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An Amended Crow Search Algorithm for Hybrid Active Power Filter Design

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Abstract: Hybrid Active Power Filter (HAPF) imbibes the advantages of both passive and active power filters. These filters are considered one of the important technologies for mitigating harmonic pollution in electrical systems. Accurate estimation of filter parameters is a key component to reduce harmonic pollution effectively. In recent years, several optimization approaches have been reported to solve this estimation problem; still, this area is worthy of further investigation. This paper is a proposal for an estimator that can estimate the parameter of HAPF configuration accurately. For evolving this estimator, first, an objective function that mathematically embeds filter parameters and harmonic pollution is presented. For handling the optimization process, an Amended Crow Search Algorithm (ACSA) is proposed. ACSA employs a local search algorithm (in the form of a pattern search) for obtaining optimal results. The analysis of the estimation process is carried out on two HAPF configurations. Various analyses that include harmonic pollution statistical analysis along with fitness function value analysis reveal that the proposed algorithm acquires optimal results as compared with other recently published and reported algorithms. Further, the proposed filter configurations are tested with the existing filter. The results prove that the proposed filter shows promising results.

Keywords: power quality; filter; swarm intelligence; crow search algorithm; design; numerical optimization

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1. Introduction

Applications of non-linear loads have significantly increased power pollution by introducing harmonic pollution in the fundamental voltage and frequency signals. These contaminations directly affect power quality and, hence, can be considered major factors that can be taken care of while considering consumer satisfaction and comfort. Power quality issues are always considered for designing a foolproof grid, as these are related to services and devices. Power quality issues are major classifications and identifications of power quality events such as sag, swell, transient, and interruption. Mitigation technologies that involve the use of several important devices to tackle these events intelligently are also one of the major research areas of power quality.

However, in the modern context, harmonic mitigation is most important with the evolution of smart grids. With the existing diversity of consumer usage patterns of electronic devices and nonlinear loads, harmonics are inevitable in the systems. Sometimes, these harmonics are hazardous and can affect equipment health and create stability issues. Harmonics are characterized by the integer multiples of the fundamental frequency, i.e., for the third harmonic signal, the frequency will be 150 Hz for the fundamental frequency of 50 Hz. Likewise, if the frequency of the signal is not an integer multiple of the fundamental wave and if it is greater than the fundamental wave, then it is called an interharmonic signal, and if it is lower than the fundamental frequency, then it is called a subharmonic signal. The following reasons indicate the importance of mitigation technologies:

1. Since harmonic contamination is dependent on frequency, devising mitigation technologies for handling these issues becomes an important task for the designer and system operator, as eddy current losses, skin effect, and corona losses are direct functions of the frequency;
2. The presence of harmonics in the system reduces the operational efficiency of protecting devices, loads, and compensating capacitors. It badly affects the controlling devices that work on zero-crossing detection mechanisms;
3. In deregulated power scenario, the price of electricity is closely associated with the power quality. Often, power producers showcase this virtue of the delivered power to the customers. Hence, clean power can have a potential contribution to the earnings of the power-generating company.

Due to these mentioned reasons, special care is to be taken while dealing with harmonics in the system. For the last two decades, mitigation technologies have caught the attention of researchers due to their ability to deal with harmonic pollution. In power networks, these technologies have emerged in the form of filter designs. Filters can be segregated into three forms, namely, Passive Power Filters (PPF), Active Power Filters (APF), and Hybrid Active Power Filters (HAPFs). Comparative analysis of these filters leads us to the conclusion that due to the vulnerability of PPF toward the grid impedance and due to the capacity and cost issues, the usage of PPF and APF is limited. On the contrary, HAPFs are widely used because of the lower vulnerability of the filter toward grid impedance, low cost, and significantly enhanced performance in filtering [1].

Application of Optimization Algorithms for Designing Filters

Power grid impedance has a deteriorating effect on the performance of PPF; hence for this reason, the applicability of PPF is questioned in many applications. Although it possesses a very simple structure, easy implementation, and low-cost solution, the resonating effect of PPF with the power system is considered a major pitfall. Due to these issues, APF technologies are having an edge over PPF technologies. Moreover, recent research reported advocate hybrid configurations that combine the merits of both filters. Based on the following arguments authors are motivated to take up this research problem. In addition to that, for estimation of a powerful metaheuristic and its advanced version is an acute requirement.

Analog filter design was performed in reference [2]; this paper investigated the efficacy of metaheuristics for designing the analog filter circuit. A promising study with the Hierarchical Teaching Learning Based Optimization was conducted in reference [3]. Biswas et al. in [4] applied Differential Evolution and its advanced version L-SHADE. An improved teaching–learning-based optimization algorithm (HTLBO) has been applied for optimizing HAPF parameters. In addition to these studies, parameter estimation of the hybrid filter was performed with Particle Swarm Optimization, Differential Evolution Algorithm, and Bacterial Foraging Algorithm [5–7].

Large Scale Passive Harmonic Filters (LSPHFs) were designed with the help of a neural network and PSO approach. The authors optimized the cost of the filter, filter loss, and total harmonic distortion of currents and voltages at each bus simultaneously [5]. Similarly, the approach based on the orthogonal array technique and ant direction hybrid differential evolution algorithm (ADHDEOA) was developed for designing LSPHFs [6]. A similar approach based on Ant Colony Optimization (ACO) has been developed for estimating the parameters of HAPF [8]. An optimal design method for Passive Power Filters was proposed in the approach. The authors applied a modified BAT algorithm for solving multi-objective design problems of PPF design in reference [9]. Recently, the application of the Crow Search Algorithm (CSA) [10] has been explored with many engineering problems along with standard optimization problems [11–14]. A recently developed MPA-SCA algorithm has been employed for designing the filter for grid application [15]. These recent applications are suitable proof that indicates the capability of optimization algorithms for solving such design problems. Further, the application mentioned in [10,11] shows that CSA has the capability to solve electrical engineering design problems very efficiently. For the development of an effective optimization algorithm, we require an effective balance between exploration and exploitation. To maintain this balance, sometimes local search algorithms are employed. An effective mechanism based on local search has been showcased in reference [16] for improvement in Artificial Bee Colony Algorithm. Based on this discussion, in this paper, we propose a local search-based CSA named as Amended Crow Search Algorithm (ACSA). The following are the research objectives for this study:

1. To develop an optimization framework for parameter estimation of the configuration of two well-known hybrid filter configurations;
2. To develop an objective function that explicitly inculcates harmonic pollution in account for solving parameter estimation problem of Hybrid Active Power Filter;
3. To develop a framework based on the local search strategy derived from pattern search algorithm for the development of ACSA;
4. To evaluate the applicability of ACSA-HAPF designs based on different test cases and evaluation methods.

The remaining part of this paper is organized as follows: In Section 2, the problem formulation is discussed. In Section 3, the development of the ACSA is explained. In Section 4 numerical results of the application of the proposed variant on test benches are reported. Last but not least, all major findings are summarized and presented in the conclusion section.

2. Problem Formulation

Active Power filter plays a vital role in harmonic mitigation as it injects voltage harmonic at the terminal. This injected voltage harmonic is proportional to the harmonic components of the supply current. Hence, a linear relationship between these two can be characterized as $v_{af} = ki_{sh}$. This equation contains a proportionality constant (k) that is filter gain. At fundamental frequency, this provides zero impedance. From here, it is implied that active filter components are virtual harmonic resistors that provide zero impedance at fundamental frequency [15]. This works enumerates the optimization of the three best parameters, i.e., k, x_l, and x_c, with the structure consisting of source and load as non-linearities. Source harmonic voltage and current non-linearities are accounted for in v_{sh} and i_{sh}, respectively, and those of the loads are in v_{lh} & i_{lh}.

Utility supply voltage and nonlinear load are expressed by the Thevenin voltage source and harmonic current source, respectively and are presented as follows:

$$v_s(t) = \sum_h v_{sh}(t) \tag{1}$$

$$i_l(t) = \sum_h i_{lh}(t) \tag{2}$$

The source impedance of the h-th harmonics is

$$z_{sh} = r_{sh} + jx_{sh} \tag{3}$$

The load impedance of the h-th harmonics is

$$z_{lh} = r_{lh} + jx_{lh} \tag{4}$$

The load admittance of the circuit is

$$y_{lh} = g_{lh} - jb_{lh} \tag{5}$$

At higher level harmonic, '$h \geq 2$' after analyzing the equivalent circuit of Figure 1 for the series realization of the filter topology. The following relationship is identified between the voltage and current of the load and supply end, respectively.

$$i_{sh} = \frac{a + jb}{c + jd} \tag{6}$$

$$v_{lh} = \frac{e + jf}{c + jd} \tag{7}$$

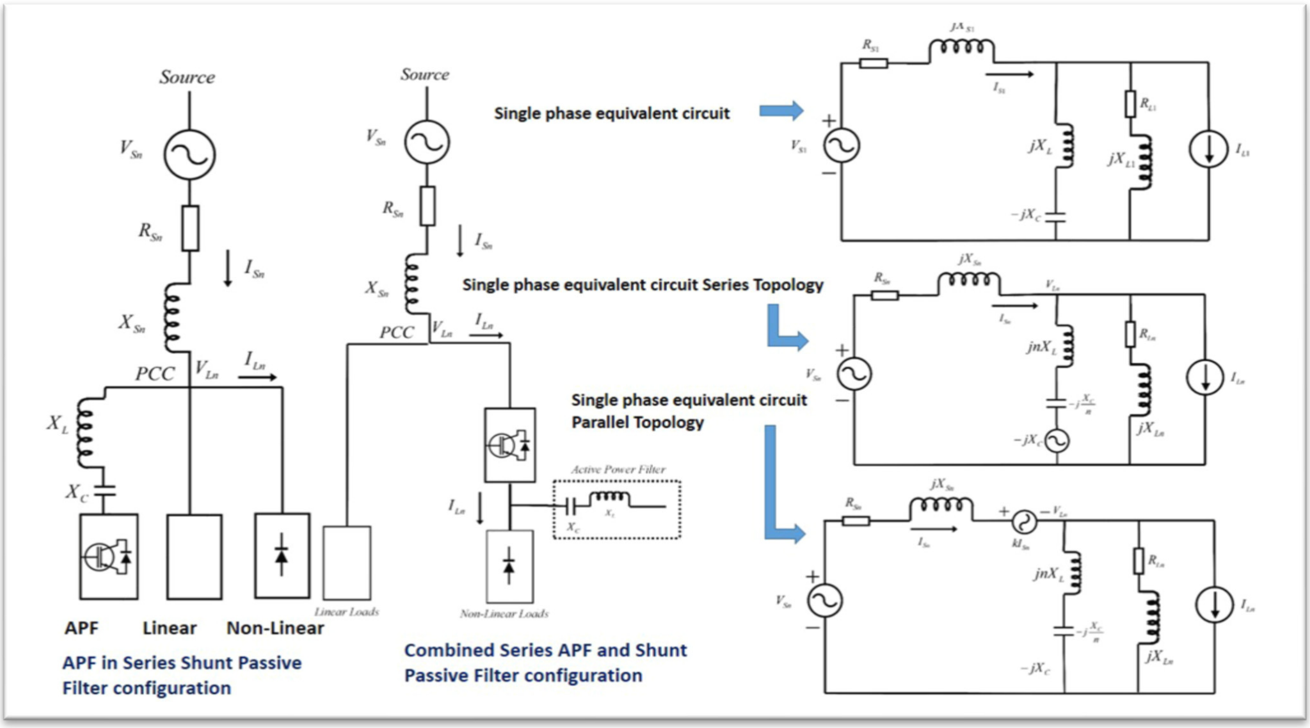

Figure 1. Filter topologies considered for parameter estimation.

At higher level harmonic, i.e., '$h \geq 2$' after analyzing the equivalent circuit of Figure 1 for the series realization of the filter topology. The following relationship is identified between the voltage and current of the load and supply end, respectively.

$$v_{lh} = \frac{e + jf}{c + jd'} \tag{8}$$

$$v_{lh} = \frac{e + jf'}{c + jd'} \tag{9}$$

where

$$a = v_{sh} r_{lh} - i_{lh} x_{lh} \left(h_{xl} - \frac{x_c}{h} \right) \tag{10}$$

$$b = v_{sh} \left(x_{lh} + h x_l - \frac{x_c}{h} \right) + i_{lh} r_{lh} \left(h_{xL} - \frac{x_c}{h} \right) \tag{11}$$

$$c = \beta_{tlh} + k r_{lh} - (x_{lh} + x_{sh}) \left(h_{xl} - \frac{x_c}{h} \right) \tag{12}$$

$$\beta_{tlh} = r_{sh} r_{lh} - x_{sh} x_{lh} \tag{13}$$

$$d = x_{tlh} + k x_{lh} - (r_{lh} + r_{sh})\left(h_{xl} - \frac{x_c}{h}\right) \tag{14}$$

$$x_{tlh} = r_{lh} x_{sh} - r_{sh} x_{lh} \tag{15}$$

$$e = v_{sh}\left[k r_{lh} - x_{lh}\left(h x_l - \frac{x_c}{h}\right)\right] + i_{lh} x_{tlh}\left(h_{xl} - \frac{x_c}{h}\right) \tag{16}$$

$$f = v_{sh}\left[k x_{lh} + r_{lh}\left(h x_l - \frac{x_c}{h}\right)\right] - i_{lh} \beta_{tlh}\left(h_{xl} - \frac{x_c}{h}\right) \tag{17}$$

$$d' = x_{tlh} + k x_{lh} + (k + r_{lh} + r_{sh})\left(h_{Xxl} - \frac{x_c}{h}\right) \tag{18}$$

$$f' = v_{sh}\left[k x_{lh} + (k + r_{lh})\left(h x_l - \frac{x_c}{h}\right)\right] - i_{lh} \beta_{tlh}\left(h_{xl} - \frac{x_c}{h}\right) \tag{19}$$

It can be observed from the equations that compensated utility supply harmonic current is inverse to gain k. Usually, in active filter configuration, this phenomenon is identified as obstructing resistor that suppresses the harmonic current generated by the nonlinearity of the source. Consequently, for harmonic current, this acts as a damping resistor. This diminishes the resonance between the shunt and the passive filter and source impedance. The following mathematical expression showcases the compensated load displacement factor, and pf represents compensated load power factor.

$$dpf = \frac{p_{l1}}{v_{l1} i_{s1}} = \frac{g_{l1} v_{l1}}{i_{s1}} \tag{20}$$

$$pf = \frac{p_l}{v_l i_s} = \frac{g_{l1} v_{l1*} v_{l1} + \sum_{h \geq 2} g_{lh} v_{lh}^2}{\sqrt{\left(i_{s1}^2 + \sum_{h \geq 2} i_{sh}^2\right)\left(v_{l1}^2 + \sum_{h \geq 2} v_{lh}^2\right)}} \tag{21}$$

In subscript '1' the transmission loss formula is expressed as

$$p_{loss} = i_{s1}^2 r_{s1} + \sum_{h \geq 2} i_{sh}^2 r_{sh} \tag{22}$$

Transmission efficiency can be calculated by

$$\eta = \frac{p_l}{p_l + i_{s1}^2 r_{s1} + \sum_{h \geq 2} i_{sh}^2 r_{sh}} \tag{23}$$

Further, the expression for the voltage (compensated) and utility supply current (compensated) can be represented by following expressions:

$$Vthd = \frac{\sqrt{\sum_{h \geq 2} v_{lh}^2}}{v_{l1}} \tag{24}$$

$$Ithd = \frac{\sqrt{\sum_{h \geq 2} i_{lh}^2}}{i_{s1}} \tag{25}$$

Finally, we can calculate the harmonic pollution through the below formula, as follows:

$$hp = \sqrt{Vthd^2 + Ithd^2} \tag{26}$$

Fitness Function for Filter Design

To minimize the harmonic pollution, three parameters are considered for the optimization process: k, x_c, x_l for HAPF design. The range of these parameters can be manifested as follows:

$$\left\{ \begin{array}{l} 0 \leq k \leq 20 \\ 0 \leq x_c \leq 20 \\ 0 \leq x_l \leq 1 \end{array} \right\} \tag{27}$$

It is worth mentioning that these three parameters, namely, filter gain, composing inductance, and capacitance values, have an impact on filter performance. While designing the filter, the guidelines of IEEE Standard 519-2014 [17] are adhered to. These are based on the system voltage level and system short circuit ratio. The allowable ranges for Vthd and Ithd are respectively as follows:

$$\left\{ \begin{array}{l} Vthd \leq Vthd_{\mathrm{lim}} \\ Ithd \leq Ithd_{\mathrm{lim}} \end{array} \right\} \tag{28}$$

where Equation (28) defines the limitation as $Vthd_{\mathrm{lim}}$ and similarly, the limitation of the current can be designated as $Ithd_{\mathrm{lim}}$. These limitations are strictly adhering to the guidelines of IEEE 519-2014. On the basis of these representations, i.e., (Equations (27) and (28)), the following expression is taken as an objective function:

$$hp_{app} = abs(Vthd_{\mathrm{lim}} - Vthd) + abs(Ithd_{\mathrm{lim}} - Ithd) \tag{29}$$

While solving this optimization process, the individual harmonic is optimized with the help of the following expression:

$$\text{Maximize '}hp_{app}\text{' subject to } pf = pf_{goal} \pm \varepsilon \tag{30}$$

Different topologies, along with all four cases, are showcased in Figure 1.

3. Amended Crow Search Algorithm (ACSA)

Recently, the Crow Search Algorithm has caught the attention of researchers due to its capabilities to solve complex optimization problems. This algorithm possesses a highly adaptive and user-friendly structure that helps users experiment with the algorithm. Recently, some interesting development has been exhibited in the improvement of the convergence of the algorithm. One experiment reported sinusoidal bridging in position and memory update equation of the CSA. The developed variant has been tested on different benches of signal for estimating the harmonics components of the electrical signal [11]. An improved version of this algorithm has been implemented for feature selection and optimization problems [12]. Further, the application of the algorithm has been exhibited in hyperparameter tunning of grey models and other supervised architecture of power quality event classification [13,14].

An Amended Crow Search Algorithm is proposed with a modified bridging parameter in the position of the update expression. To understand the implementation of the proposed bridging scheme, let us consider a few encoding steps of the Crow Search Algorithm:

Step1. All the parameters of this algorithm are initialized within the acceptable values, such as a maximum number of iterations, search agent count, awareness probability (AP), and Flight Length (FL). In this implementation, the adaptive tuning of the AP and FL has not been explored;

Step2. In the second step, the position of the crow, along with memory, is initialized in the search space dimension (d). Every crow corresponds to a new position by using the following two rules:

Crow2 does not know that Crow1 is following it; as a result, Crow2 will approach the nest of Crow1. This new position of Crow1 (the follower Crow) is governed by the following expression:

$$P^{(1,iter+1)} = P^{(1.iter)} + r1 \times fl^{(1,iter)} \times (m^{(1,iter)} - P^{(1,iter)})$$

Crow2 knows that Crow1 is following it; as a result, Crow2 will try to fool Crow1 and will approach some other place. This new position of Crow1 (the follower Crow) is governed by the following expression:

$P^{(1.iter+1)} = P^{(1.iter)} + r1 \times fl^{(1,iter)} \times (m^{(1,iter)} - P^{(1,iter)})$/Random Position (if the random number is greater than awareness probability, it takes a random position).

Case 2 is based on the probability distribution, which is designated with the help of the flight length parameter.

From both expressions, we can see that the proposed position update is heavily dependent on tuning parameters FL and AP along with memory matrices of Crow. Hence, on the basis of this discussion, we introduce a local search loop based on the Pattern Search Algorithm that employs a local search up to five iterations in Phase 2, i.e., when a crow is misled by another crow.

Pattern Search for Amended Search

A patent search is a direct search method that comes from the family of derivative-free search algorithms and numerical optimization methods. For implementing PS in ACSA, we follow simple steps:

1. Evaluation of the position of the crow in stage 2, stack the position values for Filter Gain and other parameters of HAPF, and also save the fitness values of the corresponding positions;
2. Parameters are appended in two diverse directions by using the gradient rule. For calculating gradients, fitness evaluation of the successive runs, along with the change in parameter values, are observed;
3. After updating the parameters by gradient rule, the fitness function is evaluated; if the optimal solution arrives, we keep the solution; otherwise, we reject the solution and keep the previous one. This process is iterated in the inner loop of the phase five times (Algorithm 1).

Algorithm 1. The iterative Process of Amended Crow Search Algorithm

1. Start the local loop counter;
2. Calculate the change in the parameters of HAPF with the help of the Gradient Rule and append the HAPF parameters in two directions;
3. Apply the Sequential Optimization Process and choose Filter gain first and then, the remaining parameters of the filters (Inductive and Capacitive Reactance);
4. Evaluate the fitness function with every change and accept and Reject the change as per the condition of optimality;
5. Terminate the process after exhausting the iterative procedure.

Flow of the algorithm has been depicted in Figure 2, where a pattern of the search algorithm has been showcased. Here, a noteworthy observation has to be made since the CSA position update is based on the probability, and it also depends upon the values of the awareness probability and flight length; hence, there is a greater chance for stagnation in local minima.

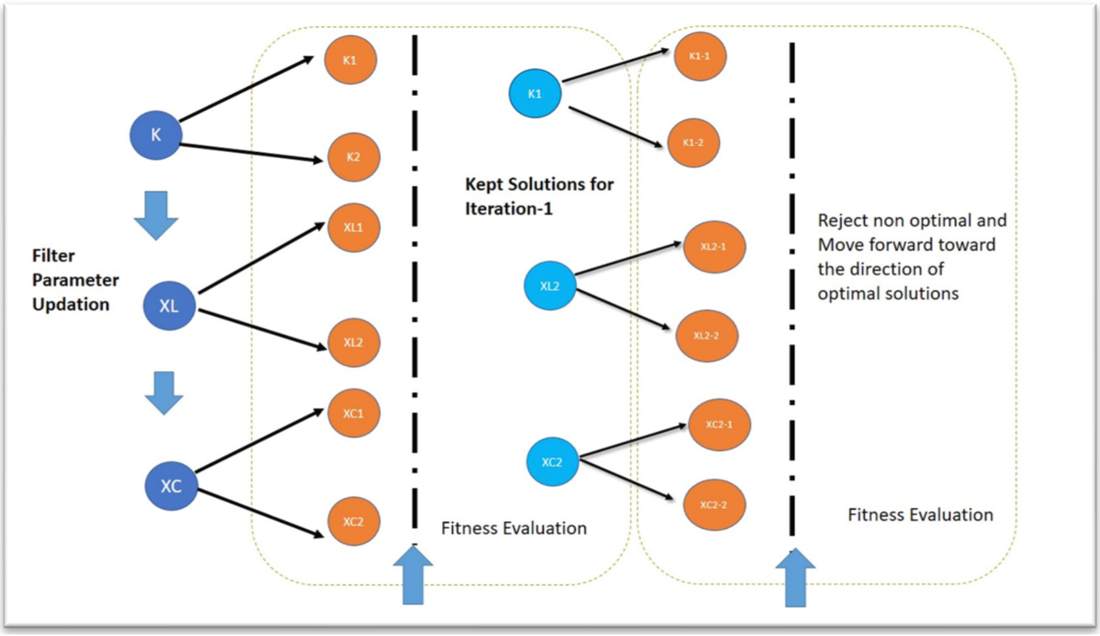

Figure 2. Implementation of Local Search in Amended Crow Search Algorithm.

This local search algorithm helps the algorithm to find out the search space effectively and provides a boosted convergence toward near-to-global optima. This algorithm helps the existing CSA framework avoid entrapment into local minima.

4. Results Analysis

To evaluate the impact of the proposed modifications on the performance of the algorithm, a harmonic pollution-based analysis has been conducted. For these, five distinct algorithms (GWO, WOA, HHO, CSA, and SCA) have been selected, and filter parameter estimation has been conducted. The following are the major conclusions obtained from this analysis:

a. The optimization routine has been repeated 30 times, and values of the harmonic pollution parameter have been calculated for every algorithm. These values are stacked in one array, and the mean, maximum, minimum, and standard deviation of these values are obtained;

b. Further, from these values (depicted in Table 1), the efficacy of the proposed algorithm in obtaining accurate parameters of the filter can be judged. It is found that the algorithm finds a suitable bridging between the exploration and exploitation phases with the modified bridging mechanism. The values of HP are aligned with the previously published results. Moreover, it has been observed that some of the algorithms, namely, SCA and WOA, exhibit high values of standard deviation in the parameter estimation process;

c. High values of standard deviation show the inability of the algorithm to solve the estimation process accurately. With these high values, it can be concluded that the filter design problem is sensitive toward the algorithm mechanism and possess a highly nonlinear nature;

d. Inspecting the values from Case-1 to Case-8, the authors observed that the variation between mean and maximum values is smaller. This observation indicates that the proposed algorithm ACSA is very effective and accurate for solving the design problem. On the other hand, SCA, WOA, and other algorithms give inaccurate results.

Table 1. Analysis of Harmonic Pollution for Amended Crow Search Algorithm.

Algorithm	Case-1				Algorithm	Case-5			
	Maximum	Minimum	STD	Mean		Maximum	Minimum	STD	Mean
SCA [18]	1.448856	0.236311	0.530824	0.664196	SCA	1.538961	0.227382	0.516208	0.539479
GWO [19]	0.493408	0.235755	0.078921	0.262403	GWO	0.459376	0.227343	0.095974	0.280593
WOA [20]	0.445305	0.235773	0.069155	0.297032	WOA	0.527085	0.227318	0.068884	0.266792
CSA [10]	0.493042	0.235827	0.101241	0.429355	CSA	0.458836	0.227334	0.097015	0.404364
ACSA	0.493027	0.235812	0.120879	0.407646	ACSA	0.458821	0.22741	0.051678	0.446843
HHO [21]	1.448856	0.236311	0.530824	0.664196	HHO	1.538961	0.227382	0.516208	0.539479
Algorithm	Case-2				Algorithm	Case-6			
	Maximum	Minimum	STD	Mean		Maximum	Minimum	STD	Mean
SCA [18]	2.781007	2.732259	0.017291	2.750023	SCA	2.994494	2.70499	0.062621	2.771687
GWO [19]	2.76437	2.741872	0.006483	2.751549	GWO	2.953492	2.740731	0.070926	2.784176
WOA [20]	8.750862	2.671969	1.339977	3.060029	WOA	2.853276	2.69237	0.038325	2.771023
CSA [10]	2.9529	2.748966	0.081267	2.907062	CSA	2.949347	2.684705	8.63×10^{-2}	2.907657
ACSA	2.952703	2.690854	0.10314	2.887101	ACSA	2.949586	2.751122	8.56×10^{-2}	2.900906
HHO [21]	2.781007	2.732259	0.017291	2.750023	HHO	2.994494	2.70499	0.062621	2.771687
Algorithm	Case-3				Algorithm	Case-7			
	Maximum	Minimum	STD	Mean		Maximum	Minimum	STD	Mean
SCA [18]	5.928603	5.677806	0.080314	5.743679	SCA	5.916098	5.666813	0.093673	5.749411
GWO [19]	38.69551	3.934576	7.388896	7.357326	GWO	41.90414	5.571101	11.12974	10.8523
WOA [20]	41.00736	5.543984	12.3609	11.70034	WOA	36.96037	1.93019	9.824782	10.00604
CSA [10]	5.888007	5.887952	1.66×10^{-5}	5.887969	CSA	5.888667	5.672008	0.060736	5.868386
ACSA	5.888005	5.887955	1.54×10^{-5}	5.887974	ACSA	5.888006	5.887948	1.63×10^{-5}	5.887967
HHO [21]	5.928603	5.677806	0.080314	5.743679	HHO	5.916098	5.666813	0.093673	5.749411
Algorithm	Case-4				Algorithm	Case-8			
	Maximum	Minimum	STD	Mean		Maximum	Minimum	STD	Mean
SCA [18]	6.561753	6.343699	0.06756	6.405037	SCA	496.3862	2.793472	109.2909	32.58135
GWO [19]	33.29548	2.377242	9.731524	11.46938	GWO	29.16094	6.493424	8.009502	12.17118
WOA [20]	35.80203	2.901182	8.878828	11.23005	WOA	27.04237	1.254234	5.913472	9.749383
CSA [10]	80.27465	5.967958	17.49414	17.83506	CSA	45.31236	4.056495	8.817461	10.52432
ACSA	40.76756	6.25924	10.17947	14.54976	ACSA	29.71758	6.492036	$5.82 \times 10^{+0}$	10.60139
HHO [21]	6.561753	6.343699	0.06756	6.405037	HHO	496.3862	2.793472	109.2909	32.58135

Further, for evaluation of the capabilities of ACSA, an analysis of fitness function values obtained from the optimization run. As it is a known fact that metaheuristic-based algorithms give different answers in every optimization run due to randomness in nature. Hence, the reporting of the results should be in terms of statistical parameter calculations. These parameters are known as the mean, maximum, minimum, and standard deviation of the fitness values obtained from the optimization runs. Here, Table 2 shows the statistical attributes obtained from the optimization runs.

Table 2. Analysis of Fitness Function Values for Amended Crow Search Algorithm.

Cases	Parameters	SCA [18]	GWO [19]	WOA [20]	CSA [10]	HHO [21]	ACSA
Case-1	Mean	−9.10328	−9.33796	−9.59058	−9.40278	−9.25919	−9.63677
	SD	0.642582	0.108618	0.095012	0.136469	0.305745	0.165506
	Max	−8.14792	−9.32026	−9.386	−9.32077	−8.48741	−9.39076
	Min	−9.67366	−9.6748	−9.67504	−9.67503	−9.67428	−9.67504
Case-2	Mean	−6.44891	−6.78382	−1.38319	−6.50687	−6.51822	−6.54087
	SD	0.261048	0.000688	23.86347	0.101771	0.213466	0.138216
	Max	−6.20066	−6.78255	100	−6.46297	−5.92163	−6.46302
	Min	−6.77524	−6.78487	−6.78502	−6.78479	−6.78151	−6.78499
Case-3	Mean	−1.89393	8.305361	23.61121	−1.76545	8.464069	−1.76544
	SD	0.109313	31.35932	45.24906	3.73×10^{-5}	31.30597	2.91×10^{-5}
	Max	−1.67799	100	100	−1.76538	100	−1.76538
	Min	−2.05023	−2.08313	−2.08387	−1.76549	−1.99496	−1.76548
Case-4	Mean	−0.89175	−0.13287	0.359678	0.85779	0.556368	0.612018
	SD	0.147984	1.052616	0.917454	0.437766	0.799542	0.766013
	Max	−0.44186	1	1	1	1	1
	Min	−1.07148	−1.10087	−1.0892	−0.4428	−1.00297	−1.10185
Case-5	Mean	−9.23289	−9.60963	−9.63201	−9.44075	−9.2848	−9.3846
	SD	0.620599	0.135475	0.095022	0.130066	0.261343	0.071097
	Max	−8.03216	−9.3664	−9.27301	−9.36797	−8.66788	−9.36797
	Min	−9.66455	−9.68655	−9.68668	−9.68667	−9.66196	−9.68636
Case-6	Mean	−6.59211	−6.74522	−6.67754	−6.53541	−6.52537	−6.55596
	SD	0.235935	0.109231	0.189649	0.096793	0.203477	0.121008
	Max	−6.14447	−6.49176	−6.16353	−6.49218	−5.91236	−6.49218
	Min	−6.7822	−6.79107	−6.79132	−6.79124	−6.79132	−6.79132
Case-7	Mean	−1.91137	33.78636	23.60986	−1.79384	23.78867	−1.76546
	SD	0.129985	49.84994	45.25007	0.088304	45.14408	3.38×10^{-5}
	Max	−1.6719	100	100	−1.76441	100	−1.76535
	Min	−2.04358	−2.07982	−2.08432	−2.08486	−2.06681	−1.7655
Case-8	Mean	0.052851	0.276124	0.673487	0.788545	0.915925	0.422099
	SD	0.845179	0.910051	0.683218	0.574427	0.375996	0.835854
	Max	1	1	1	1	1	1
	Min	−0.81515	−0.85589	−0.85286	−0.85916	−0.6815	−0.85911

It can be seen in Table 2 that ACSA showcases excellent optimization virtues as the fitness values obtained during the optimization process are on par with other optimization algorithms. Hence, it can be seen from the results that the proposed modifications are meaningful and yield better results in terms of the accuracy of the optimization.

Apart from the fitness function value analysis and harmonic pollution analysis, THD analysis is also required for judging the efficacy of the filter. A similar analysis has been conducted by us in our previously reported approach. Hence, we compare the THD of the proposed filter with other filters proposed in reference. Results are shown in Table 3.

Table 3. The analysis; the following points are concluded from this analysis.

Series	ITHD (%)		VTHD (%)		Parallel	ITHD (%)		VTHD (%)	
	Ref [15]	Proposed	Ref [15]	Proposed		Ref [15]	Proposed	Ref [15]	Proposed
Toplogy-1	0.12497	**0.1248**	0.19999	**0.198**	Toplogy-1	0.12044	**0.12**	0.19284	**0.1895**
Topology-2	2.67705	**2.651**	0.544	**0.543**	Topology-2	2.7084	**2.707**	0.50027	**0.5001**
Topology-3	4.6085	**4.595**	3.30646	**3.2356**	Topology-3	4.6155	**4.593**	3.3118762	**3.3054**
Topology-4	4.9987	**4.8896**	3.89803	**3.6897**	Topology-4	4.9869	**4.963**	4.1404734	**4.13024**

It is observed that THD values of voltage are higher for series Topology-3 and 4, and corresponding values of current THDs are also comparatively high. As discussed in our previous work, since all these values were in the acceptable range (below 5%), the results may be accepted for implementation [17]. Furthermore, the proposed implementation yields a lower value of THD. Hence, it is proved that the proposed implemented filter is able to deal with odd harmonics more efficiently.

Further, investigating the results of parallel topology, THD values of voltage and currents are high for Topology-3 and 4. It is also worth mentioning that these values are lower in the case of proposed implementation. These values are highlighted in boldface.

Here, the THD has been computed in the presence of [5, 7, 11, and 13th] harmonic contamination. However, the optimal THD values of the proposed implementation indicate that the proposed modification in crow search is useful, and the filter is successful for all evaluated cases. Further, the visualization of the results has been presented in Figure 3 (for ITHD) and Figure 4 (for VTHD).

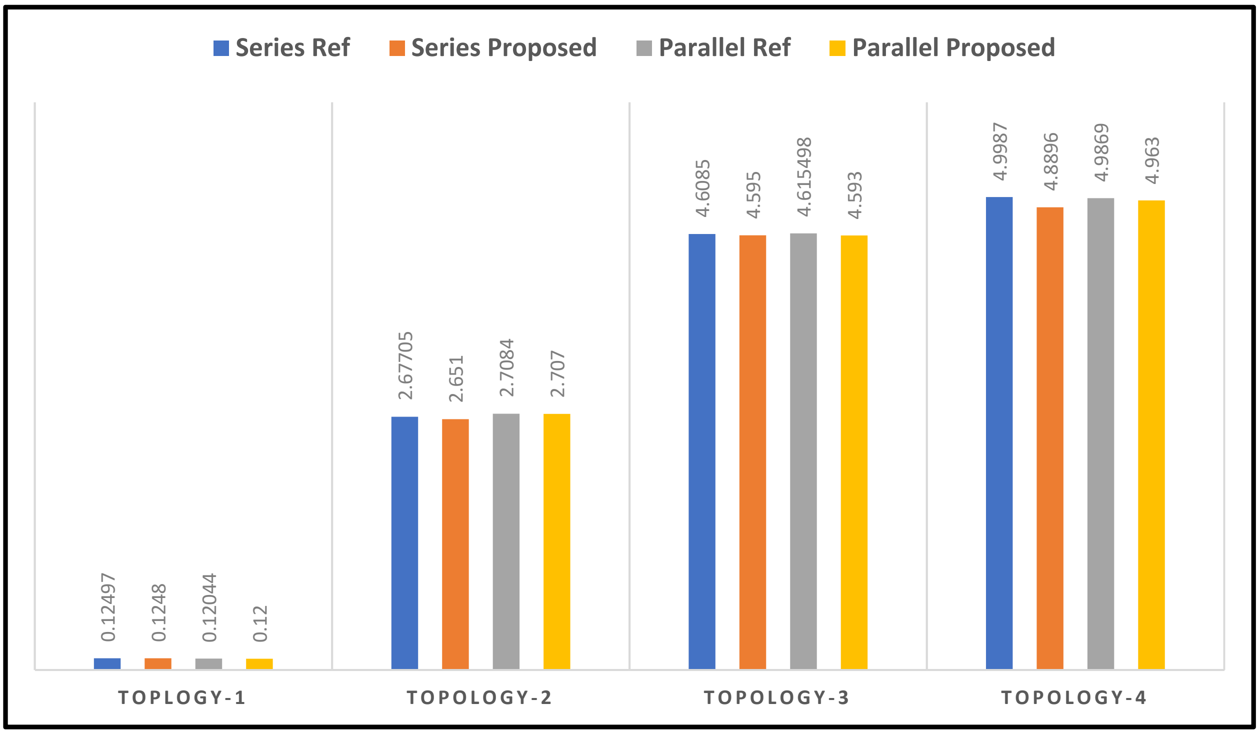

Figure 3. ITHD Comparison with proposed Filter.

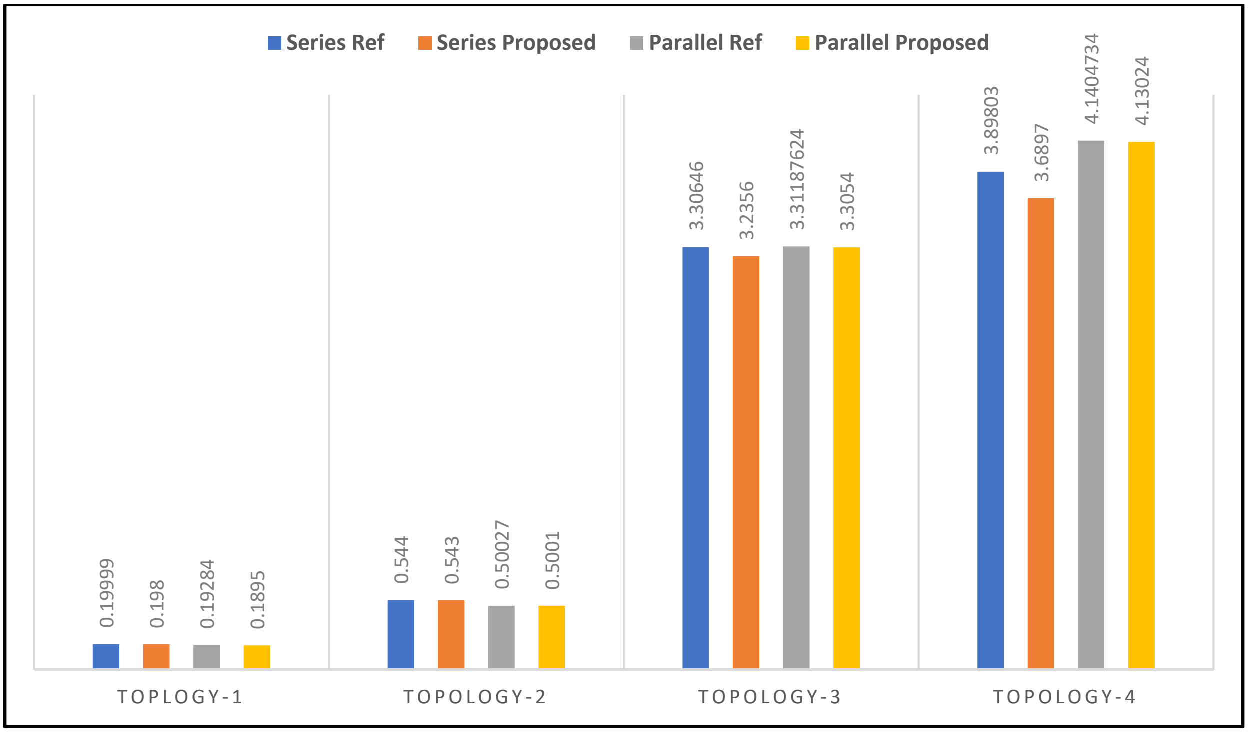

Figure 4. VTHD comparison with proposed filter.

5. Conclusions

This paper has showcased an application of a local search algorithm for the accurate estimation of HAPF parameters. Series and Parallel topologies are considered for this work. The objective of reduction in harmonic pollution through both topologies has been achieved. It has been observed that the optimization performance of the proposed ACSA is satisfactory when compared with some recent nature-inspired algorithms and other published approaches.

Following are some noteworthy observations:

1. The proposed HAPF design is based on the explicit involvement of filter parameters for achieving minimum values of an objective function that is an indicator of signal health. A fair comparison has been executed between some contemporary optimizers for solving this optimization problem;
2. It has been observed that the proposed design exhibits satisfactory performance in the estimation of components of HAPF. This conclusion is based on the optimal values obtained by ACSA for error in the objective function and HP values;
3. The efficacy of this design has been validated by various tests, significance analysis, and statistical calculations. These are, namely, statistical attribute analysis and comparison of filter performance with the help of THD analysis of the existing proposed filter of (MPASCA). All these analyses indicate that there are positive implications for proposed modifications in CSA.

It will be interesting to develop a hybrid version of ACSA and a memetic version of ACSA to solve this challenging problem.

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