.2515e-6 at the end of the estimation process. This value varies from experiment to experiment, while the PSO parameters remain identical.

Chapter 4. experimental studies

4.1.3. Verification of the significance of the factors in the case of a linear system without noise evaluated with PSO

The following figures present the results of the simulations performed. From Fig. 4.4, it can be seen that the AvSAE in this experiment is lower in cases where the correction factor is 2 or 2.4. From Fig. 4.5, it is reported that for momentum, the value of 0.8 is the best.

Fig. 4.4. Scatter plot of AvSAE versus correction factor

Fig. 4.5. Scatter plot of AvSAE versus momentum

4.1.4. Verification of the significance of the factors in the case of a linear system without noise estimated with GA

Scatter plot of AvSAE versus GA parameters are shown in Fig. 4.7 and Fig. 4.8. The best values of the crossover and mutation factors are 0.2 and 0.275.

Fig. 4.7. Scatter plot of AvSAE versus cross factor

Fig. 4.8. Scatter plot of AvSAE versus mutation rate

The result of the null hypothesis "The crossover factor does not affect the accuracy of the GA algorithm" and "The mutation factor does not affect the accuracy of the GA algorithm" is:

```
The crossover factor is significant F = 20.7891, P = 0.1764
The mutation rate is significant F = 0.9961, P = 0.1764
```

4.1.5. Comparison of linear system evaluation with GA and PSO

The problem at hand is to compare the estimation algorithms for the case of a linear system. The comparison of the estimation algorithms in the noise-free case is performed in two ways:

- 1. Visually, through the graphs in Figures 4.10 and 4.11, which show the AvSAE for both algorithms. From the analysis and comparison of the obtained values, it can be concluded that PSO has a better performance in the considered case;
- 2. By calculating the mean values of AvSAE, estimated parameters and comparing. The results are presented in Table 4.3, they give a reason to conclude that PSO has better estimation accuracy.

Fig. 4.10. AvSAE value for the two algorithms PSO (in red) and GA (in blue)

Fig. 4.11. Sorted AvSAE values for the two algorithms PSO (in red) and GA (in blue)

4.1.1. Test of an analog bandpass filter with Chebyshev characteristic using GA

The AvSAE scatter diagrams for this case are given in Fig. 4.12 and Fig. 4.13. Both factors are significant. The best fit of the factor values is: Mutation probability: 0.275; Crossover: 0.6.

Fig. 4.12. AvSAE scatter plots versus crossover and mutation for an analog bandpass filter, under GA

4.1.2. Testing an analog bandpass filter using an PSO

The significance test of the factors (file Scatter_f_test4.m) in this case gives the results presented in Table 4.5. The momentum factor is not significant here. The scatter plots for this case are given in Fig. 4.14 and Fig. 4.15. The best value of the correction is 0.2.

Table 4.5: Results of performing a significance test for the analog bandpass filter factors in the PSO

Correction Factor is significant	Inertia is not significant (F < P)
F = 0.7656; P = 0.1764	F = 2.1952e-04; P = 0.1764

Fig. 4.14. AvSAE scatter plots versus correction and momentum for an analog bandpass filter, at PSO

4.1.3. Comparison of analog bandpass filter model evaluation with GA and PSO

The best estimates for the two algorithms along with the original coefficient values are shown in Table 4.6. The PSO algorithm provides higher estimation accuracy in most cases (Fig. 4.16 and Fig. 4.17).

			AvSA		b3		a1		a2		a3		a4		a5		a6
		E															
	Origin																
al																	
	GA		1.684		7.42282e+		206.2		384583		4.91724e+		3.79658e+		2.12272e+		9.56584e+
				06		23		.3		07		10		12		14	
	PSO		2.865		6.02475e+		169.7		372317		3.95752e+		3.63998e+		1.68886e+		9.29076e+
Η		2		06		53		.7		07		10		12		14	

Table 4.6. Best estimates of filter parameters for the two algorithms

Fig. 4.16. AvSAE value for the two algorithms PSO (in red) and GA (in blue), when estimating an analog bandpass filter

Fig. 4.17. Sorted AvSAE values for the two algorithms PSO (in red) and GA (in blue), when estimating an analog bandpass filter

The error from estimating the coefficients of a third-order analog bandpass filter with Chebyshev characteristic is quite significant and the estimation is not of sufficient quality. This can be seen from the comparison plots (Fig. 4.16 and Fig. 4.17), where the GA reports a smaller error, but nevertheless the AvSAE is in the order of **10**, in contrast to the linear system estimator, which has values below 0.1.

This large value of estimation error is due to the very high degree of non-linearity of the digital filter transfer function, which represents the 6th order part of polynomials.

Furthermore, the filter transfer function coefficients depend on several real physical parameters (active resistances and capacities) and are interrelated. They do not represent independent parameters, which creates serious problems for their identification procedures.

The other problem is the large number of estimated coefficients and the large difference in their nominal values, as well as the presence of coefficients with negative values.

The conclusion that is drawn is that the algorithms used (GA and PSO), as they stand, are not suitable for estimating the coefficients of the filter transfer function. The independent real physical parameters - active resistances and capacitances - have to be estimated.

4.2. Preparing the Matlab code and testing the PLL using GA and PSO using a 3rd order filter

4.2.1. Testing a frequency synthesizer with PLL loop and 3rd order low pass filter using GA

The null hypothesis test found that the crossover parameter (Crossover_p) and the mutation probability (Mutation_r), using the genetic algorithm procedure, were not significant.

Fig. 4.18(a) and Fig. 4.18(b) show the lattice plots of the AvSAE error distribution versus crossover parameter (Crossover_p) and mutation probability (Mutation_r), respectively.

Fig. 4.18. *Lattice plots of the AvSAE error distribution as a function of (a) the crossover parameter (Crossover_p) and (b) the mutation probability (Mutation_r), respectively*

Testing a frequency synthesizer with PLL loop and 3rd order low pass filter using PSO

Fig. 4.20(a) and Fig. 4.20(b) show the lattice plots of the AvSAE error distribution versus Correction Factor and Inertia Factor, respectively.)

Fig. 4.20. Lattice plots of the AvSAE error distribution, respectively, versus (a) the Correction Factor and (b) the Inertia Factor)

4.2.2. Comparison of GA and PSO estimation results using a 3rd order filter

The output signal of the estimated model is shown together with that of the original model in Fig. 4.22. A reasonably good match of the two-timing diagrams can be noted.

Fig. 4.22. Output signal of the original model (dashed line) and the estimated model (solid line)

Fig. 4.23. shows the averaged AvSAE absolute error for the two algorithms, depending on the test sequence number. After sorting the AvSAE values (Fig. 4.24.), it can be noticed that in most cases PSO provides higher estimation accuracy than GA.

Fig. 4.23. Average absolute AvSAE error for the two algorithms, depending on the test sequence number

Similarly to the studies conducted in the previous paragraph 4.2, it is concluded that the parameters of the digital gating filter model cannot be estimated with high enough accuracy using real-coded GA and PSO algorithms.

Fig. 4.24. Absolute error AvSAE values for the two algorithms sorted by size

The duration of the Monte Carlo simulation tests for the GA algorithm is 1 h 54 min and 06 s and is 1 min less than that of the PSO. This indicates that GA is 0.88% faster than PSO. The estimation accuracy of PSO is on average about 2.5 ... 3 times higher than that of GA.

4.2.3. Testing a frequency synthesizer with PLL loop and 4th order low pass filter using GA

Test the null hypothesis that the crossover parameter (Crossover_p) and the mutation probability (Mutation_r), using the genetic algorithm procedure) are not significant?

The combined lattice diagram reflecting the influence of the two factors Crossover_p and Mutation_r in the genetic algorithm is demonstrated in Fig. 4.26. It can be noted that statistically the best value of Crossover_p is 0.6 and that of Mutation_r is 0.5.

Fig. 4.26. Composite lattice plot of AvSAE error distribution versus crossover parameter (Crossover_p) and mutation probability (Mutation_r), respectively

4.2.4. Testing a frequency synthesizer with a PLL loop and a 4th-order low-pass filter using an PSO

The test of the null hypothesis found that the Correction Factor and Inertia Factor using the PSO procedure were not significant and gave the following result:

Correction Factor is significant (F > P)

F = 7.2175; P = 0.1764Inertia is significant (F > P) F = 5.3160; P = 0.1764

4.2.5. Comparison of GA and PSO estimation results using a 4th order filter

The output signal of the estimated model is shown together with that of the original model in Fig. 4.30. The reasonably good agreement of the two time-diagrams can be noted.

Fig. 4.30. Output signal of the original model (dashed line) and the estimated model (solid line)

Fig. 4.31 shows the averaged AvSAE absolute error for the two algorithms, depending on the test sequence number. After sorting the AvSAE values (Fig. 4.32), it can be noticed that in most cases PSO provides higher estimation accuracy than GA.

Fig. 4.31. Average absolute AvSAE error for the two algorithms, depending on the test sequence number

Fig. 4.32. Absolute error AvSAE values for the two algorithms sorted by size

And in these tests, GA is 0.92% faster than PSO.

The accuracy of the PSO estimation is again on average about 2.5 ... 3 times higher than the GA.

4.6. Conclusions

Chapter four of the thesis presents tests of a linear system **with and without noise**, using a real coded GA and performing a planned Monte Carlo experiment. An analysis of the significance of the factors in testing the linear system is also performed.

A noiseless linear system with PSO was tested. The constraints in this problem are chosen as follows: from 1.6 to 2.4 for the correction factor, from 0.4 to 0.8 for the momentum parameter.

A program has been developed to check the significance of the factors, in the case of a linear system without noise, evaluated with PSO. In this experiment, it is seen that AvSAE is lower in cases where the correction factor is 2 or 2.4. It is found that for momentum, the value of 0.8 is the best.

The significance of the factors is checked in the case of a linear system without noise estimated with GA. The best values of the crossover and mutation factors were found to be 0.2 and 0.275. A comparison of the estimation of a linear system with GA and PSO was performed.

A frequency synthesizer model with PLL loop using GA and PSO is tested using a 3rd order filter, by applying real coded GA and PSO, and performing a planned Monte Carlo experiment. An analysis of the significance of the factors in testing the filter model is conducted.

The combined lattice diagram reflecting the influence of the two factors Correction Factor and Inertia is demonstrated in Fig. 4.21. It can be noted that statistically the best value of Correction Factor is 2.4 and that of Inertia is 0.6.

A Matlab code has been created to test the cooling system model of communication equipment in structure identification, using integer-coded GAs and PSOs and performing a planned Monte Carlo experiment. A factor significance analysis is conducted. For this purpose, special functions implementing the procedures of integercoded GAs and PSO-algorithms are written. They determine the values of the structural indices (na, nb and nk) of the ARX - polynomial model (idpoly) of the cooling system.

Atest was performed in identifying the structure of a model of the cooling system of communication equipment using GA. In this study, the data taken from Feedback's PT326 laboratory experimental model is used as input.

Testing was performed in the identification of the structure of a model of the cooling system of communication equipment using PSO.

CONCLUSION

In chapter one of the dissertation, a literature review on the specific issues is conducted. The advantages and disadvantages of existing methods and algorithms are presented. The features of the main parametric and structural optimization procedures affecting telecommunication models are specified. The problems of the literature survey are analyzed. In order to achieve the stated goal, the objectives of the dissertation are defined. The relevance of the problem of determining the distance to the short circuit location is emphasized.

Chapter two of the thesis presents a Monte Carlo method for conducting simulation with stochastic models. Emphasis is placed on sensitivity analysis in order to determine the input parameters that affect the uncertainty in the model output.

The use of Artificial Intelligence (AI) methods in system identification is justified. The individual functional blocks are described and the hardware platform of the implemented module is given.

Chapter three presents the use of artificial intelligence methods and techniques in assessing the state of components in telecommunication systems.

The creation of test models of basic telecommunication devices in the Matlab environment is discussed.

A choice of nonlinear structure that independently combines linear and nonlinear regressors and the nonlinearity structure itself, such as the binary splitting tree, is presented. The most detailed methods are developed for the class of regression models.

The problem of determining the structure of an ARX-model is presented. Test models of telecommunication devices to which the identification methods based on artificial intelligence techniques will be applied are described.

Chapter four focuses on experimental research.

In the first paragraph of chapter four of the thesis, tests of a linear system **with and without noise** are presented using a real coded GA and performing a planned Monte Carlo experiment. An analysis of the significance of the factors in testing the linear system is also performed.

The significance of the factors is checked in the case of a linear system without noise estimated with GA. The best values of the crossover and mutation factors were found to be 0.2 and 0.275. A three-dimensional scatter plot of AvSAE versus the crossover and mutation factors in GA is presented.

A comparison of the estimation of a linear system with GA and PSO is made. The comparative results of linear system evaluation are tabulated.

The error from estimating the coefficients of a third-order analog bandpass filter with Chebyshev characteristic is quite significant and the estimation is not of sufficient quality. This can be seen from the comparison plots (Fig. 4.16 and Fig. 4.17), where the GA reports a smaller error, but nevertheless the AvSAE is in the order of **10**, in contrast to the linear system estimator, which has values below 0.1.

This large value of the estimation error is due to the very-high degree of nonlinearity of the digital filter transfer function, which is a parton of 6th order polynomials.

Furthermore, the filter transfer function coefficients depend on several real physical parameters (active resistances and capacitances) and are interrelated. They do not represent independent parameters, which creates serious problems for their identification procedures.

The other problem is the large number of estimated coefficients and the large difference in their nominal values, as well as the presence of coefficients with negative values.

The conclusion that is drawn is that the algorithms used (GA and PSO), as they stand, are not suitable for estimating the coefficients of the filter transfer function. The independent real physical parameters - active resistances and capacitances - have to be estimated.

A frequency synthesizer model with PLL loop using GA and PSO is tested using a 3rd order filter, by applying real coded GA and PSO, and performing a planned Monte Carlo experiment. An analysis of the significance of the factors in testing the filter model is conducted.

Testing of a frequency synthesizer model with PLL loop and 4th order low pass filter using PSO is done. In Fig. 4.27(a) and Fig. 4.27(b), the lattice plots of AvSAE error distribution versus Correction Factor and Inertia Factor, respectively, are presented.)

Testing the structure of a model of the cooling system of communication equipment using integer-coded GAs and PSOs and performing a planned Monte Carlo experiment was performed. A factor significance analysis is also conducted. For this purpose, special functions implementing the procedures of integer-coded GAs and PSO - algorithms are written. In this study, data taken from Feedback's PT326 laboratory experimental setup is used as input. In most cases, the procedure applying the genetic algorithm (GA) returns the values: na = 4, nb = 5, nk = 2.

CONTRIBUTIONS OF THE DISSERTATION Scientific and applied contributions:

- 1. Existing methods, techniques and tools of artificial intelligence for estimating the structure and parameters of basic components and nodes of telecommunication systems are studied, systematized and analyzed.
- 2. Numerical experiment and Monte-Carlo simulation methods are applied to investigate the capabilities of GA and PSO algorithms for automated determination of the parameters and structure of specific classes of modules and devices in telecommunication systems.
- 3. Procedures implementing the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) method have been developed and the importance of factors affecting the qualities of the considered algorithms has been investigated and a comparative analysis has been conducted.

Applied contributions:

- 1. Tests of a linear system **with and without noise**, using a real coded GA and performing a Monte Carlo experiment are conducted and presented.
- 2. Matlab codes for testing an analog bandpass filter using real coded GAs and PSOs, and performing Monte Carlo simulations were created and investigated. The significance factors in testing the filter model are conducted and analyzed.
- 3. Tests of a digital frequency synthesizer model using 3rd and 4th order filters using real coded GA, Monte Carlo simulation and PSO are conducted and presented.
- 4. A software tool in Matlab environment has been developed and investigated to test a model of the cooling system of communication equipment in structure identification, using integer-coded GAs and PSOs and performing a planned Monte Carlo experiment. A significance analysis of the factors was carried out, and special functions implementing the procedures of integer-coded GAs and PSO-algorithms were written for this purpose. The values of the structural indices (na, nb and nk) of the ARX - polynomial model (idpoly) of the cooling system were determined.
- 5. Testing was performed in the identification of the structure of a model of the cooling system of communication equipment using GA and PSO. Data taken from Feedback's PT326 laboratory experimental model is used as input.

LIST OF PUBLICATIONS RELATED TO DISSERTATION WORK

1. Lyubomirov, S.; Shehova, D.; Popov, R.; **Ismail, S.**, Development of software modules for realization of APRS-based Tracker with application in engineering education, Conference: 14th International Technology, Education and

Development Conference, 2nd-4th of March, 2020, Valencia, Spain, ISBN:978-84-09-17939-8, ISSN:2340-1079, doi:10.21125/inted.2020.1420, pp. 5254-5252. - **Web of Science**

- 2. Lyubomirov, S., Shehova, D., **Ismail, S.** (2021). Online teaching of mobile Communication systems during the COVID-19 pandemic using MATLAB/OCTAVE, EDULEARN21: 13th annual International Conference on Education and New Learning Technologies, 5th and 6th of July, 2021, ISSN: 2340-1117. **Web of** Science.
- **3.** Shehova, D., Lyubomirov, S. **Ismail, S**. (2021). Structural identification of systems using artificial intelligence algorithms in the training of students, EDULEARN21: 13th annual International Conference on Education and New Learning Technologies, 5th and 6th of July, 2021, ISSN: 2340-1117. **Web of Science**
- 4. **Sezgin Ismail.** Evolutionary optimization algorithms status and perspectives. Third National Scientific Conference "Man and the Universe", Union of Scientists in Bulgaria - Smolyan, 25-26 November 2021, Scientific Proceedings, Volume III, Part 3, pp. 573 - 583, ISSN:1314-9490 (online).
- Ismail S., Lyubomirov S. (2021) Identification of systems. Problems and modern methods. Third National Scientific Conference "Man and the Universe", Union of Scientists in Bulgaria - Smolyan, 25-26 November 2021, Scientific Proceedings, Vol. III, Part 3, pp. 602 - 610, ISSN:1314-9490 (online).