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Bio-inspired heuristics hybrid with interior-point method for active noise control systems without identification of secondary path[#]

Muhammad Asif Zahoor RAJA[‡1], Muhammad Saeed ASLAM[2], Naveed Ishtiaq CHAUDHARY[3], Wasim Ullah KHAN[1]

[1]*Department of Electrical Engineering, COMSATS Institute of Information Technology, Attock Campus, Attock 43600, Pakistan*
[2]*Pakistan Institute of Engineering and Applied Sciences, Islamabad 45650, Pakistan*
[3]*Department of Electronic Engineering, International Islamic University, Islamabad 44000, Pakistan*
E-mail: muhammad.asif@ciit-attock.edu.pk; msaeedengr@gmail.com; naveed.ishtiaq@iiu.edu.pk; engr_wasi47@yahoo.com
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Abstract: In this study, hybrid computational frameworks are developed for active noise control (ANC) systems using an evolutionary computing technique based on genetic algorithms (GAs) and interior-point method (IPM), following an integrated approach, GA-IPM. Standard ANC systems are usually implemented with the filtered extended least mean square algorithm for optimization of coefficients for the linear finite-impulse response filter, but are likely to become trapped in local minima (LM). This issue is addressed with the proposed GA-IPM computing approach which is considerably less prone to the LM problem. Also, there is no requirement to identify a secondary path for the ANC system used in the scheme. The design method is evaluated using an ANC model of a headset with sinusoidal, random, and complex random noise interferences under several scenarios based on linear and nonlinear primary and secondary paths. The accuracy and convergence of the proposed scheme are validated based on the results of statistical analysis of a large number of independent runs of the algorithm.

Key words: Active noise control (ANC); Filtered extended least mean square (FXLMS); Memetic computing; Genetic algorithms; Interior-point method
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1 Introduction

In active noise control (ANC) systems, an anti-noise signal of the same magnitude and with a 180° phase shift is generated to cancel out undesired noise interference. ANC systems are generally used for reducing low-frequency noise (Kuo and Morgan, 1995; Zhang et al., 2001), while passive noise control (PNC) systems are effective in canceling out only high-frequency noise interference with the help of sound-absorbing materials. ANC systems have been extensively studied because industrial noise power is based mostly on low frequencies. Many investigators have implemented a filtered extended least mean square (FXLMS) algorithm to design an ANC system owing to its simplicity (Akhtar et al., 2006; Wu et al., 2014; Akhtar and Nishihara, 2015). Despite its effectiveness in attenuating low-frequency noise, FXLMS has several limitations, the most important of which is its convergence to local minima (LM) during the adaptive process. Moreover, an FXLMS algorithm

‡ Corresponding author
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ORCID: Muhammad Asif Zahoor RAJA, http://orcid.org/0000-0001-9953-822X

requires identification of the secondary path before adaptation. To overcome such limitations, intelligent control strategies based on fuzzy and neural networks have been adopted (Chang and Shyu, 2003; Chang and Luoh, 2007). However, these methods cannot cope with nonlinear effects arising from nonlinear behavior of a noise source or acoustic plant in practical situations. While nonlinear methods, including Volterra filters with FXLMS (VFXLMS), have been used to diminish undesired noise (Tan and Jiang, 2001; Zhou and DeBrunner, 2007; George and Panda, 2013), they require prior identification of the secondary path. Recently, meta-heuristic algorithms based on adaptive genetic algorithms and particle swarm optimization algorithms have been applied to overcome the limitations of identification of a secondary path and the LM issue in ANC systems. These meta-heuristic algorithms include fuzzy inference systems (Kurczyk and Pawelczyk, 2014a), swarm intelligence (George and Panda, 2012; Rout et al., 2012), adaptive genetic algorithms (Chang and Chen, 2010), delay-based adaptive strategies (Kurczyk and Pawełczyk, 2014b), and bacterial foraging optimization method (Gholami-Boroujeny and Eshghi, 2012, 2014). The optimization performance of these algorithms degrades considerably after the execution of a large number of runs. The strength of these algorithms can be exploited by their hybridization with efficient local search methodologies. The aim of this study is to explore hybrid computing techniques (HCTs) based on variants of local and global search methodologies for cancellation of undesirable noise.

HCTs based on bio- and nature-inspired techniques and rapid local convergent algorithms have been used extensively for optimizing many linear and nonlinear systems. These methods address effectively the problems arising in a variety of fields such as nonlinear equations (Raja et al., 2016a), system identification (Gotmare et al., 2017), atomic physics (Raja et al., 2016b), thermodynamics (Ahmad et al., 2017), and robotics systems (Iacca et al., 2013). This provided the motivation for the present study aiming to apply an accurate, effective, and reliable HCT to ANC systems.

In this study, artificial intelligence algorithms based on HCTs are designed for ANC systems using variants of genetic algorithms (GAs) and interior-point method (IPM) without identification of secondary paths. Variants of GAs are developed by taking different reproduction operators including crossover, mutation, selection, and elitism to extract the potential for robustness, convergence, multi-objectives, multi-modality, and constrained handling (Sivanandam and Deepa, 2007; Reeves, 2010). The optimization power of GA variants is further enhanced by the hybridization with an efficient IPM for rapid local convergence. The ability of GA-IPM design schemes to enhance the performance of HCT-based ANCs for sinusoidal, random, and complex random input noise variations is evaluated in different scenarios by taking linear and nonlinear functions in primary and secondary paths. The reliability and effectiveness of the schemes are validated through the results of statistical analysis based on large sets of data generated by a large number of independent runs of an HCT-based ANC.

2 System model for ANC

A system model for ANC is shown in Fig. 1 and its block diagram in Fig. 2. In the ANC system, the unwanted noise is detected by microphones. The ANC system processes the unwanted noise such that speakers produce an artificial anti-noise signal to be combined with the unwanted noise signal for noise cancellation. In the proposed model, the FXLMS algorithm is replaced by GAs to prevent the LM problem. The proposed GA method does not require identification of the secondary path for the ANC system. The parameters of the system model of ANC are described as follows: $x(n)$ represents the unwanted noise interference, $d(n)$ the measurement of noise by a microphone in the ear cup, $y(n)$ the output signal of the ANC system, $y'(n)$ the output of the speaker to cancel the measured noise, and $e(n)=d(n)-y'(n)$ the difference between the measured noise and the speaker output. $P(z)$ represents the transfer function of the primary path from the location of undesired noise interference to the microphone, $S(z)$ the transfer function of the secondary path from the speaker to the microphone, while $W(z)$ a finite-impulse response (FIR) or Volterra filter in this ANC system. Details about the system model can be found in Chang and Chen (2010), George and Panda (2012), Rout et al. (2012), and Kurczyk and Pawelczyk (2014a).

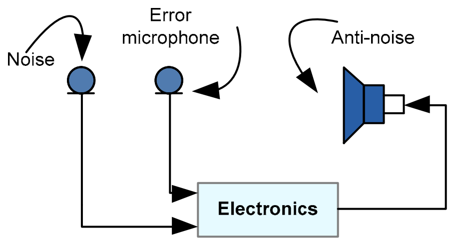

Fig. 1 Generic active noise control (ANC) model

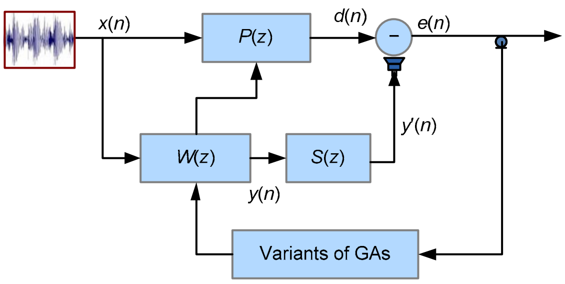

Fig. 2 Block diagram of an adaptive ANC system with variants of genetic algorithms

3 Proposed methodology

The proposed methodology is presented here based on HCTs for finding the design variables for ANC systems. The HCTs are based on GA variants and IPMs. The design scheme is described in two parts; in the first part, a fitness function for the system model of the ANC is formulated, while in the second part necessary descriptions about the optimization methods are given.

3.1 Mathematical modeling for ANC system

The mathematical modeling is presented for the formulation of a fitness function for an adaptive ANC system as shown in Fig. 2, for FIR or Volterra filter type GAs.

In designing a fitness function for an ANC system for adaptive heuristic procedures like GAs, the FIR or Volterra filter of L-tap weights $\boldsymbol{W}$ has to be used:

$$\boldsymbol{W}_j(n)=[w_j(0,n),w_j(1,n),\ldots,w_j(L-1,n)],\quad j=1,2,\ldots,p, \tag{1}$$

where $\boldsymbol{W}_j(n)$ denotes the coefficient vector of the j^{th} population of FIR filter $W(z)$ at time n and p the initial population for the algorithm. The filtering of noise $x(n)$ for the population p in terms of the coefficients of the FIR filter is given by (Chang and Chen, 2010)

$$[y_1(n), y_2(n), \cdots, y_p(n)]^{\mathrm{T}} = \begin{bmatrix} w_1(0,n) & w_1(1,n) & \cdots & w_1(L-1,n) \\ w_2(0,n) & w_2(1,n) & \cdots & w_2(L-1,n) \\ \vdots & \vdots & & \vdots \\ w_p(0,n) & w_p(1,n) & \cdots & w_p(L-1,n) \end{bmatrix} \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-L+1) \end{bmatrix}, \tag{2}$$

$$[y_1'(n), y_2'(n), \cdots, y_p'(n)]^{\mathrm{T}} = \begin{bmatrix} y_1(n) & y_1(n-1) & \cdots & y_1(n-L_1+1) \\ y_2(n) & y_2(n-1) & \cdots & y_2(n-L_1+1) \\ \vdots & \vdots & & \vdots \\ y_p(n) & y_p(n-1) & \cdots & y_p(n-L_1+1) \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_{L_1} \end{bmatrix}, \tag{3}$$

where $[s_1, s_2, \cdots, s_{L_1}]$ denotes the impulse response of the secondary path $S(z)$. Similarly, in the case of a Volterra filter, Eq. (2) can be written as Eq. (4) (see the next page).

Define the residual noise as

$$\begin{bmatrix} o_1(n) \\ o_2(n) \\ \vdots \\ o_p(n) \end{bmatrix} = \begin{bmatrix} \max(|e_1(n)|,|e_1(n-1)|,\cdots,|e_1(n-L+1)|) \\ \max(|e_2(n)|,|e_2(n-1)|,\cdots,|e_2(n-L+1)|) \\ \vdots \\ \max(|e_p(n)|,|e_p(n-1)|,\cdots,|e_p(n-L+1)|) \end{bmatrix}, \tag{5}$$

where

$$e_j(n)=d(n)-y'(n),\ \ j=1,2,\ldots,p. \tag{6}$$

The residual noise of the ANC system is minimized by defining the fitness functions of p populations as

$$f_j=\frac{1}{o_j},\ \ j=1, 2, \ldots, p. \tag{7}$$

The smaller the value of o_j, the higher the fitness f_j and hence the residual error of the ANC system is minimized.

$$\begin{bmatrix} y_1(n) \\ y_2(n) \\ \vdots \\ y_{p-L/2}(n) \\ y_{p-L/2+1}(n) \\ y_{p-L/2+2}(n) \\ \vdots \\ y_p(n) \end{bmatrix} = \begin{bmatrix} w_1(0,n) & w_1(1,n) & \cdots & w_1(L-1,n) \\ w_2(0,n) & w_2(1,n) & \cdots & w_2(L-1,n) \\ \vdots & \vdots & & \vdots \\ w_{p-L/2}(0,n) & w_{p-L/2}(1,n) & \cdots & w_{p-L/2}(L-1,n) \\ w_{p-L/2+1}(0,n) & w_{p-L/2+1}(1,n) & \cdots & w_{p-L/2+1}(L-1,n) \\ w_{p-L/2+2}(0,n) & w_{p-L/2+2}(1,n) & \cdots & w_{p-L/2+2}(L-1,n) \\ \vdots & \vdots & & \vdots \\ w_p(0,n) & w_p(1,n) & \cdots & w_p(L-1,n) \end{bmatrix} \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-L/2+1) \\ x^2(n) \\ x^2(n-1) \\ \vdots \\ x^2(n-L/2+1) \end{bmatrix}. \tag{4}$$

3.2 Training of design parameters

The procedure for training design parameters to minimize the residual error of the ANC system is given here with the help of a hybrid of GA variants and IPM. A brief description, subject terms, and flow diagrams are provided in this subsection.

Fig. 3 shows an overall schematic of the designed scheme, consisting of the ANC problem, mathematical modeling, and a flow diagram of optimization techniques.

3.2.1 Genetic algorithms

A GA is a mathematical model of the process of natural evolution and is used as an optimization mechanism for solving different problems effectively (Zhang et al., 2011; Tan et al., 2012; Hoseini and Shayesteh, 2013). In GAs, the process of finding a good solution to the optimization problem is dependent on an exhaustive global search of sufficiently large number of candidate solutions (Sivanandam and Deepa, 2007). GAs incorporate fundamental reproduction operators such as selection, crossover, and mutations to find the unknown parameters of the optimization problem. They usually follow four basic steps to solve a problem-specific objective function. The first step is to describe a problem in terms of unknown variables. The second step is to formulate a fitness function. The third step is to determine the dependency on parameters to control a problem and the last step is to provide verification of results after obtaining the best global solution of the problem.

3.2.2 Interior-point method

The best performance of an evolutionary optimization technique based mainly on GA variants is observed whenever they are combined in a hybrid with a local search algorithm in the optimization process. Therefore, in this study the best global individual from GAs is fed into IPM as initial weights or start points.

3.2.3 Variant of hybrid computing techniques (HCTs)

Variants of GAs are constructed with appropriate use of reproduction operators (Table 1). Each GA variant is hybridized with IPM to fine tune the optimization parameters. Built-in programs for GAs and IPM in the MATLAB optimization toolbox are used for optimizing the fitness function (7). The implementation of design methods consists of three phases: optimal tuning of the program and tool parameters for GAs and IPMs, optimization of parameters with variants of HCTs, and testing the performance of HCTs for a sufficiently large number of independent runs. Fixed settings of parameters are used for all 12 variants of the GA (Table 2) and IPM (Table 3), for a realistic performance comparison. A slight variation in these settings may result in premature convergence, i.e., drastically degraded outputs. Therefore, the parameter settings for the routine running of GAs are finalized based on great care, exhaustive experimentation, experience, knowledge of the problem, and understanding of the optimization mechanism. Finally, the details of the steps for the hybrid GA-IPM approaches are listed in Algorithms 1 and 2.

4 Results and discussion

In this section, in-depth investigations of the proposed design schemes are made based on results of simulations for three problems of an ANC system involving three different input noise variations. The effectiveness of a GA-based ANC system (an FIR

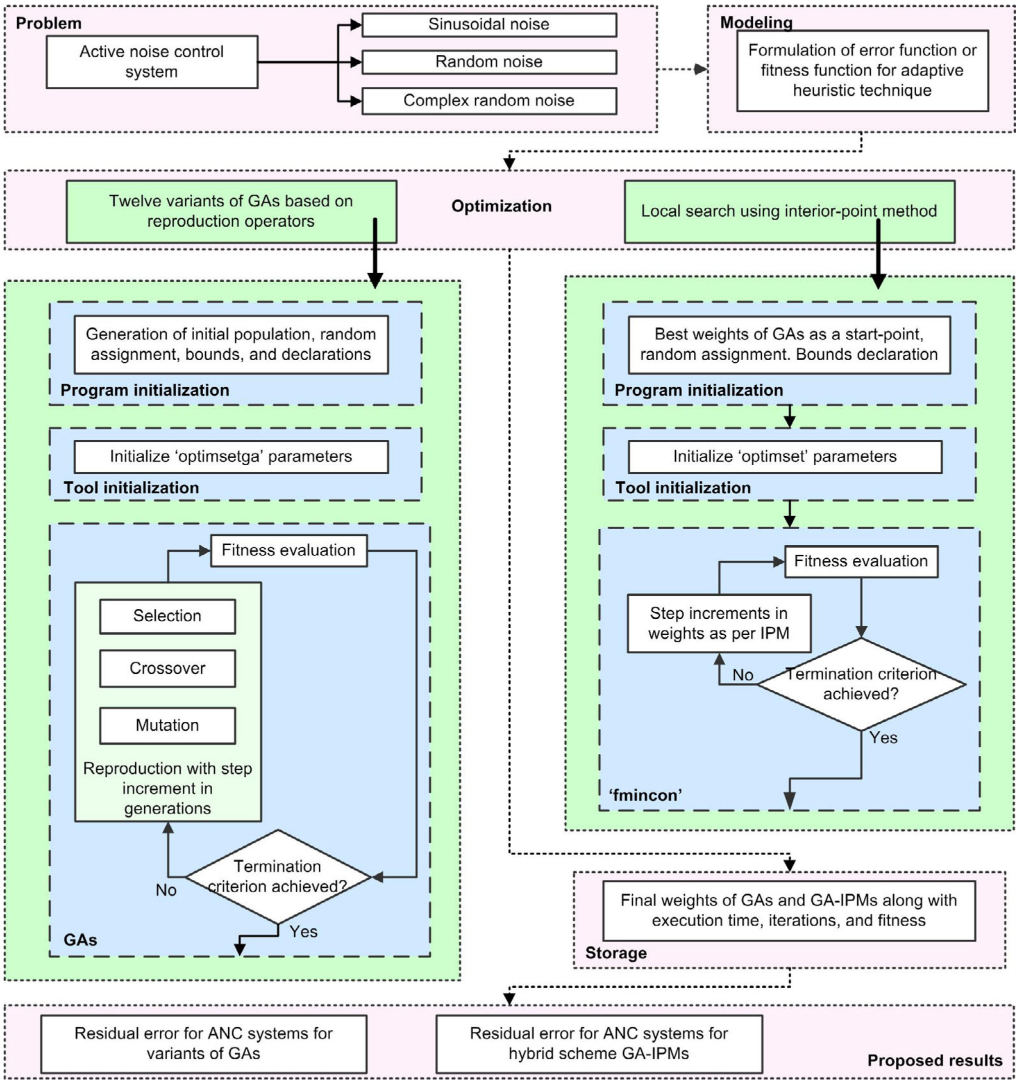

Fig. 3 Generic flow chart of evolutionary algorithm based on GAs

Table 1 Variants of hybrid computing techniques based on GA operators and IPM

Method	Selection	Crossover	Mutation	Hybrid
GA-IPM-1	Stochastic uniform	Heuristic	Adaptive feasible	Interior-point
GA-IPM-2	Stochastic uniform	Heuristic	Gaussian	Interior-point
GA-IPM-3	Stochastic uniform	Arithmetic	Adaptive feasible	Interior-point
GA-IPM-4	Stochastic uniform	Arithmetic	Gaussian	Interior-point
GA-IPM-5	Reminder	Heuristic	Adaptive feasible	Interior-point
GA-IPM-6	Reminder	Heuristic	Gaussian	Interior-point
GA-IPM-7	Reminder	Arithmetic	Adaptive feasible	Interior-point
GA-IPM-8	Reminder	Arithmetic	Gaussian	Interior-point
GA-IPM-9	Roulette	Heuristic	Adaptive feasible	Interior-point
GA-IPM-10	Roulette	Heuristic	Gaussian	Interior-point
GA-IPM-11	Roulette	Arithmetic	Adaptive feasible	Interior-point
GA-IPM-12	Roulette	Arithmetic	Gaussian	Interior-point

Table 2 Parameter settings for genetic algorithms

Parameter	Setting	Parameter	Setting
Initial population	[−1, 1]	Population size	40
Scaling function	Rank	Chromosome size	20
Fitness limit	10^{-10}	Generation	200
Crossover fraction	0.80	Tolerance	10^{-20}
Constrain tolerance	10^{-20}	Stall generation limit	200
Elite count	4	Migration direction	Central
Initial penalty	10	Migration interval	20
Penalty factor	100	Others	Default

Table 3 Parameter settings for interior-point method

Parameter	Setting
Start point	Best weights of GAs
Derivative	Solver approximate
Subproblem algorithm	IDI factorization
Scaling	Objective and constraints
Maximum function values	6000
Finite difference types	Central
Hessian	BFGS
Maximum iteration	1000
X-tolerance	10–30
Nonlinear constrain tolerance	0
Fitness limit	10–12
Others	Default

filter with a coefficient length L=20) is analyzed for each of the three problems by considering variations in primary and secondary paths. The noise reduction performance of each variant of the hybrid approach is evaluated using both linear and nonlinear transfer functions of primary and secondary paths. The linear transfer functions of the primary and secondary paths are FIR filters:

$$P_{\text{linear}}(z)=z^{-5}-0.3z^{-6}+0.2z^{-7}, \tag{8}$$

$$S_{\text{linear}}(z)=z^{-2}-1.5z^{-3}+z^{-4}. \tag{9}$$

The nonlinear functions of the primary and secondary paths are based on the assumption that the primary noise $d(n)$ at the canceling point is generated with the third-order polynomial:

$$d(n)=t(n-2)+0.8t^2(n-4)+0.04t^3(n-4), \tag{10}$$

where

$$t(n)=x(n-3)-0.3(n-4)+0.2(n-4). \tag{11}$$

Algorithm 1 Hybrid GA-IPMs

1 // Program and tool initialization for GAs
Create the initial population with randomly generated bounded real values to represent chromosomes or individuals. Each individual has a number of elements equal to the number of unknown variables in the ANC model. Set the values of bounds and declarations for GA routines, and initialize the options for the GA tools 'optimset' with values listed in Table 1, e.g., the number of generations and initial population range (IniPopRange)

2 // Fitness evaluation
Calculate the fitness value for each individual in the population based on Eq. (7)

3 // Ranking
Rank each individual in the population according to its fitness value and declare the best individual (the one with the maximum fitness value)

4 // Termination criteria
if predefined fitness (FitnessLimit) value is achieved
|| predefined number of generations is executed
|| stoppage criteria on the basis of values of the tolerances (function tolerances (TolFun) and nonlinear constraints tolerance (TolCon)) are fulfilled
then
Terminate the execution of the GA program
go to step 6
end if

5 // Reproduction
A new population for each GA variant is created by invoking the routines of operators (Table 3) at each generation increment
go to step 2 with the newly generated population

6 // Hybridization
IPM is used as a hybrid local search algorithm with GA variants, as per the subroutine given in Algorithm 2

7 // Storage
Store the values of optimized weight vectors along with their fitness, number of generations executed, and time taken by the algorithms for this run

8 // Statistical analysis
Repeat the procedure from steps 1 to 7 for multiple independent runs for each GA-IPM variant to obtain a sufficiently large set of data for reliable statistical analysis

Also, the anti-noise signal $y'(n)$ at the canceling point is assumed to be generated with the nonlinear secondary path as

$$y'(n)=r(n-2)+1.5r(n-3)-r(n-4), \tag{12}$$

where

$$r(n)=0.06\tanh(1.5y(n)). \tag{13}$$

Algorithm 2 Hybridization

1 // Initialization
MATLAB built-in formulation for constraint optimization problems based on function ‘fmincon’ is used with the algorithm setting ‘interior-point’ with bounds, declarations, and initialization of parameters for the ‘optimset’ tool, as listed in Table 2. The initial weight vectors of IPMs are the best global individuals from the GA variants
2 // Evaluation of fitness
Calculate the fitness value for each individual of the population based on Eq. (7).
3 // Termination criteria
if predefined number of cycles (‘MaxIter’) is executed || predefined value of the tolerance (‘TolFun’, ‘TolCon’, or X-tolerance (TolX)) is achieved || predefined maximum number of functions (‘MaxFunEvals’) is evaluated and a termination criterion is fulfilled **then**
  go to step 8 of Algorithm 1
end if
4 // Weight updating
for each step increment in IPM optimization **do**
  Update variables
  go to step 2
end for

In this study, the ability of 12 variants of GA- and GA-IPM-based controllers to enhance the performance of ANC was compared. The parameter settings used for GA and IPM are given in Tables 2 and 3, respectively. Analytical results were implemented by a personal computer with dual 1.6 GHz central processing units and 2 GB dynamic random access memory running the MATLAB software package in a Windows 7 environment.

4.1 Problem 1: ANC system with pure-sine-wave noise

In this problem, the proposed schemes were applied to ANC systems by taking 300-Hz sinusoidal noise. The effectiveness of ANC was verified and validated for each variant of the GA-IPM hybrid computing approach in all three following cases of the primary path $P(z)$ and secondary path $S(z)$:

Case 1: ANC with linear primary (LP) and nonlinear secondary (NLS) paths.

Case 2: ANC with nonlinear primary (NLP) and linear secondary (LS) paths.

Case 3: ANC with NLP and NLS paths.

Twelve variants of the proposed GA-IPM schemes (Table 1), with parameter settings provided in Tables 2 and 3 for the GAs and IPMs, respectively, were applied to reduce the residual noise (Eq. (5)) of the ANC system of problem 1 in each case.

The optimization procedure for GA-1 (see Table 1) in terms of iterative update of fitness, current best individual, distance between the individuals, fitness of each individual, selection function, and stopping criteria, is presented in Fig. 4 for the case 1 ANC system. The best result obtained through GA-1 was given to IPM for further refinement. The optimization process of the GA-IPM-1 technique based on the current best point, total function evaluation, current fitness values, maximum constraint violation, step size, and first-order optimality is graphically shown in Fig. 5. Accordingly, these parameters were determined for all 12 variants of GAs and GA-IPMs for all three cases.

The value of fitness in dB, obtained using MATLAB built-in function ‘db’, was determined for 100 independent runs of each GA-IPM. The results are given in Table 4 (for GAs) and Table 5 (for GA-IPMs), in terms of statistical parameters of the best (maximum fitness), mean (average fitness), and standard deviation (STD). The fitness values of the GA-IPM hybrid computing approaches are superior to those of the variants of GAs around 20 dB on the basis of mean values. Comparing the results of variant GAs and GA-IPMs, fitness values are similar but better results were achieved by GA-4, GA-8, and GA-12, and accordingly by GA-IPM-4, GA-IPM-8, and GA-IPM-12.

Fig. 6 shows the fitness values for 100 independent runs of GA-1 and GA-IPM-1, where values sorted in ascending order of fitness are shown against the indices of independent runs. About 40% to 50% of runs of GA-1 gave fitness values of more than 25 dB, while in the case of GA-IPM-1, around 90% of runs gave fitness values of more than 40 dB. The sorted fitness values for 100 independent runs of GA-2 to GA-12 and GA-IPM-2 to GA-IPM-12 are shown in Figs. S1 and S2, respectively, in the supplementary materials. The trends are similar to those observed for GA-1 and GA-IPM-1.

A comparative study of the variants of GA-IPM was conducted based on computational complexity (CC) parameters, i.e., mean execution time (MET),

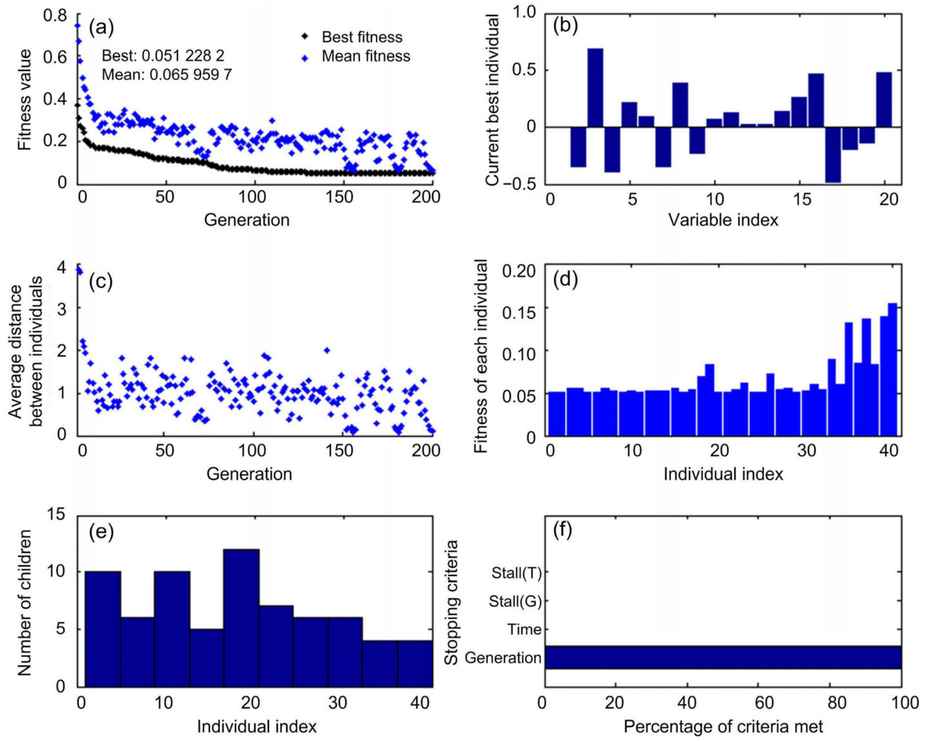

Fig. 4 GA-1 optimization process for case 1 of the ANC system

(a) Iterative update of fitness; (b) Current best individual; (c) Average distance between individuals; (d) Fitness of each individual; (e) Selection function; (f) Stopping criteria

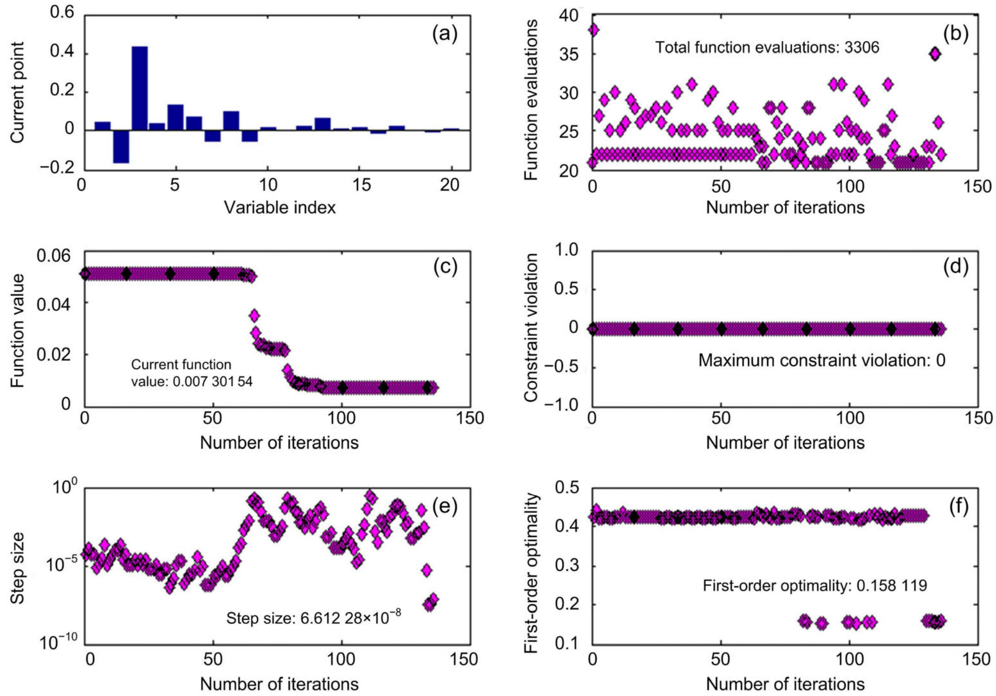

Fig. 5 GA-IPM-1 optimization process for case 1 of the ANC system

(a) Current best point; (b) Total function evaluation; (c) Current fitness values; (d) Maximum constraint violation; (e) Step size; (f) First-order optimality

Table 4 Performance of the proposed algorithm (GA) based on 100 independent runs for the ANC system given in problem 1

Method	Fitness (dB)								
	Case 1			Case 2			Case 3		
	Best	Mean	STD	Best	Mean	STD	Best	Mean	STD
GA-1	39.792	24.331	32.164	38.030	23.519	31.328	33.664	23.731	32.342
GA-2	34.686	23.564	30.649	35.666	23.189	30.570	31.370	23.654	32.340
GA-3	29.268	24.205	35.950	33.404	24.203	35.153	31.517	24.379	34.378
GA-4	35.515	27.671	37.860	35.502	26.977	37.153	34.856	27.322	38.280
GA-5	36.774	23.545	31.065	34.106	23.948	32.187	35.217	24.100	32.720
GA-6	35.714	23.692	32.340	33.426	23.553	31.246	36.084	23.485	31.324
GA-7	31.634	24.205	35.418	30.499	24.122	34.704	32.769	23.724	33.768
GA-8	34.546	27.619	38.691	35.080	27.522	36.809	37.857	27.316	36.128
GA-9	35.441	23.030	31.411	34.222	23.248	31.436	33.659	23.174	31.086
GA-10	32.925	23.191	31.937	35.623	22.659	30.282	32.790	23.054	31.412
GA-11	32.015	23.401	32.808	31.515	22.867	32.348	30.350	23.499	32.821
GA-12	34.681	26.273	35.940	33.406	26.338	36.917	35.242	26.647	36.539

Best: maximum fitness; Mean: average fitness; STD: standard deviation

Table 5 Performance of our proposed algorithm (GA-IPM) based on 100 independent runs for the ANC system given in problem 1

Method	Fitness (dB)								
	Case 1			Case 2			Case 3		
	Best	Mean	STD	Best	Mean	STD	Best	Mean	STD
GA-IPM-1	43.582	41.223	42.142	43.492	39.950	39.766	43.488	41.747	51.825
GA-IPM-2	43.582	41.196	40.573	43.478	40.747	39.067	43.496	38.929	36.489
GA-IPM-3	43.590	41.573	40.100	43.479	41.068	39.733	43.485	38.255	36.694
GA-IPM-4	43.586	42.644	51.871	43.495	41.619	44.372	43.484	41.821	45.368
GA-IPM-5	43.585	39.718	37.361	43.481	39.440	39.295	43.462	38.895	36.557
GA-IPM-6	43.578	42.098	47.497	43.434	40.567	44.047	43.477	38.497	36.528
GA-IPM-7	43.600	42.011	41.910	43.484	41.403	42.802	43.488	39.719	37.279
GA-IPM-8	43.587	42.602	50.204	43.496	41.936	47.118	43.475	41.950	44.907
GA-IPM-9	43.583	41.170	40.307	43.496	39.851	38.082	43.497	40.781	41.580
GA-IPM-10	43.585	42.613	56.347	43.474	39.900	37.118	43.487	39.499	37.245
GA-IPM-11	43.581	42.655	55.783	43.498	40.867	38.904	43.492	39.611	37.949
GA-IPM-12	43.592	42.793	53.491	43.478	42.838	61.762	43.504	42.519	52.873

Best: maximum fitness; Mean: average fitness; STD: standard deviation

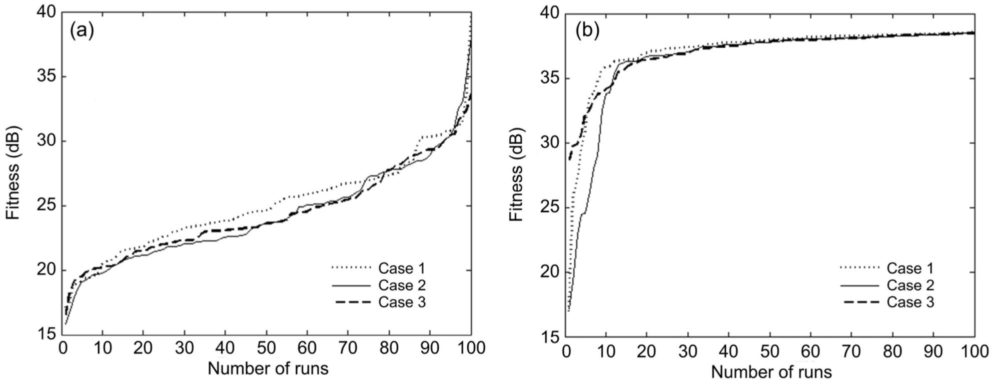

Fig. 6 Sorted results of GA-1 (a) and GA-IPM-1 (b) for 100 independent runs based on values of fitness for problem 1

mean number of generations (MGs), and mean value of maximum function evaluations (MFEs). The values of CC parameters were determined based on 100 independent runs of each algorithm. Results are given in Table 6 for all three cases of problem 1. There are no significant differences in the CC values among the algorithms, but the values are lowest for GA-IPM-4 and GA-IPM-8.

4.2 Problem 2: ANC system for random noise

In this problem, the proposed schemes were applied to ANC systems responding to narrow-band random noise. The reliability and effectiveness of ANC were determined for each variant of the hybrid GA-IPM scheme for all three cases with different primary paths $P(z)$ and secondary paths $S(z)$.

Case 1: ANC with LP and NLS paths

Case 2: ANC with NLP and LS paths

Case 3: ANC with NLP and NLS paths

The proposed GA-IPM algorithms were applied to this problem in a similar way as in problem 1. The values of fitness were calculated for 100 independent runs of each GA-IPM. The results are listed in Table 7 (for GAs) and Table 8 (for GA-IPMs), in terms of statistical operators of the best, mean, and STD. The fitness values of the GA-IPM hybrid approaches are higher than those of GA variants around 1–2 dB on the basis of mean values. A comparison of the results for GAs and GA-IPMs shows that their fitness values are similar but better results are obtained by GA-4, GA-8, and GA-12 based ANC controllers and GA-IPM-4, GA-IPM-8, and GA-IPM-12 based hybrid ANC controllers.

Fig. 7 shows the fitness values for 100 independent runs of GA-1 and GA-IPM-1. About 85%–88% of runs of GA-1 gave fitness values of more than 50 dB, compared with around 90% in the case of GA-IPM-1. The sorted fitness values from 100 independent runs of GA-2 to GA-12 and GA-IPM-2 to GA-IPM-12 are shown in Figs. S3 and S4, respectively, in the supplementary materials. The results are similar to those observed for GA-1 and GA-IPM-1.

A comparative study of GA-IPM hybrid computing techniques was conducted based on values of CC parameters. The results are listed in Table 9, based on calculation from 100 independent runs of each scheme for all three cases of problem 2. There are no remarkable differences in the values of CC parameters. However, a slightly better speed was achieved using GA-IPM-4, GA-IPM-8, and GA-IPM-12.

4.3 Problem 3: ANC system with complex random noise

In this scenario, the proposed schemes were applied responding to unwanted complex random noise. The performance of the ANC controller based on 12 variants of GA-IPMs was investigated in the case of a nonlinear primary path $P(z)$ as in Eq. (10), and a secondary path $S(z)$ as in Eq. (12).

Table 6 Comparison of our proposed algorithms based on the computational complexity parameter for the ANC systems given in problem 1

Method	MET (s)			MGs			MFEs		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
GA-IPM-1	31.1	33.7	38.1	334.6	361.7	411.9	23 186	24 308	26 510
GA-IPM-2	27.7	30.9	31.1	325.8	369.4	382.3	22 816	24 646	25 167
GA-IPM-3	28.2	27.3	27.3	333.8	335.6	344.8	23 183	23 256	23 636
GA-IPM-4	25.9	25.2	24.8	316.2	323.9	336.7	22 408	22 733	23 310
GA-IPM-5	29.8	32.8	31.2	338.3	375.3	364.9	23 368	24 973	24 516
GA-IPM-6	27.7	34.9	34.8	319.5	387.2	392.5	22 548	25 455	25 693
GA-IPM-7	24.8	25.3	22.2	302.3	324.7	317.7	21 784	22 737	22 448
GA-IPM-8	23.9	26.5	24.4	397.1	347.8	319.0	21 572	23 762	22 477
GA-IPM-9	26.7	31.6	27.7	311.9	366.3	346.3	22 193	24 554	23 687
GA-IPM-10	28.1	30.6	32.8	328.9	351.6	378.8	22 903	23 846	25 050
GA-IPM-11	26.3	25.9	26.1	308.3	317.0	328.7	22 013	22 404	22 871
GA-IPM-12	28.0	26.1	29.8	321.4	315.5	353.0	22 614	22 353	23 959

MET: mean execution time; MGs: mean number of generations; MFEs: mean value of maximum function evaluations

Table 7 Performance of our proposed algorithm (GA) based on 100 independent runs for the ANC systems given in problem 2

Method	Fitness (dB)								
	Case 1			Case 2			Case 3		
	Best	Mean	STD	Best	Mean	STD	Best	Mean	STD
GA-1	68.394	53.769	58.393	68.701	54.432	59.235	70.658	54.040	58.909
GA-2	69.851	53.966	58.067	67.817	52.264	55.964	75.146	53.230	56.526
GA-3	61.806	48.567	53.151	61.626	49.202	54.716	60.000	48.615	54.060
GA-4	72.841	61.668	70.141	70.710	61.396	69.948	73.103	62.306	70.772
GA-5	66.933	53.838	58.572	68.380	53.636	58.485	66.315	52.983	57.376
GA-6	67.861	54.130	57.618	69.231	53.789	57.147	70.777	54.116	58.552
GA-7	62.021	50.487	55.926	65.405	49.703	55.499	61.922	50.142	55.811
GA-8	72.477	61.584	69.380	70.409	61.425	69.828	71.445	62.644	70.576
GA-9	67.556	53.141	57.106	64.409	52.700	57.700	68.358	53.366	56.706
GA-10	65.306	52.064	54.682	68.963	51.779	55.582	65.142	52.227	56.436
GA-11	60.895	47.669	52.108	63.819	46.692	49.589	59.819	47.989	52.744
GA-12	69.382	59.965	68.543	71.598	60.424	68.575	68.856	60.096	68.232

Best: maximum fitness; Mean: average fitness; STD: standard deviation

Table 8 Performance of our proposed algorithm (GA-IPM) based on 100 independent runs for the ANC systems given in problem 2

Method	Fitness (dB)								
	Case 1			Case 2			Case 3		
	Best	Mean	STD	Best	Mean	STD	Best	Mean	STD
GA-IPM-1	65.735	53.820	57.239	69.474	54.138	58.359	68.483	54.197	58.367
GA-IPM-2	73.935	54.541	59.103	69.686	51.663	53.770	77.888	52.840	56.335
GA-IPM-3	64.128	49.843	53.086	65.740	49.579	52.589	64.172	48.293	50.856
GA-IPM-4	72.770	61.985	70.023	71.370	61.439	68.739	72.438	62.449	70.182
GA-IPM-5	69.145	53.536	56.599	68.211	53.846	57.893	66.688	53.880	58.506
GA-IPM-6	72.020	54.055	56.524	71.799	53.892	55.803	72.553	54.536	58.435
GA-IPM-7	67.882	50.385	53.604	69.138	49.931	54.486	62.787	49.926	51.388
GA-IPM-8	72.574	61.752	69.365	69.289	61.649	69.886	72.540	61.786	67.671
GA-IPM-9	69.535	53.089	56.572	65.178	51.796	51.426	70.274	53.798	56.828
GA-IPM-10	70.092	52.534	55.583	68.378	52.078	55.232	68.764	52.284	55.503
GA-IPM-11	61.206	48.305	51.617	64.329	46.769	45.062	65.480	47.989	49.023
GA-IPM-12	70.587	59.265	64.212	70.066	60.762	68.253	69.655	60.376	68.497

Best: maximum fitness; Mean: average fitness; STD: standard deviation

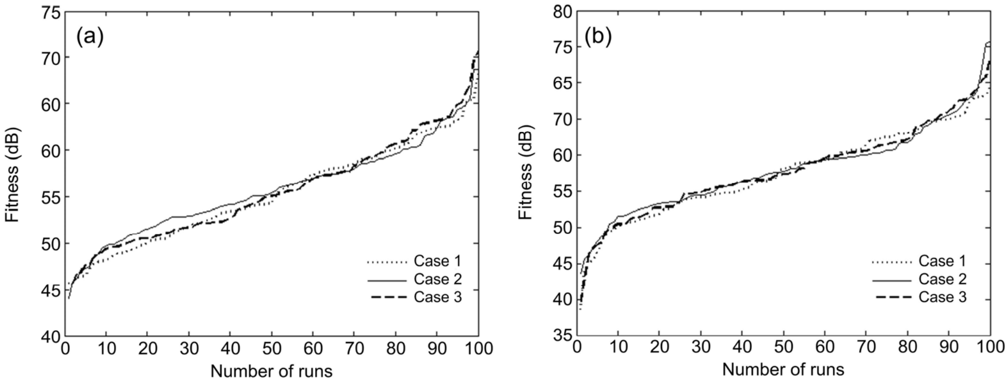

Fig. 7 Sorted results of GA-1 (a) and GA-IPM-1 (b) for 100 independent runs based on values of fitness for problem 2

Table 9 Comparison of our proposed algorithms based on the computational complexity parameter for the ANC systems given in problem 2

Method	MET (s)			MGs			MFEs		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
GA-IPM-1	31.1	33.7	38.1	206.4	206.7	206.4	23 283	23 290	23 294
GA-IPM-2	63.0	66.1	64.4	206.6	206.0	205.9	23 289	23 273	23 278
GA-IPM-3	61.8	64.6	63.2	206.5	206.4	206.6	23 282	23 282	23 289
GA-IPM-4	61.4	64.1	63.1	206.4	206.2	206.2	23 283	23 268	23 276
GA-IPM-5	64.0	67.0	64.6	206.6	206.4	206.9	23 285	23 279	23 286
GA-IPM-6	64.7	68.8	74.0	206.9	206.2	206.6	23 293	23 289	23 290
GA-IPM-7	60.4	62.8	61.2	206.7	206.4	206.5	22 699	22 675	22 691
GA-IPM-8	60.3	63.2	61.9	206.4	206.6	206.5	22 680	22 695	22 692
GA-IPM-9	61.0	64.2	62.9	206.5	206.5	206.6	22 696	22 685	22 691
GA-IPM-10	60.1	63.2	61.4	206.5	206.6	206.5	22 694	22 687	22 691
GA-IPM-11	61.6	65.1	64.5	206.5	206.2	206.8	22 682	22 679	22 698
GA-IPM-12	61.5	64.3	61.9	206.3	206.3	206.4	22 691	22 685	22 691

MET: mean execution time; MGs: mean number of generations; MFEs: mean value of maximum function evaluations

The GA-IPM design approaches were applied to this problem using a procedure similar to that used in the last examples, and the fitness values were determined for 100 independent runs of each method. The results for statistical parameters of the best, mean, and STD are given in Table 10. The values from the GA-IPM hybrid approaches are generally better than those from GAs for each statistical performance indicator. A comparative study showed that high fitness values were achieved by all algorithms, but more accurate results were obtained by GA-based ANC controllers constructed with GA-4, GA-8, and GA-12 and by hybrid ANC controllers GA-IPM-4, GA-IPM-8, and GA-IPM-12. The sorted fitness values from 100 independent runs in each case from GA-1 to GA-12 and GA-IPM-1 to GA-IPM-12 are plotted in Fig. S5 in the supplementary materials to compare their performance. The GA-IPM hybrid ANC controllers performed better than the GA-based controllers in terms of accuracy and convergence.

A comparative study of the GA-IPM hybrid computing techniques was conducted based on values of CC parameters and the results are listed in Table 11, based on data generated from 100 independent runs of each scheme. There are no marked differences in the values of CC parameters determined by the GA-IPM hybrid ANC controllers.

The results of this study were compared with those reported for FIR- and Volterra-based adaptive GAs (FAGA and VAGA) (Chang and Chen, 2010). For cases 1–3 of problems 1 and 2, the average gains in the performance of the memetic algorithm were around 7–10 dB and 5–8 dB, respectively. Compared with the results of FAGA, a gain of around 8 dB was achieved for problem 3. The proposed variants consumed around 350, 210, and 210 iterations for each case of problems 1, 2, and 3, respectively, while FAGA and VAGA each took 500 iterations (Tables 6, 9, and 11). Therefore, our proposed methodologies had superior accuracy and computational complexity.

5 Conclusions

ANC controllers based on variants of GAs and GA-IPMs were designed by taking different sets of routines for reproduction operators for selection, crossover, and mutation operations, and were applied effectively for the optimization of residual error of ANC systems. The reliability and effectiveness of the designed schemes based on variants of GAs and GA-IPMs were evaluated for an ANC system with three problems including sinusoidal, random, and complex random noises, and for different scenarios of linear or nonlinear primary and secondary paths. Results showed that all of these schemes achieved relatively small mean values of residual error: for the GAs, around 22.9–27.8 dB for problem 1, 46.6–62.3 dB for problem 2, and 43.5–58.5 dB for problem 3; for the GA-IPMs, the respective values

Table 10 Performance of proposed algorithms (GA and GA-IPM) based on 100 independent runs for the ANC systems given in problem 3

Method	Fitness (dB)			Method	Fitness (dB)		
	Best	Mean	STD		Best	Mean	STD
GA-1	60.811	47.906	50.481	GA-IPM-1	63.681	48.466	51.552
GA-2	64.218	47.425	51.126	GA-IPM-2	63.552	47.850	49.941
GA-3	56.057	45.945	52.321	GA-IPM-3	57.188	46.418	50.994
GA-4	70.974	58.507	66.840	GA-IPM-4	68.517	58.570	66.121
GA-5	64.492	47.104	49.000	GA-IPM-5	63.790	47.427	49.277
GA-6	61.334	47.643	49.398	GA-IPM-6	62.871	47.316	46.245
GA-7	58.248	46.505	52.768	GA-IPM-7	60.498	46.890	51.179
GA-8	69.357	57.677	64.789	GA-IPM-8	72.522	58.221	63.921
GA-9	65.168	47.105	51.628	GA-IPM-9	64.406	46.250	45.740
GA-10	59.384	45.535	48.902	GA-IPM-10	60.615	45.803	46.374
GA-11	56.324	43.590	49.778	GA-IPM-11	61.276	44.251	48.042
GA-12	66.700	56.155	64.095	GA-IPM-12	66.003	56.270	63.587

Best: maximum fitness; Mean: average fitness; STD: standard deviation

Table 11 Comparison of our proposed algorithms (GA-IPM) based on the computational complexity parameter for the ANC systems given in problem 3

Method	MET (s)	MGs	MFEs
GA-IPM-1	96.5	207.0	23 306
GA-IPM-2	88.4	206.4	23 285
GA-IPM-3	85.7	206.6	23 277
GA-IPM-4	86.5	206.7	23 287
GA-IPM-5	87.7	206.8	23 292
GA-IPM-6	90.6	206.3	23 269
GA-IPM-7	83.6	206.2	22 685
GA-IPM-8	85.0	205.8	22 671
GA-IPM-9	84.0	206.2	22 689
GA-IPM-10	84.3	206.6	22 708
GA-IPM-11	88.6	206.8	22 703
GA-IPM-12	85.4	206.4	22 694

MET: mean execution time; MGs: mean number of generations; MFEs: mean value of maximum function evaluations

were 36.2–42.8 dB, 46.7–62.4 dB, and 44.2–58.5 dB for the three problems. Comparative studies of the GA variants and their hybrids showed that there were no noticeable differences in accuracy, but the results from GA-1, GA-4, and GA-12 and their respective memetic algorithms were better. Thus, for better performance of bio-inspired heuristics based on variants of GAs, stochastic uniform, arithmetic, and Gaussian routines should be incorporated for selection, crossover, and mutation operators, respectively. Computational complexity analysis based on MET, MG, and MFE values showed only a small variance in the results for GA and GA-IPMs for each case of all three problems. The ability of the designed variant GAs and GA-IPMs to reduce the residual error of the ANC system was superior for random noise, inferior for sinusoidal noise, and intermediate in the case of complex random noise.

In the future, further improvement in the results may be achieved using variants of artificial intelligence algorithms as alternatives to GAs to optimize the residual error of ANC systems. The proposed methodology may be extended to the design and development of ANC systems with better performance for both real-life appliances and classified defense related equipment. In addition, alternative designs of residual error functions through nonlinear Volterra, fractional, or kernel-filter based GA modeling could be a good choice for modeling the cancellation of unwanted noise.

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List of electronic supplementary materials