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PAPERS

Controller design of isolated power-electricity island using genetic algorithm

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The contribution presents the use of Genetic Algorithm for searching of the optimal parameters of a set of speed controllers of an isolated power-electricity island. Nine PI-controllers are designed. The cost function which is minimised using the Genetic Algorithm represents the integral of the control error area. Robustness aspects of the control design are considered as well.

K e y w o r d s: power-electricity system, isolated island, speed control, controller design, robust control, genetic algorithm

1 Introduction

Evolutionary optimisation methods and Evolutionary Computation (EC), are powerful means for solving complex or even extremely complex design tasks in many areas as mathematics, construction, process control and all this in various practical application domains as industry, transport, robotics, economics/finance *etc* [1, 2]. The presented contribution shows the application of this approach for controller design in the power-electricity system. The use of EC in process control and in controller design has the potential to find (sub)optimal parameters of a non-trivial (or even very complex) control loop [3, 4, 5]. As an example of a complex power-electricity controller design problem we consider here the rotor speed controllers design of a possible isolated island in south-west Slovakia, which consists of 4 hydro turbine-generators, two CCGT (gas-steam turbine-generator) blocks, a nuclear block in rotor-speed regulation mode and additionally a pressure controller and a steam flow controller of the nuclear block with the appropriate transmission infrastructure and loads. First we shortly introduce how the Genetic Algorithm (GA), which is one of the most frequently used representatives of evolutionary computation approaches, can be used for controller design problems. Next the model of the considered power electricity island is described which is part of the existing model of the Power Electricity System of Slovak Republic and we explain the GA-based design procedure for 9 PI-controllers.

2 Controller evolution and the genetic algorithm

2.1 Control performance evaluation

The aim of the control system design is to ensure required static and dynamic behaviour of the controlled process. This behaviour is usually represented in terms of the known concepts: overshoot, settling time, decay rate, damping, steady state error or various integral performance indices [3, 4], *etc*. Without loss of generality let us consider a simple feedback loop (closed-loop) (Fig. 1), where the controlled process is a continuous-time dynamic system, the controller is a dynamic system with known structure and unknown parameters, y is the controlled variable, u is the control variable, r is the reference variable, e is the control error ($e = r - y$) and d is the disturbance.

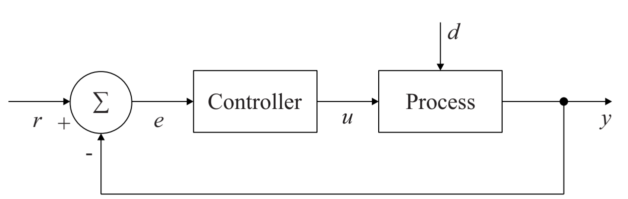

Fig. 1. Simple feedback loop, y-controlled variable, u-control variable, r-reference variable, e-control error ($e = r - y$), d-the disturbance

Consider an appropriate simulation model of this closed-loop to be available. Let us analyse the closed-loop behaviour using the simple integral performance index "Integral of Absolute Error" defined as

$$I_{AE} = \int_0^T |e(t)|\mathrm{d}t \tag{1}$$

where T is the simulation time. The discrete form of this performance index is

$$I_{AE} = \sum_{k=1}^{N} T_s|e_k| \tag{2}$$

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where T_s is the simulation step (sampling period) and N is the number of simulation steps. Using other performance indices, various aims and time-response properties can be achieved [3, 4]. The controller design principle is an optimisation task – search for such a controller parameter, which minimizes the cost function (fitness function). The evaluation of the cost function consists of three steps. The first step is the transformation from the representation form of the controller in the GA domain (parameter vector – chromosome) into the simulation model (decoding of the genotype into the phenotype). The second step is the computer simulation of the closed-loop time-response in some simulation environment (in our case it is Matlab/Simulink [8]) and the last step is the performance index evaluation.

If it is necessary to damp oscillations or reduce overshoot, it is possible to insert additional terms into the integral, which include absolute values of the first order or also the second order derivatives of the control error

$$J = \int_0^T \big(\alpha|e(t)| + \beta|e'(t)| + \gamma|e''(t)|\big)\mathrm{d}t \tag{3}$$

where α, β, γ are weight coefficients. Note, that the control error derivatives can be replaced with the absolute values of output derivatives $(|y'(t)|, |y''(t)|)$. In the discrete case the integral is replaced by the sum and the derivatives are replaced by the differences. Sufficient results can be obtained using the very simple performance index in the form

$$J = \alpha\eta + (1-\alpha)t_s \tag{4}$$

where η is the overshoot, t_s is the settling time and $0 < \alpha < 1$ is the weight coefficient. Tracking the required reference response $y_r(t)$ is achieved via minimizing

$$J = \int \big(y_r(t) - y(t)\big)^2 \mathrm{d}t\,. \tag{5}$$

Control value minimisation can be achieved using performance indices of the type

$$J = \int \big(\alpha e^2(t) + (1-\alpha)u^2(t)\big)\mathrm{d}t \tag{6}$$

where u is the control variable. A universal performance index, which combines some above-mentioned aspects is

$$J = \int_0^T \big(|e(t)| + a|e'(t)| + b|u(t)| + c|u'(t)|\big)\mathrm{d}t \tag{7}$$

where e' is the control error derivative, u is the control variable and u' is its derivative. This performance index includes oscillation damping (increasing a), minimisation of the absolute value of the control signal u (increasing b) and minimisation of control signal change u' (increasing c).

2.2 Genetic algorithm

The used GA algorithm operates contemporarily over a set of potential solutions (population of chromosomes) and uses three basic operators over chromosomes which are the selection, mutation and crossover. Before explanation of the algorithm let us define the basic data structures which are genes, chromosomes and the population and the basic operators which are selection, mutation and crossover. A potential solution of the controller in the closed loop - chromosome is a vector of the searched parameters of the considered controller (chromosome = [P, I, D] in case of a PID controller, *etc*). Each parameter of the chromosome (P, I or D) is a gene. A set of selected number of chromosomes (say 20 or 100) is called population. The selection operator selects chromosomes from the population which will survive without modification and chromosomes (parents) which will be modified by mutation and crossover to produce children. There exist several selection methods, but in general more fit individuals have higher chance to be selected [1, 2]. Mutation is such an operation where some gene (genes) of a chromosome is (are) randomly changed to other value (values). Crossover combines genes of two (or more) chromosomes to produce new children.

Block scheme of the used scheme of GA with examples of basic genetic operations is shown in Fig. 2. The Genetic Algorithm is as follows:

(1) Random initialization of the population of N chromosomes.
(2) Fitness function calculation of each chromosome of the population (simulation and evaluation of the cost function (1), (2) or another).
(3) If the predefined number of generations is reached, or the required terminating conditions are reached then finish, otherwise continue to step 4.
(4) Selection of *parents1* for crossover, selection of *parents2* for mutation (marked "P" in Fig. 2), using Stochastic Universal Sampling Selection [1, 2], selection of best chromosome(s) ("B") and random chromosomes which both will survive without modification ("U").
(5) Modification of *parents1* by *crossover* = *children1*. Modification of *parents2* by the *mutation* = *children2*.
(6) Completion of the new population: *children* + *best* + *unchanged chromosomes* ("Ch+B+U").
(7) Back to step (2).

2.3 Robust controller design

Consider $c = \{c_1, c_2, \ldots, c_q\}$ to be the set of designed controller parameters and let the $s = \{s_1, s_2, \ldots, s_r\}$ be the set of parameters of the controlled system. During the operation of the plant, the parameters s_i can move within some uncertainty space

$$s_{i,\min} \le s_i \le s_{i,\max} \quad i = 1, 2, \ldots, r\,, \tag{8}$$

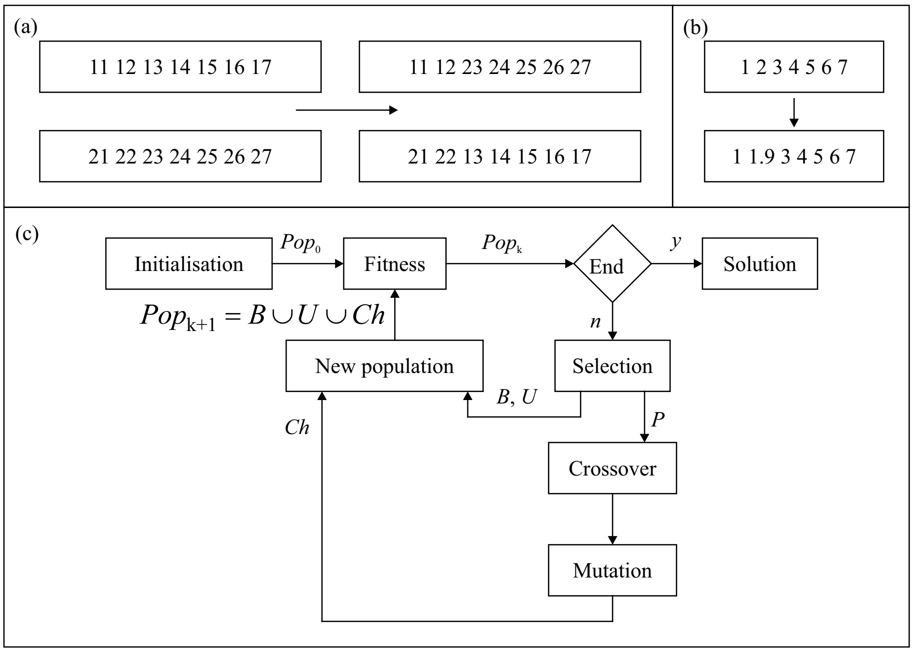

Fig. 2. Principle of genetic algorithm: (a) – example of crossover, (b) – example of mutation, (c) – block scheme of genetic algorithm. Pop_0-initial population, Pop_k-population in the k-th generation, P-group of individuals for genetic operations $(Parents = parents1+parents2)$, B-group of best individuals (at least one), U-group of unchanged individuals, Ch-group modified parents P using genetic operations $(children)$

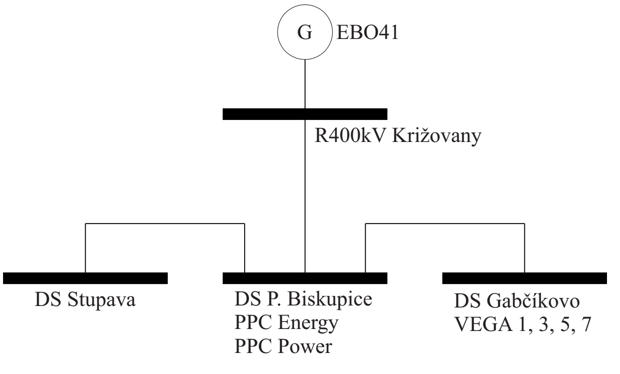

Fig. 3. Considered power-electricity island in SW Slovakia

where $s_{i,\min}$ and $s_{i,\max}$ are the minimum and maximum possible values of the i-th system parameter, respectively. Consider W different physical working points of the controlled process, defined by different vectors s, which are to be controlled by the robust controller. For that case consider the cost function in the additive form

$$J = \sum_{i=1}^{W} J_i \tag{9}$$

comprising performance evaluation, for instance (1), in all W working points. It is also recommended to include the measured noise from the real system or other possible disturbances or expected situations in the simulation model.

3 Controller design of the power-electricity island and the experiment setting

3.1 Simple controller design – single working point

Let us consider the power-electricity system in island operation which is located in south-west Slovakia. Consider that this island is an isolated system, which is not connected to the remaining Power-Electricity System of the Slovak Republic and the European power-electricity system as well. The Island (Fig. 3) consists of the nodes Stupava, Podunajské Biskupice, Gabčíkovo and Križovany which are connected on the level 400 kV using lines V498, V439 and V429. The total load of this island is 484.6 MW. The following generation is connected to the island: VEGA 1,3,5,7 (Gabčíkovo, hydro turbine-generators), PPC Power, PPC Energy (P.

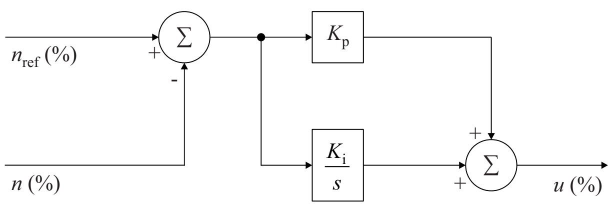

Fig. 4. Rotor speed PI-controller

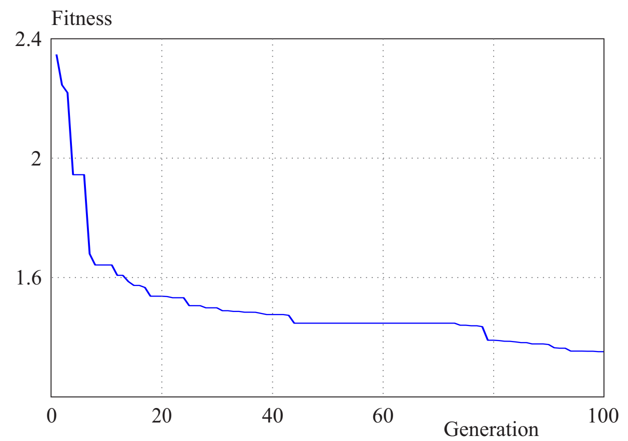

Fig. 5. Graph of the fitness function evolution of the robust 9-controller configuration

Biskupice, combined cycle power plant CCGT) and EBO41 (Jaslovské Bohunice, nuclear power plant block). The model of each block consists of a turbine, synchronous generator, speed controller, excitation system with voltage controller, power system stabiliser and the block transformer. All the power plants maintain the island frequency through the speed controllers.

The design aim is to find optimal parameters of the 7 speed controllers of blocks VEGA 1,3,5,7 and PPC Power, PPC Energy and Nuclear power plant block EBO 41. The steam flow and pressure controller parameters of the nuclear power plant are needed to design as well. The turbines are modelled according to [9].

The block scheme of the speed controllers is shown in Fig. 4. The free controller parameters are K_p (proportional gain) and K_i (integral gain). The general representation of a chromosome of the population in the GA is in the following form

$$ch = [K_{p,1}, K_{i,1}, K_{p,2}, K_{i,2}, K_{p,3}, K_{i,3}, K_{p,4}, K_{i,4}, K_{p,5}, K_{i,5}, K_{p,6}, K_{i,6}] \quad (10)$$

index 1 belongs to 4 blocks VEGA1,3,5,7 (equal parameters of all 4 blocks are considered), index 2 belongs to PPC Power, index 3 belongs to PPC Energy, index 4 belongs to the EBO 41 speed controller, index 5 to the EBO 41 pressure control and index 6 to the EBO 41 steam flow control. Nine PI-controllers are designed.

The population size of the GA was set to 50 chromosomes, the mutation rate used was set to 0.1, crossover rate was set to 0.8. The used cost function which is to be minimized is according (1) in form

$$I_{AE} = \int_0^T |e(t)| \mathrm{d}t \to \min \quad (11)$$

where $e = f_{\text{ref}} - f$, f_{ref} is the reference voltage frequency ($f_{\text{ref}} = 1$), f is the output voltage frequency, T is the simulation time of the experiment. The experiment scenario consists of the 30 MW generation outage (VEGA1) in time 10s and the 48 MW load outage in time 100 s.

100 generations on a parallel platform with six i7-intel cores with Matlab takes approximately an hour of computation time. The obtained results are in Fig. 5 and Fig. 6.

In Fig. 5 the graph of the fitness function (11) evolution is depicted. Each point of the graph represents the best reached fitness in the current generation. In Fig. 6 the island frequency time-response is shown for the proposed 9-controller configuration obtained by the GA (solid line). For comparison the "manual" controller design (experimental approach) is shown (dashed line). The original and optimized values of the parameters are shown in Tab. 1. The considered search space of all controller parameters was set between 0 and 100.

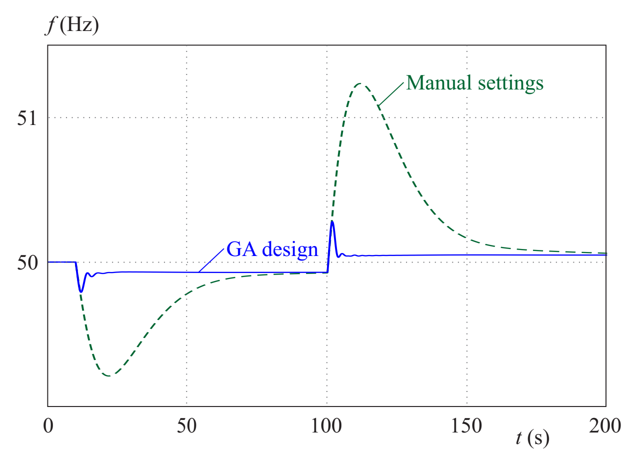

Fig. 6. Output voltage frequency after the 30 MW generation outage in time 10s and the 48 MW load outage in time 100 s, solid line – GA based parameter design, dashed line – manual parameter setting

3.1 Robust controller design – design in more working points

Next, let us consider, that the power electricity island operates in several working points, each working point is defined by some value of load of each particular block. Consider three different working points where all sources in the power electricity island expect the nuclear block EBO41 are loaded by 10 %, 50 % or 70 % respectively of their maximal possible load of each particular block. The total load of the island depends also on the working

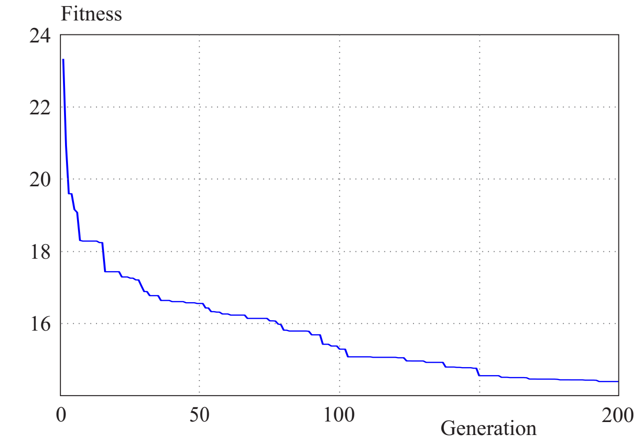

Fig. 7. Graph of the fitness function evolution of the robust 9-controller configuration

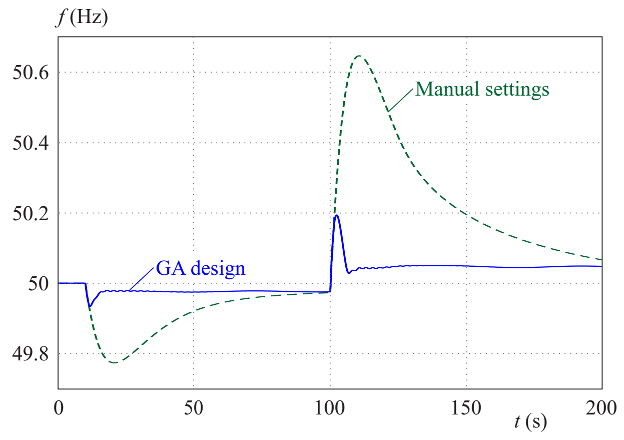

Fig. 8. Output voltage frequency after the 10 MW generation outage in time 10 s and 28 MW load outage in time 100 s

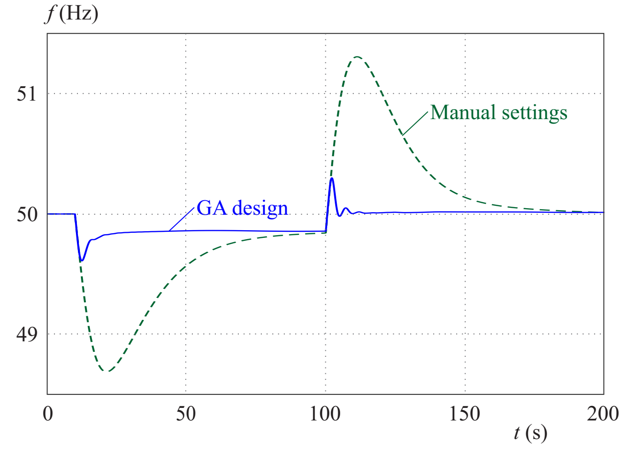

Fig. 9. Output voltage frequency after the 50 MW generation outage in time 10s and 54 MW load outage in time 100s. Solid line Robust GA-based parameter design, dashed line manual parameter setting

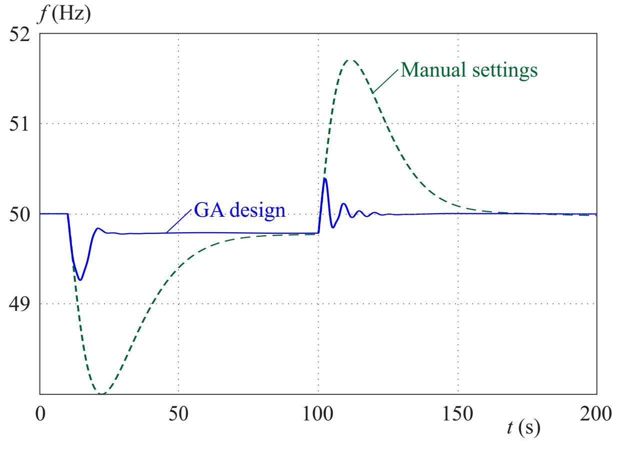

Fig. 10. Output voltage frequency after the 50 MW generation outage in time 10s and 54 MW load outage in time 100s. Solid line Robust GA-based parameter design, dashed line manual parameter setting.

point. The cost function for the GA-based minimization is according to (9) in form

$$J = \sum_{i=1}^{W} J_i \tag{12}$$

where $i = 1, 2, 3$ is the number of the working point with 10 %, 50 % or 70 % respectively of maximal load of each block.

In Fig. 7 the evolution of the fitness function (12) is shown. In Fig. 8 are the time-responses of output voltage

Table 1. Controller parameters

Controller Parameter	Manual settings	GA design 1 working point	GA design 3 working points
EGA1,3,5,7 speed control K_p	5	13.21	9.23
EGA1,3,5,7 speed control K_i	0.1	7.11	2.98
PPC Power speed control K_p	2	97.88	97.35
PPC Power speed control K_i	0.1	9.58	8.77
PPC Energy speed control K_p	1	39.31	46.59
PPC Energy speed control K_i	0.2	9.19	9.82
EBO41 speed control K_p	1	9.01	9.53
EBO41 speed control K_i	0.1	16.07	14.53
EBO41 pressure control K_p	2	6.88	9.89
EBO41 pressure control K_i	0.025	0.25	1.07
EBO41 fuel control K_p	5	3.72	4.72
EBO41 fuel control K_i	2.5	2.84	2.27

frequency after the 10 MW generation outage in time 10 s and 28 MW load outage in time 100 s. In Fig. 9 are the output voltage frequencies after the 50 MW generation outage in time 10 s and 54 MW load outage in time 100 s. Finally, in Fig. 10 the output voltage frequencies after the 70 MW generation outage in time 10 s and 67 MW load outage in time 100 s are shown. Solid lines represent the GA-based robust parameter design, dashed lines are the results of manual parameter setting for the same 3 loads. The optimized parameters results are summarized in Tab. 1.

4 Conclusion

In the presented contribution an evolutionary computation – based design procedure of a power-electricity system is described. The genetic algorithm is able to find the (sub) optimal solution of the nine PI-controllers of rotor speed, pressure and fuel in an isolated power-electricity island. As shown, it is possible to consider robustness aspects of the controllers when some type of uncertainty is present in the designed process. In our case the uncertainty was represented by the changing load in the power electricity island.

The GA-based design approach is simple from point-of-view the user. Moreover, it has no limitation on the complexity degree of the controlled object or the used cost function and additional conditions. The two practical limitations of the method are the condition of existence of an appropriate model of the controlled object and the computation time. The computation times can be much higher in comparison to alternative ("conventional") design methods. Besides the rotor-speed control design the presented approach can be used to design of voltage controllers, system stabilisers, power controllers as well as to solve optimization problems on higher hierarchical levels of the power-electricity systems as the secondary voltage control, tertiary voltage control level [6, 7] or other complex optimization problems.

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