POWER RESPONSE OPTIMIZATION OF INVERTER GRID PARALLEL OPERATION USING P-W AND Q-V CURVES, AND PHASE FEEDBACK BASED ON GENETIC ALGORITHM

Helder Zandonadi Maia João Onofre Pereira Pinto Ernane Antônio Alves Coelho
Universidade Federal de Mato Grosso do Sul Universidade Federal de Uberlândia
Cidade Universitária s/n, C. P. 549, CEP: 79.070-900 Avenida João Naves de Ávila, 2121. CEP: 38.400-902
Campo Grande – MS, Brazil Uberlândia – MG, Brazil
helderzmaia@batlab.ufms.br jpinto@nin.ufms.br ernane@ufu.br

Abstract **– The aim of this work is to optimize the response of a scheme to parallel an inverter to the grid. The approach not only is based on P-ω and Q-V curves, but also in phase angle feedback. This scheme requires determination of 4 parameters (K_d, K_p, K_v, ω_f), which interfere in the power dynamic response (overshoot and rise time). Trial and error method was used in the past resulting in poor performance. In this work, genetic algorithm is used to find the parameters set that leads to near optimum response. A brief review of the paralleling approach and the GA based methodology is presented; simulation and experimental results are given showing its feasibility.**

Keywords **– Grid Parallel Operation, Genetic Algorithms, Dynamic Response**

I.INTRODUCTION

The parallel operation of inverters is a challenging subject. In general this topic is addressed due the necessity of paralleling Uninterruptible Power Supplies (UPS). However, the increasing importance of Distributed Generation Systems, and the necessity of connecting different types of energy resources among them, and sometimes, to obtain grid connection operation, has further increased the importance of such subject.

In general the inverter–inverter parallel connection as well as inverter-grid parallel connection can be seen as the same type of problem. Although there are physical differences, this problem is similar to the problem faced in power systems when parallel operation among generators and/or stiff AC system is demanded [1], [2].

The great advantage of using the power system analogy approach is that the control of the power flow among the inverters and/or the grid can be done by looking into local variables, resulting in a strategy that does not require communication among the units. The result is an increased reliability of the whole system [3].

Traditionally, the power flow control strategy uses the fact that the active power flow has the frequency as the dependent variable, while the reactive power depends on the voltage magnitude. Therefore, the P-ω and Q-V curves, which are used to emulate the dynamic of a synchronous machine, are used to control the power flow.

A drawback of this technique is that it results in a substantial overshoot in the active power dynamic response [4]. The use of a phase feedback loop was proposed in order to decrease such overshoot, and the performance was improved [5].

The problem with either approach is that they are parameter dependent, i. e., if only P-ω and Q-V curves are used, it is necessary to find K_p, K_v, and ω_f, which represent the slopes of those curves and cut-off frequency of the power measuring filter [6], [7]. On the other hand, if the phase angle feedback loop is also used, then it is also necessary to find K_d, which is the feedback gain.

Therefore, the tuning of the parameters can be seen as a multi-variable search. There is no need to say that any change in one of these parameters may change radically the response. The results presented in the literature, for both techniques, are based on trial and error search. However, such multi-variable problem surely does not reach the optimum or near optimum result based on human trial and error search. Therefore it is necessary to find a better tuning method.

Genetic Algorithm (GA) is a powerful global search technique based on the evolutionary theory, used mainly for optimization type of problem [8]. Among other features, this technique is intrinsically parallel, and easy to program. Furthermore, it does not have any requirement regarding the function to be optimized, i. e., the function does not have to be continuous, to have derivative, and so on. Despite the best solution might not be found, these algorithms will certainly find a solution near to the best. This is an intelligent optimization that has shown excellent results in many different applications [9], [10], [11]. Therefore, it seems to be one candidate to solve the parameters tuning problem of the schemes used to parallel inverters and/or the grid.

Therefore, the aim of this work is to optimize the parameters of a scheme to parallel an inverter to the grid using genetic algorithm. The approach used was based in both, P-ω and Q-V curves scheme, and phase angle feedback. The parameters to be determined via GA are K_d, K_p, K_v and ω_f, and the goal is to minimize the overshoot and the rise time of the power angle dynamic response. A brief review of the paralleling approach, as well as the GA based methodology is presented, and finally simulation and experimental results are given showing its feasibility.

II.CONTROL SCHEME

Figure 1 gives an overview of the system. It includes the voltage controlled PWM inverter, the grid, the connection impedance, and the control. The reference block generates the sinusoidal reference for controller using the frequency and amplitude signal given respectively by P-ω and Q-V curves. The calculation of the active power and reactive power are done in the power calculation block based on the algorithm proposed in [4]. The control also includes the

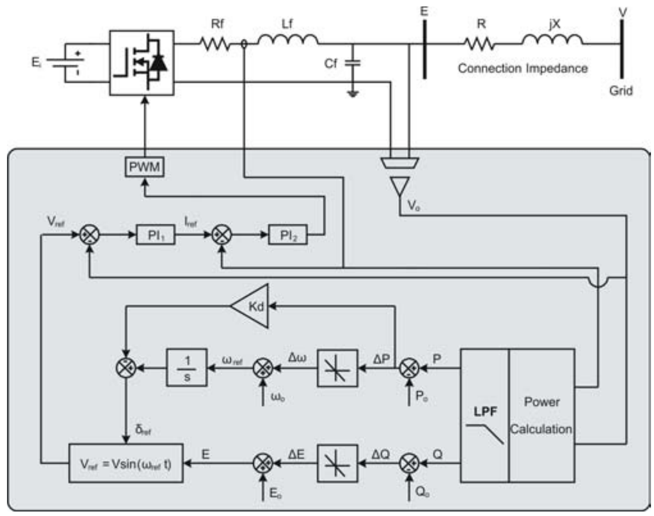

Fig. 1. System Overview.

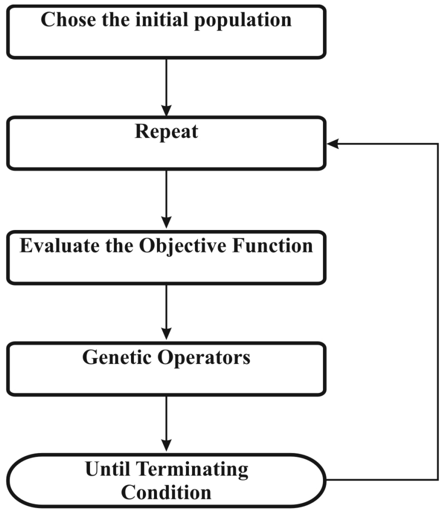

Fig. 2. Genetic Algorithm basic flow chart.

phase angle loop through K_d. Therefore the two schemes discussed previously can be implemented only by setting K_d to zero or non-zero values.

The small signal model of the system given in [4], results in (1). This is a third order homogeneous linear equation, where $\Delta\delta(t)$ is the load angle variation around the equilibrium point δ_e. The angle response is given by (2).

$$\frac{d^3\Delta\delta(t)}{dt^3}+a\frac{d^2\Delta\delta(t)}{dt^2}+b\frac{d\Delta\delta(t)}{dt}+c\Delta\delta(t)=0 \quad (1)$$

$$\delta(t)=\Delta\delta(t)+\delta_e \quad (2)$$

The constants *a*, *b* and *c* in (1) are found using equations (3) to (5), respectively. In such equations the parameters k_{qe}, k_{qd}, k_{pe}, and k_{pd} can be obtained directly from the connection impedance. The parameters K_d, K_p, K_v and ω_f, are the ones to be found by the GA.

$$a=\omega_f(2+K_v k_{qe})+K_d\omega_f k_{pd} \quad (3)$$

$$b=(1+K_d k_{pd})(1+K_v k_{qe})\omega_f^2+K_p\omega_f k_{pd}-K_d K_v k_{pe} k_{qd}\omega_f^2 \quad (4)$$

$$c=K_p\omega_f^2[k_{pd}(1+K_v k_{qe})-K_v k_{pe} k_{qd}] \quad (5)$$

The power angle, given in Equation (6), controls the power flow, and, as can be seen it is function of K_d, K_p, K_v, and ω_f, besides the operation point and the connection impedance. As the operation point and connection impedance are given, the dynamic response is defined by the control parameters.

$$\delta(t)=f(K_d,K_p,K_v,\omega_f) \quad (6)$$

III.GENETIC ALGORITHM

Genetic Algorithm is a global search technique based on the biological processes of evolution that exhibits self-organization and adaptation only due to experience with the environment [8]. This search is an interactive procedure that maintains the population structure of the solution candidates, or population. Each candidate is called chromosome. The chromosomes, through the generations, are able to exchange "knowledge" between each other in order to find the best chromosome that fits the problem. Within each generation the chromosomes undergo the so-called genetic operators, which are: reproduction, crossover, and mutation. The figure of quality that measures the performance of each solution is the fitness function. Figure 2 shows a GA flow chart.

Despite the fact that the genetic operators are stochastic, the evolution performed by the GA always improve the populational mean. This is due to the driving role played by the fitness function. The fitness function directs the search and the genetic operators exploit the intrinsic information in the population to evolve better solutions. The fitness function is analog to the environment conditions in natural selection. It's the environment that determines which individuals are the most apt.

The reproduction operator mimics the chance of one individual to reproduce. As in natural selection the probability of reproduction is greater for the most apt individuals. However, is important not eliminate the chances of the least fitted, because they contribute to the genetic variability of the population.

From the selected group to reproduction each couple has a probability to exchange its genetic information. The objective of the crossover operator is to explore the information in the best solutions to evolve better ones.

The mutation operator is applied to each gene of the chromosomes in the population. Usually the mutation rate is set to a low value, as occur in nature. The purpose of this operator is to explore new regions of the search space, avoiding that the GA stay trapped on local optima.

So, the current problem can be solved by finding an objective function or fitness function that optimizes the power angle dynamic response. The fitness function used when K_d is null is given in (7), where Cr is the chromosome used by the GA, and it is composed by the parameters K_p, K_v, and ω_f for null K_d, as given in (8).

$$fitness(Cr)=2\,overshoot(Cr)+risetime(Cr) \quad (7)$$

$$Cr=\{K_d, K_p, K_v, \omega_f\}, K_d \neq 0 \quad (8)$$

Equation (7) gives a clear idea of what is aimed to optimize, i. e., the objective is to minimize the overshoot and the rise time. Since there is a compromise between these two parameters, they both where put in the same equation, and it is desired to optimize their weighted sum, being the overshoot with the double of the weight of the rise time because the overshoot can cause damage to the system.

The power angle response for null K_d is strictly crescent until the occurrence of the overshoot. Due to this the performance metrics used in (7) can describe how much better one response is. The distinct behavior of the response for non null Kd makes necessary the introduction of a new performance metric to assess the quality of a given response. Thus the metric Integral Absolute Error (IAE) is used as the fitness function for the case with phase feedback, (9).

$$fitness(Cr)=\int |\delta(t)-\delta_e|\,dt \quad (9)$$

IV. SIMULATION RESULTS

The system operating point whose dynamic response was optimized by GA is in Table I. Where E_e is the inverter desired steady state voltage and V_e the grid's nominal voltage. The operating point is basically the steady state values corresponding to a desired operation condition and mathematically is the linearization point for small signal analysis. The connection impedance was 0.5 + j 3.44 Ω and the grid frequency 60 Hz.

TABLE I.
System operating point

Variable	Value	Unity
δ_e	0.1558	rad
P_e	511.69	W
Q_e	80.39	var
E_e	107.11	V RMS
V_e	103.4	V RMS

The values that control parameters could assume, the chromosomes for the GA, were limited according to Table II. These constraints arise from the physical characteristics of the system and possibility the GA to focus the search in areas with physical meaning.

TABLE II.
Chromosomic constraints

Variable	Minimum Value	Maximum Value
K_d	0.0	3.0×10^{-4}
K_p	0.0	1.0×10^{-1}
K_v	0.0	1.7×10^{-2}
ω_f	1.2	1.0×10

The GA utilized simulation results to obtain the fitness of each individual. The simulation was preferred over the use of the differential equation because besides the equation gives the tendency of the response it can not account for the oscillatory effect of the low pass filters used in the measuring of the active and reactive power. This is a direct consequence of the linearization that must be carried out in order to obtain the small signal model.

The simulation model was constructed by modeling each component of the control system depicted in Figure 1 as a discrete state space equation. It is possible because each subsystem is linear and only the interactions between them are nonlinear. Therefore an accurate simulation model can be constructed easily yet be hard to obtain an analytic mathematical equation that relates the control parameters directly with the power angle response.

This constitutes one more strength of the GA approach since it does not requires linearity or other mathematic restrictions. It only requires the definition of an adequate fitness function. That way it permits the use of a model as accurate as necessary.

The GA begins with 20 random quartets/triplets whose parameters lies inside the intervals defined in Table I. For each of the 20 individuals a simulation is performed in order to determine the power angle response fitness. By applying the genetic operators the GA evolves a new population of solutions and the process repeats itself until the maximum number of generations is reached.

A. Without Phase Feedback

In the case without phase feedback the parameters utilized in the GA were: population of 20 individuals with elitism of 2, crossover fraction of 80%, and gaussian mutation. The stopping criteria was maximum number of generations, that was set to 200. This GA was run for 50 times and the fitness at the 200th generation of each run was registered. Table III shows the maximum, minimum, and the result closer to the average fitness observed.

These results show that the GA parameters were adequately set and that there is a compromise between the reduction of the rise time and of the overshoot. The worst response, maximum fitness, presented the minimum rise time at the expense of the worst overshoot.

Figure 3 shows the phase angle response obtained through simulation using the parameters obtained by trial and error and the parameters found by GA when the system operates without phase angle loop. The GA reduced the overshoot from 136.32% to 4.78% and increased the rise time from 25.20 ms to 253.91 ms. Figure 4 shows the active power flow for both tuning methods. One can observes that the GA increases the active power rise time but reduces the settling time and the overshoot.

B. With Phase Feedback

The GA for the case with phase feedback had the following parameters: population of 20 individuals with one elite individual, crossover fraction of 80%, and mutation fraction of 10%. The stopping criteria was the same that in the previous case. The observed results are in Table IV.

The most notable feature in the results obtained using the IAE as the fitness measure is the trend to minimize the low-pass filter cut-off frequency. This reduces the band-pass oscillation resulting in a significant reduction of the absolute

TABLE III.
Results obtained for 50 runs of the GA when $K_d = 0$

	Chromosome			Response Features	
Fitness	K_p (rad/W s)	K_v (V/var)	ω_f(rad/s)	overshoot (%)	rise time (ms)
Maximum	0.0021	0.0170	10.00	15.42	148.88
Average	0.0012	0.0166	9.74	2.95	301.28
Minimum	0.0014	0.0140	9.99	4.78	253.91

TABLE IV.
Results obtained for 20 runs of the GA when $K_d \neq 0$

	Chromosome				Absolute Error	
Fitness	K_d (rad /W)	K_p (rad/W s)	K_v (V/var)	ω_f(rad/s)	Maximum (rad)	Average (rad)
Maximum	0.0003	0.0031	0.0175	9.86	4.50×10^{-3}	1.54×10^{-3}
Average	0.0003	0.0024	0.0167	7.71	4.19×10^{-3}	1.10×10^{-3}
Minimum	0.0003	0.0008	0.0044	2.52	2.46×10^{-3}	1.50×10^{-3}

error; but, there is an increment in the rise and settling time of the active power flow.

In Figures 5 and 6 it is shown results obtained by GA and trial and error tuning. As in the case without phase feedback, it is possible to observe a considerable improvement achieved with GA tuning. Comparing figures 3 and 5 it is possible to see the improvement due to the use of phase angle loop. In figure 5, a zoom in the figure is shown to better illustrate the response with the GA tuning, since it is so fast that it seems to be a step.

V. EXPERIMENTAL RESULTS

The experimental validation of the proposed methodology was realized with the control scheme and parameters defined in the early sections. The inverter employed is composed by IGBTs in a full-bridge configuration and the switching frequency was set to 18 kHz.

The connection impedance between the inverter and the grid was a single phase 1:2 transformer with reactive inductance of 9.12 mH and resistance of 0.5 Ω.

The power flow control was realized digitally by means of an acquisition board with sampling frequency of 5kHz and analog to digital conversion with 12 bits of resolution.

There was a manual switch between the inverter and the grid. When it is closed the digital Phase Locked Loop (PLL) implemented in the acquisition board synchronizes the reference voltage generated by the control program with the grid's voltage. After 0.1 seconds the switching signals are enabled and the inverter starts.

The active power flow for the trial and error tuning, the maximum and minimum fitness obtained by GA is shown in figure 7.

Comparing figure 7 with 4 it is possible to observe that the overshoot in active power flow experimentally observed is less than that predicted by simulation.

The main factor that originates these discrepancies is the reactive power flow, figure 8. In the simulations it is considered initially null (figure 9), but in practice it is different from zero because the inverter's capacitor is connected to the grid for 0.1 seconds before the switching action starts. There is yet the problem of the precision of the measuring of the output voltage. For $K_v = 0.01$ V/var an error of 1 volt in the measured voltage implies in a deviation of 100 var from the steady state reference value.

VI. CONCLUSIONS

The GA based power angle optimization was shown successful in both the cases, with and without phase feedback loop. In the former case the overshoot was reduced from 136.32% to 4.78% and the rise time increased from 25.2 ms to 253.91 ms. In the last case the maximum absolute error was reduced from 0.3585 rad to 2.46×10^{-3} rad and the mean absolute error from 0.0195 rad to 1.50×10^{-3} rad.

In the case without phase feedback even though the rise time was increased, in order to reduce the overshoot, was a significant improvement in the settling time: from 799.68 ms to 329.23 ms. What show the GA capability of finding more stable dynamic responses.

Experimental results shown that the GA was capable of finding a better response than the trial and error search for the case without phase feedback. The experiments also showed effects of the different initial conditions and the issue that reactive power flow do not reached the reference steady state value due to noise in the measuring of the voltage.

Future works will address the direct optimization of the active power flow. This is yet more challenging once that in order to have a near optimum rise time for the active power flow is necessary an amount of overshoot in the power angle response that doesn't manifest itself as a overshoot in the power. The simulation model will be improved to consider more real initial conditions and the GA fitness function modified to account for noise susceptibility in the solution candidates.

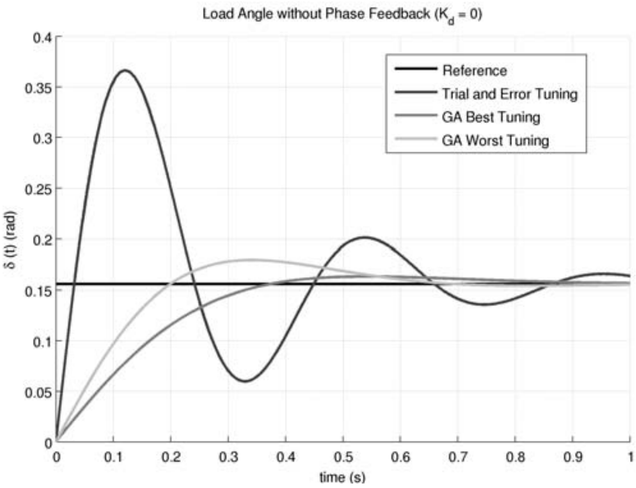

Fig. 3. Phase angle response using the parameters obtained by trial and error and by GA ($K_d = 0$).

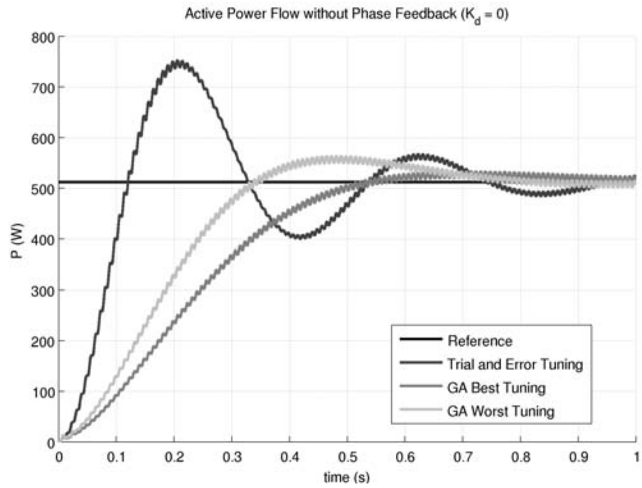

Fig. 4. Active power flow response using the parameters obtained by trial and error and by GA ($K_d = 0$).

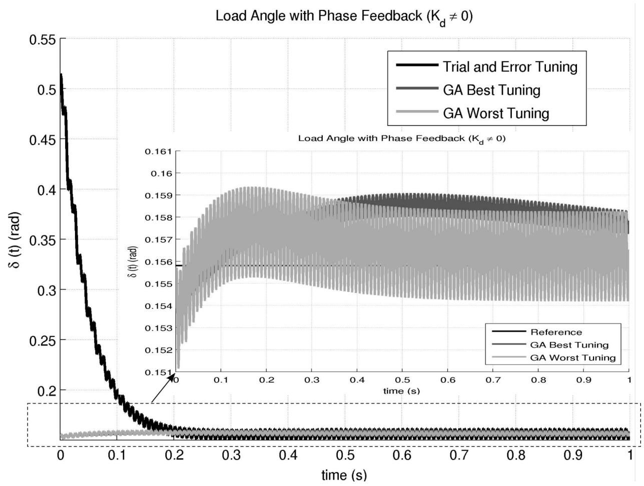

Fig. 5. Phase angle response using the parameters obtained by trial and error and by GA ($K_d \neq 0$).

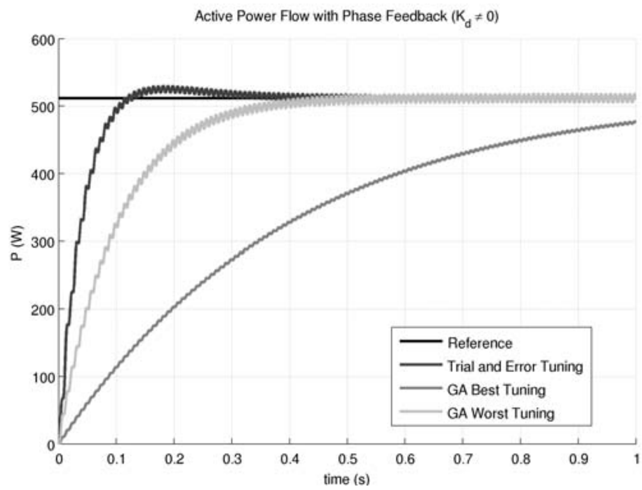

Fig. 6. Active power flow response using the parameters obtained by trial and error and by GA ($K_d \neq 0$).

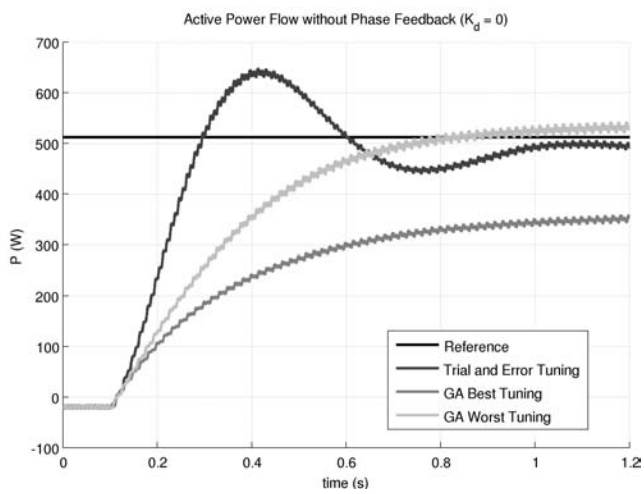

Fig. 7. Active power flow obtained experimentally without phase feedback.

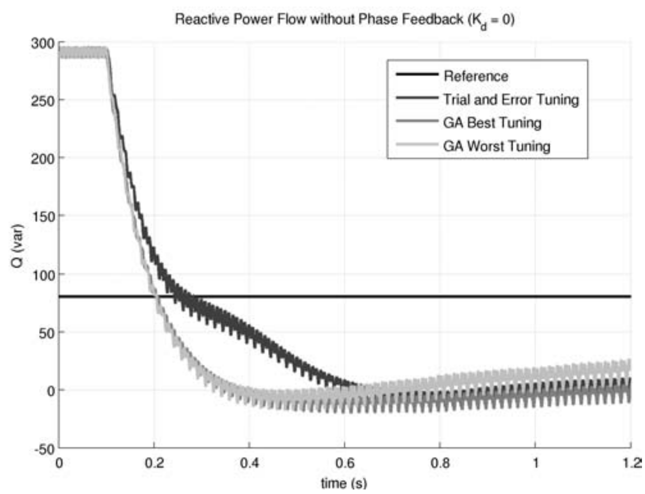

Fig. 8. Reactive power flow obtained experimentally without phase feedback.

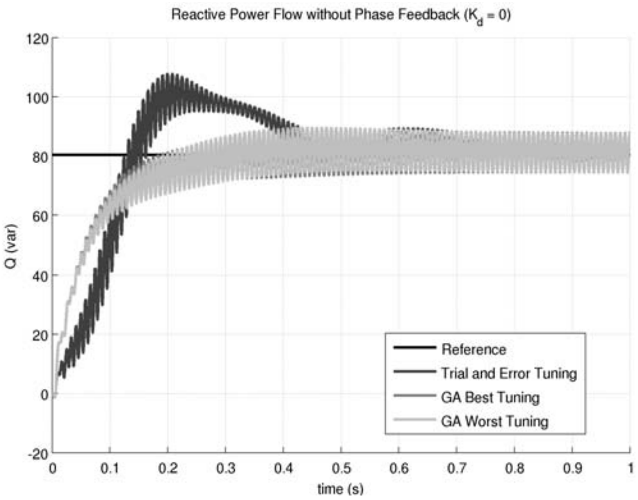

Fig. 9. Reactive power flow obtained by simulation without phase angle feedback.

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