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Omar Abu Arqub,
Al-Balqa Applied University, Jordan

*CORRESPONDENCE
Adiqa Kausar Kiani,
adiqa@yuntech.edu.tw

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Parameter estimation of harmonics arising in electrical instruments of smart grids using cuckoo search heuristics

Naveed Ahmed Malik[1], Ching-Lung Chang[2], Naveed Ishtiaq Chaudhary[3], Zeshan Aslam Khan[4], Muhammad Asif Zahoor Raja[3], Adiqa Kausar Kiani[3]*, Ahmed H. Milyani[5] and Abdullah Ahmed Azhari[6]

[1]Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Douliou, Taiwan, [2]Department of Computer Science and Information Engineering, National Yunlin University of Science and Technology, Douliou, Taiwan, [3]Future Technology Research Center, National Yunlin University of Science and Technology, Douliou, Taiwan, [4]Department of Electrical and Computer Engineering, International Islamic University Islamabad, Islamabad, Pakistan, [5]Department of Electrical and Computer Engineering, King Abdulaziz University, Jeddah, Saudi Arabia, [6]The Applied College, King Abdulaziz University, Jeddah, Saudi Arabia

The accurate estimation of power signal parameters allows smart grids to optimize power delivery efficiency, improve equipment utilization, and control power flow among generation nodes and loads. However, practically it becomes a challenging task because of the presence of harmonic distortions. In this study, a parameter estimation of the power system harmonics is investigated through swarm intelligence–based optimization strength of the cuckoo search algorithm. The performance evaluation is conducted in detail for different generations and particle sizes and for different signal-to-noise ratios. The simulation results reveal that the cuckoo search optimization heuristic accurately estimates the amplitude and phase parameters of the power system harmonics and is robust against different signal-to-noise ratios.

KEYWORDS

cuckoo search, swarm optimization, harmonics, parameter estimation, smart grid

1 Introduction

The control of the power systems and synchronization of grid-connected electrical devices require parameters of voltage and current signals, such as amplitude, frequency, and phase (Baradarani et al., 2014; Jafarpisheh et al., 2016). Accurate information on these signal parameters allows smart grids to optimize power delivery efficiency, improve equipment utilization, and control power flow among generation nodes and loads (Sun et al., 2019). However, practically the presence of harmonics and inter-harmonic distortions in power signals complicates the situation because the amplitude and phase estimations of harmonics is challenging for evaluating the quality of service characteristics in smart grids (Rivas et al., 2020). Thus, it is imperative to investigate the development of accurate, robust, and stable estimation methods to mitigate the adverse effects of harmonics in smart grid efficiency.

Different researchers have investigated the domain of estimating power system harmonics and proposed various techniques. For example, Das et al. (2020) developed the ADALINE-based least mean square (LMS) algorithm and compared its performance with the recursive least square, while Elnady et al. (2020) presented the novel smooth variable structure filters for voltage harmonics and voltage imbalance. Santos et al. (2020) introduced the filter bank–based ESPRIT approach for increased efficiency in harmonics detection and estimation. Enayati and Moravej (2017) developed a hybrid estimation scheme by combining recursive least squares with the iterated extended Kalman filter, and Shuai et al. (2018) presented the frequency shifting/filtering method. Xu et al. (Xu and Ding, 2018; Xu and Song, 2020) investigated the parameter estimation of power signals using iterative/recursive methods, such as multi-innovation stochastic gradient (Xu and Ding, 2017), separable multi-synchronous multi-innovation gradient (Xu et al., 2022), separable Newton recursive (Xu, 2022a), separable multi-innovation Newton iterative (Xu, 2022b), and hierarchical principle-based recursive least squares (Xu et al., 2021). Chaudhary et al. introduced fractional gradient-based estimation algorithms for power signals, such as fractional LMS (Chaudhary et al., 2017) and innovative fractional order LMS (Chaudhary et al., 2020), while Zubair et al. (2018) presented the momentum term–based fractional scheme. Mehmood et al. (2020), Mehmood et al. (2021) had applied evolutionary and swarming heuristics for parameter estimation of power signals.

The schemes based on swarm and evolutionary heuristics have established their significance through effective application in solving various challenging optimization tasks (Francesca and Birattari, 2016; Jana et al., 2019; Sabir et al., 2020; AbdelAty et al., 2022; Altaf et al., 2022) such as power system harmonics estimation (Ray and Subudhi, 2012; Elvira-Ortiz et al., 2020; Ray and Subudhi, 2015; Kabalci et al., 2018; doNascimentoSepulchro et al., 2014; Singh et al., 2016). Yang and Deb (2009), Yang and Deb (2014) introduced a metaheuristic inspired by the search mechanism of cuckoo called the cuckoo search optimization (CSO) algorithm. The CSO has been used extensively for effective solutions in a number of engineering and applied problems with many variants (Li and Yin, 2015; Cuong-Le et al., 2021), such as photovoltaic model (Gude and Jana, 2020), social media sentiment analysis (Pandey et al., 2017), path planning (Song et al., 2020), power control in salt reactors (Karahan, 2021), damage detection infrastructures (Tran-Ngoc et al., 2019), chemoinformatics (Houssein et al., 2020), economic load dispatch (Yu et al., 2020), and many others. The effective performance of CSO in illustrated applications motivated us to explore parameter estimation power system harmonics through well-established optimization strength of the CSO. In this study, parameters of power system harmonics are estimated through CSO for different generation and particle size. Detailed and in-depth performance analyses are conducted to check the accuracy, diversity, and robustness of the CSO for harmonics estimation.

The remaining article is set as follows: the estimation model for power system harmonics along with the optimization procedure of CSO is described in Section 2. The results of simulation studies are elaborated in Section 3. The conclusions and future works are listed in Section 4.

2 Materials and methods

The system model for power harmonics signal is first introduced, then the proposed methodology for optimization of the fitness function for the estimation of the harmonic signal is presented in this section. The overall flow diagram of the proposed scheme is presented in Figure 1 by means of different process block structures.

2.1 System model

The general harmonic signal in terms of its constituent parameters (Malik et al., 2022) is defined as

$$s(t) = \sum_{k=1}^{K} \alpha_k \sin(\beta_k t + \gamma_k) + \delta(t) h(t) = \sum_{j=1}^{J} a_j \sin\left(b_j t + c_j\right) + d(t), \tag{1}$$

and the variables in Eq. 1 are defined as J represents harmonic order, a_j is amplitude, b_j is angular frequency represented as $b_j = 2\pi f_0$ with f_0 as fundamental frequency, c_j is phase, and d is AWGN. Then, by writing a discrete version of Eq. 1 after sampling with period p, $t_n = np$, and by assuming $h(t_n) = h(n)$, Eq. 1 is rewritten as

$$\begin{aligned} h(t_n) &= \sum_{j=1}^{J} a_j \sin\left(b_j t_n + \gamma_k\right) + d(t_n), \\ h(n) &= \sum_{j=1}^{J} a_j \sin\left(\beta_j n + c_k\right) + d(n). \end{aligned} \tag{2}$$

Expanding Eq. 2 through the fundamental trigonometric identity

$$h(n) = \sum_{j=1}^{J} \left[a_j \cos\left(b_j n\right) \sin c_j + a_j \sin\left(b_j n\right) \cos c_j\right] + d(n), \tag{3}$$

with the assumption that

$$u_j = a_j \cos c_j \text{ and } v_j = a_j \sin c_j, \tag{4}$$

using the assumptions given in Eq. 4 into Eq. 3 gives Eq. 5:

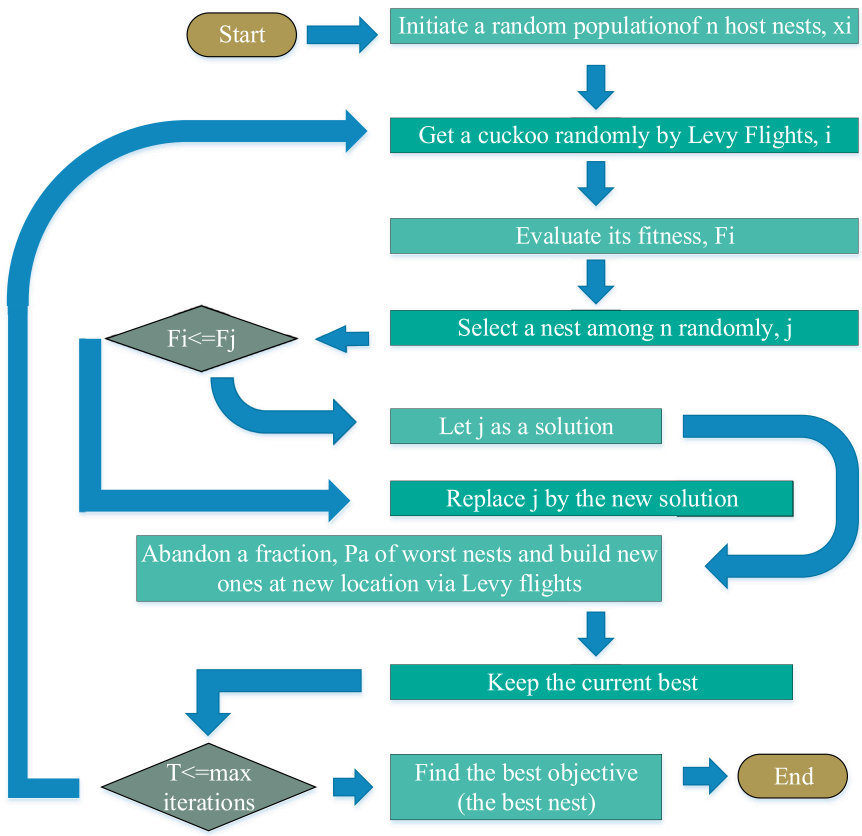

FIGURE 1
Process flow structure of the CSO algorithm.

$$h(n) = \sum_{j=1}^{J} \left[u_j \sin\left(b_j n\right) + v_j \cos\left(b_j n\right)\right] + d(n). \tag{5}$$

The harmonics estimation model with information-vector ψ and parameter-vector ζ is written as

$$\begin{gathered} h(n) = \psi^T(n)\zeta + d(n), \\ \psi(n) = \left[\sin(b_1 n), \cos(b_1 n), \sin(b_2 n), \cos(b_2 n), \ldots, \sin\left(b_j n\right), \cos\left(b_j n\right)\right], \\ \zeta = \left[u_1, v_1, u_2, v_2, \ldots, u_j, v_j\right]. \end{gathered} \tag{6}$$

The aim is to estimate the amplitude and phase parameters of the harmonics through minimizing the error-based criterion function defined as

$$\delta(n) = \text{mean}\left[h(n) - \tilde{h}(n)\right]^2 = \left[h(n) - \psi^T(n)\tilde{\zeta}\right]^2, \tag{7}$$

$h(n)$ is the actual signal, $\tilde{h}(n)$ is an estimated harmonic signal calculated through estimated parameter-vector $\tilde{\zeta}$ by using the proposed CSO-based heuristic. The relationship between the intermediate variables and the actual parameters is given by

$$a_j = \sqrt{\left(u_j\right)^2 + \left(v_j\right)^2},\ c_j = \tan^{-1}\frac{v_j}{u_j}. \tag{8}$$

2.2 Optimization method: Cuckoo search optimization algorithm

Yang and Deb (2009), Yang and Deb (2014) introduced a metaheuristic inspired by the search mechanism of cuckoo called CSO with exhaustive applications in different fields of engineering design and optimization. The formulation of the CSO is based on three fundamental concepts: firstly, each cuckoo lays a single egg in a single instance of time, while dumping the respective egg in an arbitrary selected nest; secondly, the nests with the best fitness, i.e., having the best quality of eggs, proceed to the next generations; and thirdly, the number of host nests is fixed, and the probability of discovery of next by the host cuckoo is set between 0 and 1. The basis of these three fundamental steps in the CSO is proposed with the process flow structure as shown in Figure 1.

TABLE 1 Results of parameter estimates of Example 1 for G = 500.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.5028	0.4903	0.2059	0.1384	0.1010	1.3943	1.0096	0.7530	0.5487	0.5573	9.46E-04
	100	1.4904	0.4991	0.1894	0.1581	0.0975	1.4002	1.0211	0.7449	0.6339	0.5726	9.70E-04
	150	1.5087	0.4904	0.2023	0.1463	0.0967	1.3955	1.0529	0.7615	0.6934	0.6441	8.64E-04
60	50	1.5026	0.4985	0.1989	0.1496	0.0982	1.3965	1.0456	0.7820	0.6432	0.5329	1.02E-05
	100	1.5003	0.5008	0.1978	0.1507	0.1007	1.3967	1.0410	0.7978	0.6495	0.5096	1.79E-05
	150	1.5005	0.5010	0.2018	0.1537	0.1005	1.3956	1.0455	0.7833	0.6221	0.5477	1.38E-05
90	50	1.4988	0.5024	0.1988	0.1486	0.0999	1.3964	1.0468	0.7795	0.6266	0.5078	7.40E-06
	100	1.4988	0.5009	0.1997	0.1483	0.1006	1.3954	1.0426	0.7934	0.6270	0.5264	7.11E-06
	150	1.4991	0.4975	0.2018	0.1504	0.1006	1.3965	1.0449	0.7793	0.6296	0.5074	8.01E-06
		1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	0

TABLE 2 Results of parameter estimates of Example 1 for G = 1,000.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.4952	0.4968	0.2042	0.1611	0.0934	1.4038	1.0503	0.7960	0.5386	0.5653	7.11E-04
	100	1.4977	0.4896	0.1984	0.1546	0.1018	1.3969	1.0433	0.7826	0.6401	0.5742	7.17E-04
	150	1.5014	0.5028	0.2011	0.1480	0.0941	1.3938	1.0509	0.8318	0.6224	0.6175	7.12E-04
60	50	1.5000	0.5000	0.1998	0.1501	0.1000	1.3961	1.0470	0.7862	0.6260	0.5211	7.07E-07
	100	1.4999	0.5004	0.2002	0.1500	0.1001	1.3959	1.0468	0.7881	0.6290	0.5188	8.60E-07
	150	1.5001	0.4998	0.1999	0.1497	0.0997	1.3963	1.0468	0.7855	0.6267	0.5263	8.06E-07
90	50	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7849	0.6280	0.5227	2.65E-09
	100	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0471	0.7850	0.6280	0.5229	3.54E-09
	150	1.5000	0.5000	0.2000	0.1500	0.1001	1.3960	1.0470	0.7850	0.6281	0.5228	5.67E-09
		1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	0

TABLE 3 Results of parameter estimates of Example 1 for G = 1,500.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.5062	0.5012	0.2063	0.1391	0.1015	1.3967	1.0482	0.7961	0.6084	0.4847	6.81E-04
	100	1.4972	0.5052	0.1938	0.1573	0.1014	1.3949	1.0526	0.7824	0.6144	0.5761	6.08E-04
	150	1.4962	0.5003	0.1958	0.1505	0.0907	1.3955	1.0315	0.8229	0.6524	0.5335	6.34E-04
60	50	1.5000	0.5001	0.1999	0.1501	0.0997	1.3961	1.0472	0.7848	0.6273	0.5270	6.83E-07
	100	1.5000	0.5001	0.1997	0.1498	0.1001	1.3961	1.0467	0.7847	0.6292	0.5218	6.23E-07
	150	1.5000	0.5000	0.2000	0.1498	0.0998	1.3961	1.0467	0.7841	0.6268	0.5203	6.57E-07
90	50	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6279	0.5230	6.68E-10
	100	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	7.68E-10
	150	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5231	7.82E-10
		1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	0

Proceeding by the actual behavior of the cuckoo, mathematical models were introduced by Yang et al.; by taking the new candidate solution x_i(t+1) that represents an i-*th* cuckoo at *t* flight/iteration index and considering the Levy flight, we have the following expression iterative update of CSO as

$$x_i(t+1) = x_i(t) + \alpha \odot Levy(\lambda), \quad (9)$$

TABLE 4 Results of parameter estimates of Example 1 for G = 2000.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.5024	0.5020	0.2011	0.1462	0.0958	1.3909	1.0393	0.7911	0.6087	0.5671	6.10E-04
	100	1.4909	0.4982	0.2001	0.1471	0.0913	1.3968	1.0594	0.7639	0.5954	0.6038	5.51E-04
	150	1.4930	0.5076	0.2050	0.1453	0.1043	1.3977	1.0479	0.8170	0.5725	0.5632	6.00E-04
60	50	1.5001	0.4999	0.2000	0.1502	0.1001	1.3959	1.0468	0.7849	0.6286	0.5216	5.94E-07
	100	1.5002	0.4999	0.2001	0.1498	0.0999	1.3960	1.0475	0.7848	0.6282	0.5219	5.74E-07
	150	1.5000	0.5003	0.1999	0.1498	0.0999	1.3959	1.0467	0.7848	0.6292	0.5194	6.15E-07
90	50	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5229	6.59E-10
	100	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	6.67E-10
	150	1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	6.59E-10
		1.5000	0.5000	0.2000	0.1500	0.1000	1.3960	1.0470	0.7850	0.6280	0.5230	0

TABLE 5 Results of parameter estimates of Example 2 for G = 500.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.1894	0.8090	0.2030	0.1721	0.0846	1.3078	0.9609	0.8036	0.6879	0.6185	7.91E-04
	100	1.1887	0.8069	0.1964	0.1717	0.1024	1.3088	0.9683	0.6965	0.7246	0.5261	9.62E-04
	150	1.1867	0.7975	0.1961	0.1844	0.1074	1.3148	0.9610	0.7408	0.6736	0.4660	8.57E-04
60	50	1.2029	0.8000	0.2001	0.1829	0.1022	1.3100	0.9597	0.7827	0.6976	0.5053	1.34E-05
	100	1.2018	0.7972	0.2015	0.1777	0.0971	1.3077	0.9612	0.7884	0.6951	0.5268	1.58E-05
	150	1.1984	0.7962	0.2008	0.1790	0.0979	1.3080	0.9620	0.7898	0.6939	0.5613	2.19E-05
90	50	1.1987	0.7990	0.1996	0.1796	0.0997	1.3095	0.9583	0.7956	0.7191	0.5277	1.14E-05
	100	1.1974	0.7991	0.2004	0.1790	0.0983	1.3075	0.9591	0.7817	0.7046	0.5416	1.01E-05
	150	1.2008	0.7975	0.2042	0.1780	0.1001	1.3100	0.9559	0.7866	0.6948	0.5428	2.01E-05
		1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	0

TABLE 6 Results of parameter estimates of Example 2 for G = 1,000.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.2096	0.8051	0.2019	0.1866	0.0936	1.3101	0.9696	0.8023	0.6930	0.5116	7.02E-04
	100	1.1960	0.8067	0.1974	0.1822	0.1000	1.3079	0.9672	0.7963	0.7429	0.5082	7.32E-04
	150	1.1969	0.8024	0.1955	0.1762	0.1092	1.3089	0.9584	0.8046	0.6871	0.4465	6.98E-04
60	50	1.1998	0.8001	0.1998	0.1802	0.0997	1.3092	0.9590	0.7865	0.6978	0.5212	7.53E-07
	100	1.2000	0.8002	0.1998	0.1800	0.1005	1.3094	0.9586	0.7861	0.7009	0.5285	8.08E-07
	150	1.2001	0.8001	0.2000	0.1802	0.1001	1.3088	0.9593	0.7865	0.6980	0.5252	8.10E-07
90	50	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5229	1.45E-09
	100	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7848	0.6981	0.5231	2.16E-09
	150	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9591	0.7851	0.6983	0.5229	4.69E-09
		1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	0

here α represents the step size based on the scale of the optimization problem, and generally its value is set equal to unit value in most of the cases and the Levy flight is represented with a random walk procedure on the basis of Levy distribution as

$$Levy(\lambda) \sim u = t^{(-\lambda)}, \tag{10}$$

TABLE 7 Results of parameter estimates of Example 2 for G = 1,500.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.1985	0.8005	0.2013	0.1755	0.0949	1.3134	0.9585	0.7586	0.6795	0.5023	6.40E-04
	100	1.1909	0.8036	0.1962	0.1757	0.1137	1.3091	0.9548	0.7750	0.6668	0.6236	6.61E-04
	150	1.2013	0.8014	0.1918	0.1790	0.0984	1.3135	0.9679	0.8190	0.7242	0.6072	6.39E-04
60	50	1.2001	0.8000	0.1999	0.1799	0.1000	1.3089	0.9589	0.7858	0.6976	0.5225	6.91E-07
	100	1.1998	0.7997	0.2000	0.1802	0.0999	1.3091	0.9591	0.7847	0.6988	0.5215	6.82E-07
	150	1.1999	0.7999	0.2002	0.1800	0.1001	1.3091	0.9588	0.7866	0.6979	0.5224	6.11E-07
90	50	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	6.71E-10
	100	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	6.73E-10
	150	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	7.60E-10
		1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	0

TABLE 8 Results of parameter estimates of Example 2 for G = 2000.

d	p	a_1	a_2	a_3	a_4	a_5	c_1	c_2	c_3	c_4	c_5	δ
30	50	1.1992	0.7993	0.1921	0.1931	0.1024	1.3071	0.9623	0.8177	0.7112	0.5600	5.57E-04
	100	1.1976	0.8012	0.2052	0.1809	0.1048	1.2983	0.9477	0.8055	0.7149	0.5158	5.55E-04
	150	1.2013	0.8022	0.2006	0.1794	0.1015	1.3068	0.9566	0.7844	0.7002	0.6340	6.02E-04
60	50	1.2001	0.8000	0.2002	0.1802	0.0999	1.3092	0.9590	0.7843	0.6989	0.5230	6.11E-07
	100	1.1999	0.8002	0.2000	0.1800	0.1001	1.3090	0.9591	0.7845	0.6993	0.5232	6.04E-07
	150	1.2001	0.8001	0.1998	0.1802	0.0998	1.3090	0.9594	0.7859	0.6976	0.5214	6.33E-07
90	50	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	6.67E-10
	100	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	6.73E-10
	150	1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	6.45E-10
		1.2000	0.8000	0.2000	0.1800	0.1000	1.3090	0.9590	0.7850	0.6980	0.5230	0

here λ is a constant taken between 1 and 3, and the Levy flight has an infinite mean and variance. Further details on the mathematical terms, convergence proofs, and applications can be referred from citations mentioned therein: Yang and Deb (2009); Yang and Deb (2014); Li and Yin (2015); Pandey et al. (2017); Tran-Ngoc et al. (2019); Gude and Jana (2020); Houssein et al. (2020); Song et al. (2020); Yu et al. (2020); Cuong-Le et al. (2021); Karahan (2021). Inspired by the optimization performance of the CSO algorithm, we have implemented the CSO for optimization of parameters of the system models presented in Eqs. 1–8. The CSO algorithm was implemented in the presented research based on the routine available at the MATLAB Central File Exchange (Yang, 2022). The optimization strength of the CSO may be enhanced by integrating it with the kernel theory (Arqub, 2016; Arqub, 2018; Arqub, 2020; Arqub and Al-Smadi, 2020; Sweis et al., 2022).

3 Results and discussion

Harmonics estimation of power systems is carried out in this research work by applying the CSO algorithm to two examples, and the results are given in a tabular form with the necessary discussion along with graphs. The simulations are conducted using MATLAB with a sampling frequency of 2 KHz. Three levels of additive white Gaussian noise d with 30 DB, 60 DB, and 90 DB are introduced in the system to check the heftiness of the proposed scheme. The investigation is carried out by considering four generation (G) sizes and three particle (P) sizes in the CSO. The considered values of G are 500, 1000, 1,500, and 2000, while the values of P are 50, 100, and 150.

Example 1: The harmonic signal (Malik et al., 2022) considered in the first simulation study is

$$h(t) = \begin{bmatrix} 1.5\sin(2\pi f_1 t + 1.396) + 0.5\sin(2\pi f_3 t + 1.047) + 0.2\sin(2\pi f_5 t + 0.785) \\ +0.15\sin(2\pi f_7 t + 0.628) + 0.1\sin(2\pi f_{11} t + 0.523) \end{bmatrix}. \tag{11}$$

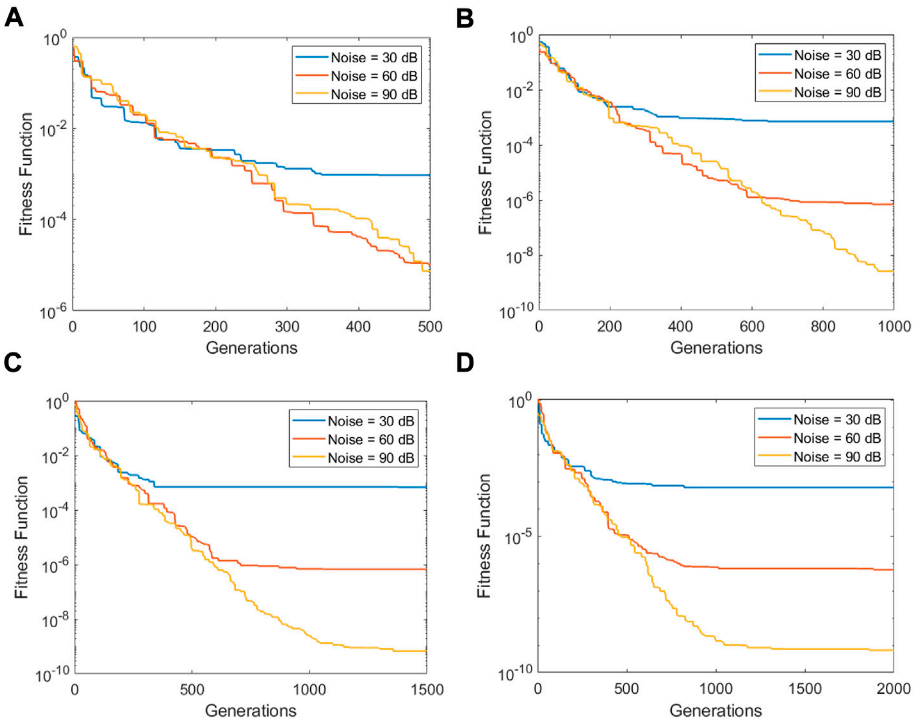

FIGURE 2
Convergence plots of Example 1: **(A)** G = 500, **(B)** G = 500, **(C)** G = 500, and **(D)** G = 500.

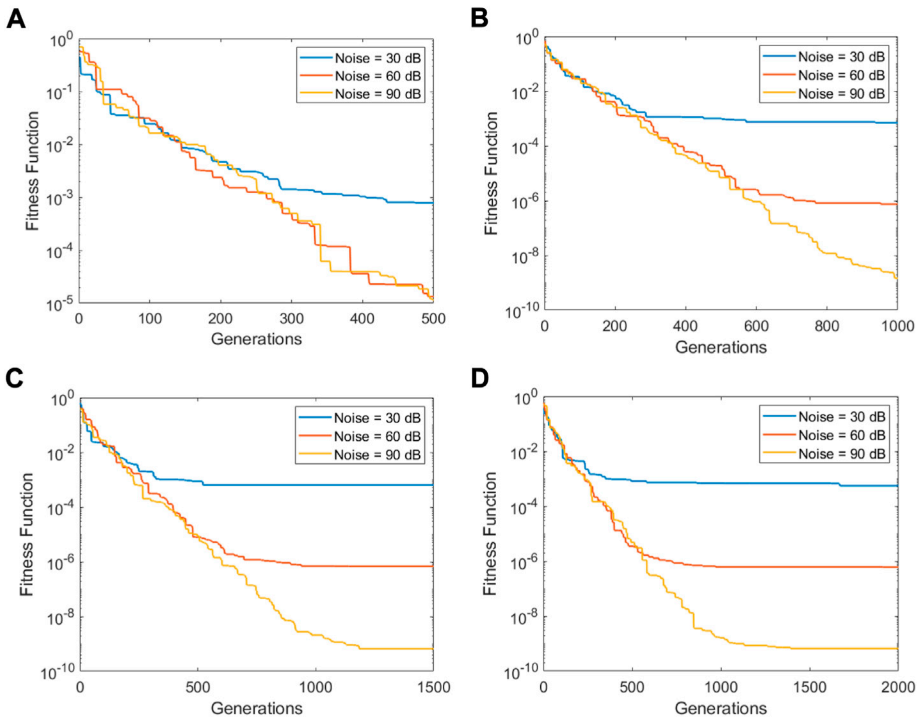

FIGURE 3
Convergence plots of Example 1: **(A)** G = 500, **(B)** G = 500, **(C)** G = 500, and **(D)** G = 500.

Ten parameters are taken under consideration in this problem. Five phase and five amplitude parameters that were taken are given below, while, f_1, f_3, f_5, f_7, and f_{11} are the frequencies with values 50 Hz, 150 Hz, 250 Hz, 350 Hz, and 550 Hz, respectively:

$$\boldsymbol{\zeta} = [a_1, a_2, a_3, a_4, a_5, c_1, c_2, c_3, c_4, c_5] = [1.50, 0.50, 0.20, 0.15, 0.10, 1.396, 1.047, 0.785, 0.628, 0.523]. \quad (12)$$

Example 2: The harmonic signal considered in the second simulation study is

$$h(t) = \begin{bmatrix} 1.2\sin(2\pi f_1 t + 1.309) + 0.8\sin(2\pi f_3 t + 0.959) + 0.2\sin(2\pi f_5 t + 0.785) \\ +0.18\sin(2\pi f_7 t + 0.698) + 0.1\sin(2\pi f_{11} t + 0.523) \end{bmatrix}. \quad (13)$$

The parameter-vector consisting of five amplitude and five phase parameters is

$$\boldsymbol{\zeta} = [a_1, a_2, a_3, a_4, a_5, c_1, c_2, c_3, c_4, c_5] = [1.20, 0.80, 0.20, 0.18, 0.10, 1.309, 0.959, 0.785, 0.698, 0.523]. \quad (14)$$

The results of Example 1 in terms of parameter estimates through the CSO along with the MSE value are given in Tables 1–4 for G = 500, 1,000, 1,500, and 2,000, respectively. While the respective results in the case of Example 2 are presented in Tables 5–8. The learning curves for Example 1 are given in Figure 2, while for Example 2, the convergence plots are provided in Figure 3. The results clearly indicate that the CSO gives a better accuracy for 90 dB SNR than it does for 60 dB and 30 dB. Moreover, the accuracy of the CSO for harmonics estimation increases by increasing the generation size.

4 Conclusion

This study exploits a swarm intelligence–based cuckoo search optimization, CSO, heuristic for parameter estimation of power system harmonics. The CSO accurately estimates the amplitude and phase parameters associated with the first, third, fifth, and eleventh harmonic components. Simulation studies conducted on the mean square error–based evaluation metric indicate that the accuracy of the CSO increases with an increase in the generation size, while increasing particle size has not shown a significant rise in the accuracy level. Moreover, the CSO has shown a robust performance in estimating the parameters of power system harmonics for different scenarios of additive white Gaussian noise.

Future studies may investigate the applying of the CSO algorithm for real-time harmonics estimation and for other engineering optimization problems (Phannil et al., 2018; Montoya et al., 2019; Beleiu et al., 2020; Yang et al., 2020; Chaudhary et al., 2021).

Data availability statement

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization: NC and MZ; methodology: NM, NC, and MZ; software: NM; validation: ZK, AK, MZ, and NC; resources: AK and CC; writing—original draft preparation: NM; writing—review and editing: NC, ZK, AK, and MZ; supervision: CC and NC; project administration: AM and AA; funding acquisition: AM and AA.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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