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Hybrid Weighted Least Square Multi-Verse Optimizer (WLS–MVO) Framework for Real-Time Estimation of Harmonics in Non-Linear Loads

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Abstract: The electric power quality has become a serious concern for electric utilities and end users owing to its undesirable effects on system capabilities and performance. Harmonic levels on power systems have been pronounced to a greater extent with the continuous growth in the application of solid-state and reactive power compensatory devices. Harmonics are the key constituents that are mainly responsible for power quality deterioration. Power system harmonics need to be correctly estimated and filtered to increase power quality. This research work focuses on accurate estimation of power system harmonics with the proposed hybrid weighted least-square multi-verse optimizer (WLS–MVO) based framework. Multi-verse optimizer replicates the phenomenon of the formation of new universes as described by multi-verse theory to solve complex real-world optimization problems. The proposed WLS–MVO framework is tested and validated by estimating the harmonics present in multiple test signals with different noise levels. Amplitudes and phases of harmonics present in the polluted signal were estimated, and the framework computational time was compared with the previously developed technique's results which are reported in the literature. There was 80% reduction in computational time and 82% improvement in terms of accuracy in estimating harmonics using WLS–MVO as compared to previously developed techniques. The performance of the developed framework is further validated by estimating the harmonics present in the real-time voltage and current waveforms obtained from axial flux permanent magnet generator (AFPMSG), uninterruptible power supply (UPS), and light-emitting diode (LED). The purposed technique technique outperforms the already-developed techniques, in terms of accuracy and computational time.

Keywords: multi-verse optimizer; weighted least square; harmonics estimation; power quality; artificial intelligence

Citation: Haseeb, A.; Waleed, U.; Ashraf, M.M.; Siddiq, F.; Rafiq, M.; Shafique, M. Hybrid Weighted Least Square Multi-Verse Optimizer (WLS–MVO) Framework for Real-Time Estimation of Harmonics in Non-Linear Loads. *Energies* **2023**, *16*, 609. https://doi.org/10.3390/en16020609

Academic Editor: Alon Kuperman

Received: 15 December 2022
Revised: 29 December 2022
Accepted: 1 January 2023
Published: 4 January 2023

1. Introduction

Electric power quality has become a serious concern for electric utilities and end users owing to its undesirable effects on system capabilities and performance [1]. Harmonic levels in power systems have been pronounced to a greater extent with the inclusion of power electronic devices like variable frequency drives (VFDs), reactive power compensatory devices on transmission and distribution networks, and incorporation of distributed generators (DG's) in the modern smart grid paradigm. Power quality issues involve the deviation and harmonic distortion in voltage and current waveforms, sag, swell, and transients [2,3]. These issues result in decreased efficiency of equipment, increased corona loss, more eddy current losses, and increased skin effect, due to their direct relationship with the frequency of the power system [4]. Moreover, the presence of unfiltered harmonics in the power system may result in the failure of transformers, and motors, overloading of neutral conductors, transformer overheating, and malfunctioning of protective devices, relays, and circuit breakers [5]. Harmonics are also responsible for power capacitor explosions in power networks and industries [6]. Researchers have been developing and introducing new techniques to mitigate and rectify the adverse effects of these power quality problems on the power grid [7–9]. To design efficient filters in order to mitigate the adverse effects of harmonics in the power waveforms, these harmonics are required to be accurately measured and estimated. Bashian et al. proposed a Taylor Kalman filter (TKF) and tuned whitening-based TKF (TW-TKF) to filter the harmonics present in power system and also to mitigate abrupt changes in amplitudes and phases of AC current and voltage of AC signals expected to occur frequently in power grids [10–12]. Harmonic estimation is the first and foremost step that forms the basis for harmonic elimination. Harmonic estimation is the complex, non-linear and multimodal optimization problem that involves determination and estimation of harmonics, sub harmonics, and inter harmonics present in the voltage and current signals [4]. Several methods and techniques have been proposed and deployed to properly estimate the harmonic contents in voltage and current signals.

Mathematical techniques that are traditionally being employed for investigating harmonics in signals include DFT (discrete Fourier transform) and FFT (fast Fourier transform) [13]. The limitations of these traditional methods have been reported in the literature which include picket-fence effect and leakage effect, requires the use of more robust techniques which exclude these limitations [14]. Statistical and stochastic methods including least mean square (LMS), weighted least square (WLS), recursive least square (RLS), absolute least value (ALV), and Kalman filter (KF) [15–18] have also been proposed and deployed to accurately estimate the harmonics.

Recent trend towards metaheuristic algorithms is receiving immense attention to accurately estimate harmonics in the power waveforms at high computational speed [19]. Their superiority over the deterministic and mathematical approaches is evident in the literature. A hybrid technique by merging firefly algorithm with least square method (FF-LS) for the proper estimation of phases and amplitudes of harmonics present in the power system is proposed in [20]. The authors presented modified–artificial bee colony algorithm (M-ABC) for the correct estimation of distribution side harmonics. Ashraf et al. proposed [21] a hybrid technique comprises of water cycle algorithm (WCA) and least square (LS) method [1] to correctly estimate the power harmonics of real-time voltage waveform obtained from axial flux permanent magnet synchronous generator (AFPMSG). Waqas et al. utilized the quantum computation-inspired particle swarm optimization (PSO) algorithm along with the least square hybrid approach for real-time estimation of harmonics present in time-varying and noisy power signals [22]. In [23], authors proposed a hybrid technique based on PSO and GA along with the famous statistical technique, Kalman Filter (KF), for harmonic estimation of dynamic and time varying signals.

In this paper, a hybrid weighted least square multi-verse optimizer (WLS–MVO) framework was proposed and developed for accurate estimation of harmonics. The said framework was implemented on standard test signals and real-time voltage and current waveforms obtained from AFPMSG, UPS, and LED. The results were compared with the previously developed techniques in literature, to ensure the competency and effectiveness of the proposed framework.

The key contributions to this paper are mentioned below:

1. The multi-verse optimizer is one of the latest optimization techniques and it has not been investigated so far for the estimation of harmonics. A hybrid (WLS–MVO) framework is proposed for the robust estimation of harmonics for standard integer, inter-, and subharmonics test signals with random noise;
2. The hybrid (WLS–MVO) framework is further tested on real-time voltage and current waveforms obtained from AFPMSG and different power electronics-based loads for the extraction and estimation of harmonics;

3. The performance of the said framework is validated and tested using some statistical tests performed on SPSS (Statistical Package for the Social Sciences).

The rest of this paper is organized as follows: Section 2 explains the mathematical formulation of harmonic estimation problem and the proposed research methodology is discussed in Section 3. Simulation results are discussed in Section 4. Section 5 discusses the statistical significance of the results. Finally, Section 6 concludes this paper.

2. Mathematical Formulation of Harmonics Estimation Problem

The harmonics present in the power signal model require the estimation of two constituent components: linear estimation of amplitudes and nonlinear estimation of phases. Harmonic estimation of the power signal is a complex problem because of the time-varying nature of power signals. Hence, there is a dire requirement for a capable and effective algorithm for its solution. Any signal can be written as the aggregation of the sum of sine and cosine functions with multiple frequencies, it can be written as:

$$Sig(t) = \sum_{n=1}^{N} K_n \sin(\omega_n t + \varphi_n) + K_{DC} \exp(-\gamma_{DC} t) \tag{1}$$

where n is the harmonic order, K_n is the amplitude of harmonics present in the signal, ω_n being the angular frequency of harmonics of higher order, φ_n is the phase angle of harmonics. The term $K_{DC} \exp(-\gamma_{DC} t)$ shows the additive DC decaying offset present in power signals. Moreover, ω_n is given by:

$$\omega_n = 2\pi f_1 \times n_t \tag{2}$$

There is always a possibility of the power signal being corrupted with the addition of noise n_t. Hence, the realistic signal can be modeled with the addition of noise given by:

$$Sig(t) = \sum_{n=1}^{N} K_n \sin(\omega_n t + \varphi_n) + K_{DC} \exp(-\gamma_{DC} t) + n_t \tag{3}$$

The processing of signal in computer simulations is easily done in discrete form. To convert continuous signal to discrete form, sampling is performed. Hence, the sampled version of above signal can be written as:

$$Sig(mT_s) = \sum_{n=1}^{N} [K_n \sin(\omega_n mT_s + \varphi_n)] + K_{DC} \exp(-\gamma_{DC} mT_s) + n_{mT_s} \tag{4}$$

where T_s being the time for sampling known as sampling time. Using the trigonometric identity for simplification, above equation can be rewritten as:

$$Sig[m] = \sum_{n=1}^{N} (K_n \sin(\omega_n mT_s) \cos\varphi_n + K_n \cos(\omega_n mT_s) \sin\varphi_n) + K_{DC} \exp(-\gamma_{DC} mT_s) + n_m. \tag{5}$$

With the application of Taylor series on the decaying DC offset term and ignoring the higher order terms, we found:

$$Sig[m] = \sum_{n=1}^{N} (K_n \sin(\omega_n mT_s) \cos\varphi_n + K_n \cos(\omega_n mT_s) \sin\varphi_n) + K_{DC} - K_{DC}(\gamma_{DC} mT_s) + n_m. \tag{6}$$

The signal, which is to be estimated written in matrix form is described below:

$$\hat{Sig}[m] = X{\cdot}H(m)^T \tag{7}$$

where, X is the vector of unknown parameters which need to be updated to estimate the signal correctly. X vector and $H(m)$ vector can be expressed as:

$$X = [K_1 \cos(\varphi_1)\ K_1 \sin(\varphi_1)\ \cdots\ K_n \cos(\varphi_n)\ K_n \sin(\varphi_n)\ K_{DC}\ K_{DC}\gamma_{DC}\ 1] \quad (8)$$

$$H(m) = [\sin(\omega_1 m T_s)\ \cos(\omega_1 m T_s)\ \cdots\ \sin(\omega_n m T_s)\ \cos(\omega_n m T_s)\ 1 - m T_s n_m.] \quad (9)$$

When the vector of unknown parameters X is identified corresponding to minimum fitness using WLS–MVO framework, the angles, and amplitudes of corresponding frequencies can be calculated using following relations:

$$K_n = \sqrt{X_{2n}^2 + X_{2n-1}^2} \quad (10)$$

$$\varphi_n = \tan^{-1}\left[\frac{X_{2n}}{X_{2n-1}}\right] \quad (11)$$

The parameters of DC decaying offset can be computed using following relations:

$$K_{DC} = \varphi_{2n+1} \quad (12)$$

$$\gamma_{DC} = \left[\frac{\varphi_{2n+2}}{\varphi_{2n+1}}\right] \quad (13)$$

The overall fitness function for the estimation of harmonics problem can be formulated as:

$$WLS = \sum \omega (Sig - \hat{Sig})^2 \quad (14)$$

where Sig denotes the actual signal, $\hat{Sig}$ denotes the estimated signal. Whereas ω is the weight that is tuned according to the optimization requirements of the harmonic estimation problem.

Performance Indices

Multiple performance indices are defined to validate the performance of the proposed framework [1,3]. In this paper, the performance indices are defined as:

- Mean square error (MSE) is given by the following relation:

$$MSE = \frac{1}{H}\sum_{h=1}^{H} (Sig - \hat{Sig})^2 \quad (15)$$

- Residual sum of squares (RSS) accounts for the difference between the actual signal and estimated signal, which is defined as:

$$RSS = \sum (Sig - \hat{Sig})^2 \quad (16)$$

- Objective function called as weighted least square (WLS) for minimizing RSS is given by:

$$WLS = \sum \omega (Sig - \hat{Sig})^2 \quad (17)$$

- Performance index (PER) is also statistical performance evaluator parameter which is given by:

$$PER = \frac{\sum (Sig - \hat{Sig})^2}{Sig^2} \quad (18)$$

3. Proposed Research Methodology

The solution to the harmonic estimation problem is significantly reported in the literature with different hybrid approaches [24–27]. The key objectives of combining both least square and meta-heuristic algorithms are to improve the convergence and accuracy of the results. The basic model of the harmonic signal involves non-linearity due to the phases of the sinusoids and noise present in the given harmonic signal. Meta-heuristic techniques are deployed for the estimation of these non-linear phases of fundamental and higher-order harmonic components whereas the least square algorithm caters to the estimation of linear amplitudes. This parallelism significantly enhances the convergence characteristics and the time required to reach an optimal solution.

Proposed Hybrid (WLS–MVO) Framework 112

The multi-verse optimizer is an efficient evolutionary algorithm to solve complex real-world optimization problems and is proposed by Aljarah et al., in 2016 [28]. This algorithm replicates the phenomenon described by multi-verse theory to form new universes. The multi-verse theory describes that there are multiple universes, each of which is formed with a big bang. These universes interact with each other to form new universes. The three main concepts of multi-verse theory have been utilized to form this optimization algorithm: blackholes, whiteholes, and wormholes. Blackholes exist in the universe, which attracts everything including light beams due to their enormously high gravitational force. Whiteholes generally cannot be seen but physicists believe that big bangs are actually the whiteholes, which is the cause of the birth of new universes. Wormholes, on the other hand, act as the time/space travel between several parts of the same universe or between different universes. Every universe comprises of inflation rate through which it expands in space. A high inflation rate corresponds to a higher probability of becoming a whitehole, whereas a lower inflation rate corresponds to higher probability of becoming a blackhole. Wormholes move objects from one universe to another randomly. The multi-verse theory also describes that different universes interact with each other through blackholes, whiteholes, and wormholes to form a stable condition. This multi-verse theory is the main inspiration for the multi-verse optimizer algorithm. MVO is the population-based optimization algorithm in which multiple universes represent the actual population for the problem to be optimized. These multiple universes are considered as main initial guess solution matrix which is given as follows:

$$Univ = \begin{bmatrix} u_1^1 & u_1^2 & \cdots & u_1^n \\ u_2^1 & u_2^2 & \cdots & u_2^n \\ \vdots & \vdots & \ddots & \vdots \\ u_d^1 & u_d^2 & \cdots & u_d^n \end{bmatrix} \tag{19}$$

where n is the total number of decision variables and d is the number of population of universes:

$$u_a^b = \begin{cases} u_a^b & s1 < ni(Univ_a) \\ u_a^b & s1 \geq ni(Univ_a) \end{cases} \tag{20}$$

where u_a^b denotes the b^{th} decision variable of a^{th} universe. $ni(Univ_a)$ specifies the a^{th} universe, whereas $ni(Univ_a)$ symbolizes the normalized inflation rate (fitness) of the a^{th} universe. s1 is the number between 0 and 1 which will be chosen randomly. The parameter u_t^b designates the b^{th} decision variable of the t^{th} universe, which is chosen randomly according to the selection technique of roulette wheel.

The whiteholes selection is accomplished by the selection procedure of roulette wheel and accordance with the normalized inflation rate. Lesser inflation rate corresponds to inflated probability of interchanging of objects (parameters) through white/blackhole tunnels. This mechanism promises the exploration (global search) of search space to avoid local convergence of optimal solution. Following equation provides higher probability of inflation rate improvement through interchanging of objects via white/blackhole tunnels:

$$u_a^b = \begin{cases} u_b + tdr \times (uB_b - LB_b) \times s4 + LB_b & s3 < 0.5 \quad s2 < wep \\ u_b - tdr \times (uB_b - LB_b) \times s4 + LB_b & s3 \geq 0.5 \quad s2 < wep \\ u_a^b & \qquad\qquad s2 \geq wep \end{cases} \tag{21}$$

where the b^{th} parameter of the best universe so far is indicated by u_b. Two coefficients are used in this equation, tdr and wep. s2, s3, s4 are random numbers between [0, 1]. uB_b and LB_b designate the upper and lower bounds of the bth variable. u_a^b is the b^{th} variable of a^{th} universe.

The two prominent coefficients tdr (traveling distance rate) and wep (wormhole existence probability) are used in this algorithm as indicated by the mathematical modeling. wep defines the probability of the existence of wormholes in the universe. tdr factor defines the distance rate or variation that an object can be transferred by a wormhole around the best universe so far. wep and tdr enhances the exploitation (local search) of the algorithm around global solutions. The adaptable formulas for wep as well as tdr are given as:

$$wep = mn + iter \times \left(\frac{mx - mn}{ITER} \right) \tag{22}$$

where mn indicates the minimum (0.2 in this work), mx designates the maximum (1 in this work), $iter$ specify the present light year (iteration) and $ITER$ describes the maximum number of light years (iterations).

$$tdr = 1 - \frac{iter^{1/pr}}{ITER^{1/pr}} \tag{23}$$

where pr (6 in this work) designates the local search (exploitation) accuracy on the top of iterations. The proposed WLS–MVO framework for harmonic estimation is shown in Figure 1.

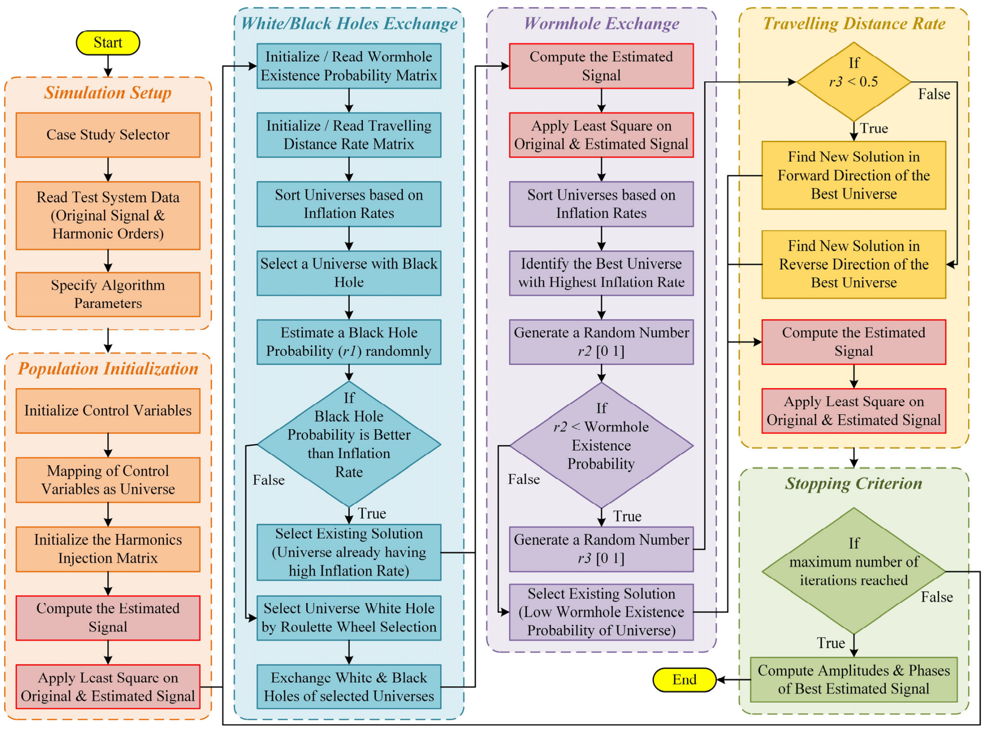


Figure 1. Proposed WLS–MVO framework for harmonic estimation.

4. Results and Discussion 125

The simulations for each case study are performed on Laptop: TOSHIBA, Intel core i7 CPU 4610 @ 3.00 GHz processor, 6 GB RAM, and 64-bit operation system (Windows 10). The WLS–MVO is programmed in MATLAB, and simulations are performed on MATLAB R2020a®. Algorithm parameters of WLS–MVO are adjusted and tuned based on individual case studies.

4.1. Estimation of Integral Harmonics in VFD 131

The test signal is the distorted voltage signal with a DC decaying component offset of $0.5 \times \exp(-5t)$ and two SNR (signal to noise ratio) levels in decibels, 0 and 10 [29]. The complete test system stating the harmonics present in the test signal are given in Ref. [30]. The given continuous time test signal is subjected to sampling and discretization as per Nyquist criterion considering, 64 samples per cycle with the sampling frequency of 3.4 kHz. The developed framework is then simulated for near-optimal estimation of harmonics for the given signal. The proposed algorithm is applied to the test system considering 250 population size and maximum iterations of 500.

The performance of the WLS–MVO is defined using four different indices as indicated by (15–18). The waveforms of actual and superimposed estimated signals together with their respective convergence characteristics are shown in Figures 2 and 3. The convergence characteristics are shown for three different performance indices defined by PER, RSS, and MSE and the algorithm reaches the optimal solution well before 100 and 200 iterations for 0 and 20 dB noise, respectively. The proposed WLS–MVO converges within 60 and 200 iterations for 0 and 20 dB noise respectively and shows smooth fitness over the remaining iterations.

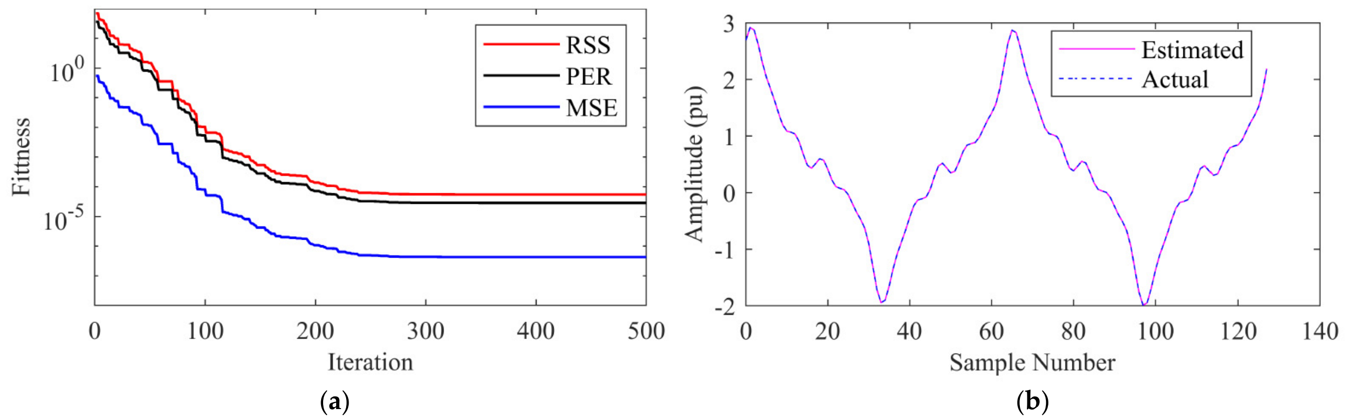


Figure 2. Convergence characteristics and estimated signals for test system 1. (**a**) Fitness value without noise. (**b**) Estimated signal without noise.

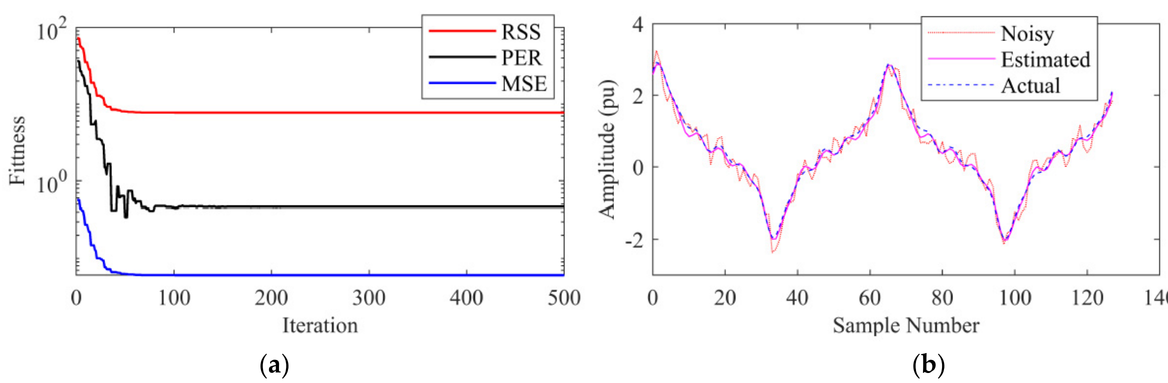


Figure 3. Convergence characteristics and estimated signals for test system 1. (**a**) Fitness value at 10 dB SNR. (**b**) Estimated signal at 10 dB SNR.

Table 1 enlists the comparison in terms of the estimation of amplitudes, phases, percentage error, and computation time for all the integral harmonics. The proposed WLS–MVO reveals its superior performance in contrast to the other optimization techniques proposed in the literature in terms of correctly estimating the harmonics present in the signal and the least computational time of 1.16 s.

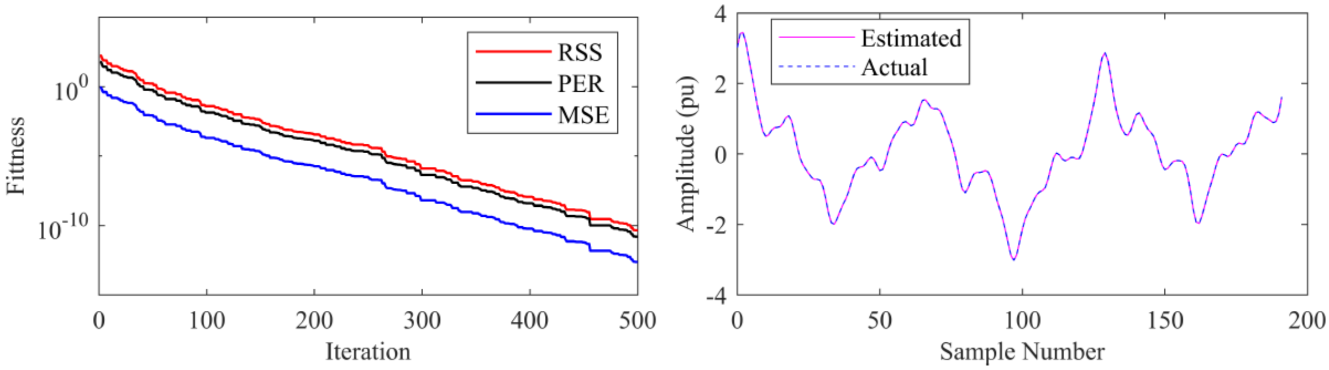
Table 1. Comparative performance of different algorithms considering integral harmonics estimation.

Algorithm	Parameters	Fund	3rd	5th	7th	11th	Run Time (s)
BFO [31]	Amplitude (V)	1.4878	0.5108	0.1945	0.1556	0.1034	10.9310
	Error (%)	0.8147	2.1631	2.7267	3.7389	3.4202	
	Phase (deg)	80.4732	57.9005	45.8235	34.5606	29.1270	
	Error (%)	0.4732	2.0995	0.8235	1.4394	0.8730	
BFO-RLS [31]	Amplitude (V)	1.4942	0.4986	0.2018	0.1526	0.0986	9.3450
	Error (%)	0.3840	0.2857	0.9021	1.7609	1.7460	
	Phase (deg)	80.3468	58.5461	45.6977	34.8079	29.9361	
	Error (%)	0.3468	1.4539	0.6977	1.1921	0.0639	
BBO-RLS [32]	Amplitude (V)	1.4953	0.5004	0.2008	0.1490	0.0999	5.8520
	Error (%)	0.3104	0.0850	0.4203	0.1961	0.0830	
	Phase (deg)	79.7888	59.5410	45.5153	36.1165	30.0124	
	Error (%)	0.2640	0.5661	1.1452	0.3238	0.0415	
WLS–MVO	Amplitude (V)	1.5002	0.5000	0.2000	0.1500	0.1000	1.1674
	Error (%)	0.0150	0.0045	0.0032	0.0018	0.0010	
	Phase (deg)	80.0017	60.0015	45.0019	36.0016	30.0011	
	Error (%)	0.0021	0.0025	0.0043	0.0044	0.0036	

4.2. Estimation of Inter- and Subharmonics in VFD 153

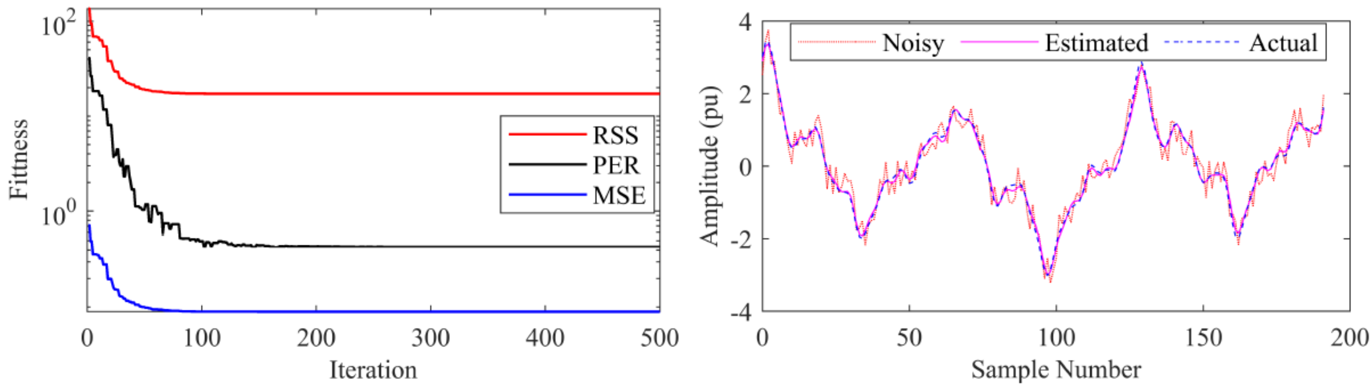
The strength of the proposed WLS–MVO is further exploited for the estimation of harmonics in different noisy environments. The integral harmonic estimation signal is deteriorated with sub and inter-harmonics considering additive random noise as well, yielding a highly complex and non-linear search space. The three subharmonic signals are subjected to different amplitudes, frequencies, and phases. The signal firstly deteriorated with subharmonic of 0.505 < 75° (20 Hz) and inter harmonics of 0.25 < 65° (180 Hz) and 0.35 < 20° (230 Hz) [1]. The very signal is then subjected to a noisy environment by considering noise of 10 dB SNR. Figures 4 and 5 show the actual and superimposed estimated signals along with their corresponding convergence characteristics at different noise levels of 0 dB and 20 dB. The strength of the WLS–MVO algorithm becomes conspicuous also in noisy conditions. The convergence characteristics are shown for three different performance indices defined by PER, RSS, and MSE and the algorithm reaches the optimal solution well before 100 and 200 iterations for 0 and 20 dB noise, respectively. The given test signal which is utilized for the estimation of harmonics is the characteristic signal generated by variable frequency drives (VFDs), power electronic equipment, and arc furnaces.

The estimated signal obtained using WLS–MVO gives the best estimation performance in terms of amplitudes and phases for fundamental, integer, inter-, and subharmonics with the least percentage of error as shown in Table 2. The actual amplitude and phase of the signal for fundamental frequency are 1.5 V and 80 degrees and an estimated signal of 1.5002 V and 80.001 indicating a percentage error of 3.38×10^{-5} and 5.38×10^{-5}, respectively. The amplitudes and phases for all the harmonics are compared with the well-known optimization techniques in the literature and robust and promising results are obtained using WLS–MVO. Also, the computational time found using WLS–MVO is 1.22 s which is the least among other optimization techniques. WLS–MVO reaches the optimal solution with a fast convergence rate. Numerical results given in Table 3 advocate the better performance of the proposed WLS–MVO algorithm under highly noisy environments.



(**a**) (**b**)

Figure 4. Inter− and subharmonic convergence characteristics along with estimated signals. (**a**) Fitness value without noise. (**b**) Error value at 10 dB SNR.



(**a**) (**b**)

Figure 5. Inter− and subharmonic convergence characteristics along with estimated signals. (**a**) Superimposed estimated signal without noise. (**b**) Estimated signal at 10 dB SNR.

Table 2. Comparative assessment of different algorithms considering inter− and subharmonics at various SNRs.

Algorithm	Parameters	Sub	Fund	3rd	Inter-1	Inter-2	5th	7th	11th	Run Time (s)
BFO [31]	Amplitude (V)	0.5250	1.4788	0.4877	0.2664	0.3729	0.2052	0.1464	0.1016	13.8330
	Error (%)	3.9950	1.4103	2.4575	6.5574	6.5295	2.5764	2.4170	1.5531	
	Phase (deg)	74.4800	79.8361	61.2316	63.9910	19.6887	47.6980	36.7362	29.3928	
	Error (%)	0.5140	0.1639	1.2316	1.0090	0.3113	2.6983	0.7462	0.6072	
BFO-RLS [31]	Amplitude (V)	0.5110	1.5029	0.4921	0.2581	0.3639	0.2009	0.1479	0.1015	12.8370
	Error (%)	1.1900	0.1952	1.5887	3.2372	3.9651	0.4541	1.4149	1.4800	
	Phase (deg)	74.8100	79.9148	59.0760	65.3445	19.8677	46.2780	36.4473	30.0643	
	Error (%)	0.1830	0.0852	0.9240	0.3445	0.1323	1.2783	0.4473	0.0643	

Table 2. *Cont.*

Algorithm	Parameters	Sub	Fund	3rd	Inter-1	Inter-2	5th	7th	11th	Run Time (s)
BBO-RLS [32]	Amplitude (V)	0.4943	1.4984	0.5003	0.2458	0.3497	0.2008	0.1485	0.0999	6.7525
	Error (%)	1.1255	0.1046	0.0785	1.6506	0.0788	0.4452	0.9557	0.1000	
	Phase (deg)	74.9321	79.9500	59.5228	65.1706	19.9775	45.5200	36.1179	30.0123	
	Error (%)	0.0905	0.0625	0.7452	0.2625	0.1125	1.1565	0.3275	0.0410	
WLS–MVO	Amplitude (V)	0.5050	1.5000	0.5000	0.2500	0.3500	0.2000	0.1500	0.1000	1.2204
	Error (%)	3.38×10^{-5}	2.06×10^{-6}	1.87×10^{-5}	7.88×10^{-5}	4.27×10^{-5}	1.22×10^{-4}	4.80×10^{-5}	1.89×10^{-4}	
	Phase (deg)	7.50×10^{1}	8.00×10^{1}	6.00×10^{1}	6.50×10^{1}	2.00×10^{1}	4.50×10^{1}	3.60×10^{1}	3.00×10^{1}	
	Error (%)	5.38×10^{-6}	1.35×10^{-6}	6.52×10^{-5}	1.48×10^{-4}	9.14×10^{-5}	4.32×10^{-5}	3.70×10^{-7}	1.32×10^{-4}	

Table 3. Comparative assessment of different algorithms considering PER index.

Algorithm	BFO [31]	BFO-RLS [31]	BBO-RLS [32]	WLS–MVO
No noise	0.1178	0.087	0.0658	5.50×10^{-5}
40 dB	0.138	0.092	0.075	0.007794238
20 dB	0.8073	0.787	0.5735	0.050778
10 dB	5.2549	4.5482	3.8555	0.46455

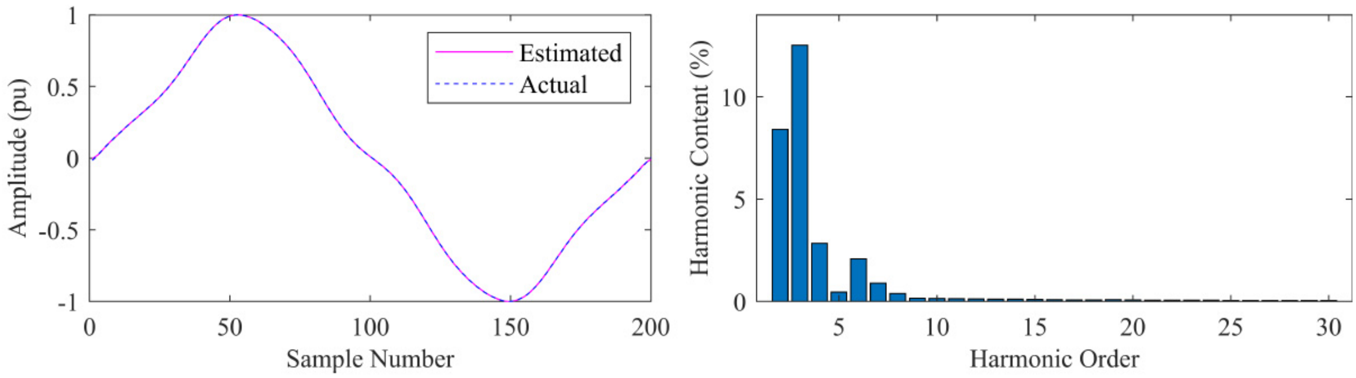
The performance index of WLS–MVO defined by (18) using PER which is measured at different noise levels of 10, 20, and 40 dB is shown in Table 3. The PER values of WLS–MVO are compared with other optimization techniques in the literature and promising results are obtained. The least values of PER obtained with WLS–MVO indicate the accuracy with which it can effectively estimate the signal and harmonics and the superiority of WLS–MVO over the other optimization techniques.

4.3. Real-Time Voltage Signal Harmonics Estimation of AFPMSG 186

Conventional thermal power plants are being replaced with renewable energy sources (RES) due to high fuel prices and associated pollution with conventional thermal energy sources [33–37]. Solar and wind are the most common RESs being used today for electrical energy production [38–40]. Modern wind turbines technologies include the usage of axial flux permanent magnet generators (AFPMSGs) instead of radial flux permanent magnet generators (RFPMGs) due to their optimum flux density, higher torque-weight ratio, higher efficiency, lightweight, and more importantly it has zero cogging torque losses [41]. In this study [42], a three-phase and multi-stage AFPMSG design is developed. The voltage (per unit) waveform obtained from AFPMSG is considered for estimating the harmonics. The voltage waveform is recorded using oscilloscope taking the sampling frequency of 10 kHz. The voltage waveform of AFPMSG is shown in Figure 6 with the superimposed estimated voltage signal. The harmonics estimation using proposed WLS–MVO algorithm was carried out for the first 30 integer harmonics. The execution of harmonics estimation is carried out by taking 300 iterations and 50 number of populations. Figure 6b shows the amplitudes of 30 integer harmonics present in the voltage signal of AFPMSG. The ratings of the AFPMSG can be verified from this study [42].

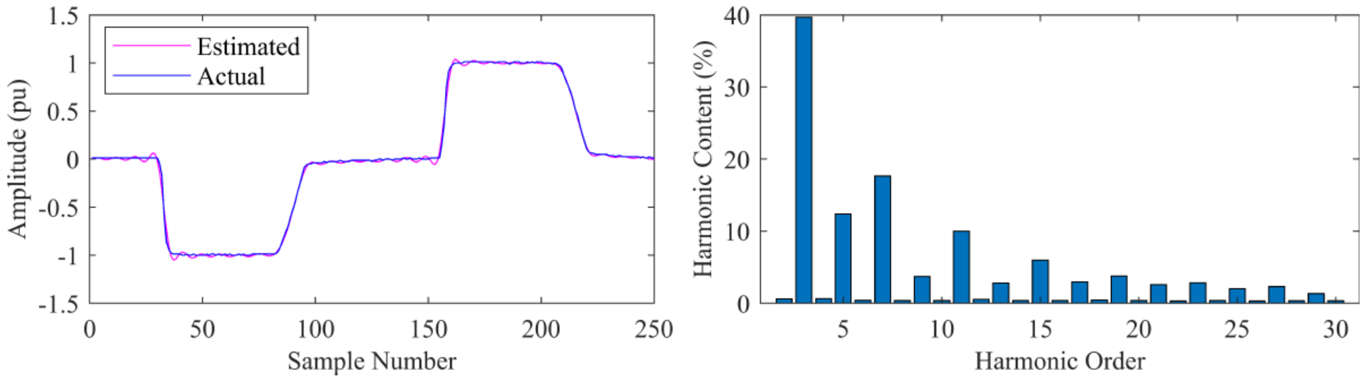
4.4. Real-Time Voltage Signal Harmonics Estimation of UPS 203

UPS are extensively deployed for powering the load in emergency or in load shedding conditions. However, the quality of UPS is characterized by the output voltage waveform being fed to the load [43]. The output waveform relies solely on the power electronic circuitry and the control algorithms that directly translates into cost. The voltage waveform for the experimental setup is recorded from a Homage Tron (Duo) UPS available in our facility for a 250 no. of samples per cycle. As per the ratings of UPS, it is of 1 KVA, having output 170–280 (AC) and input of 12 V (DC). The output waveform is as shown in Figure 7 with a superimposed estimated signal. The harmonics in the voltage waveform estimated using WLS–MVO are shown in Figure 7 for 30 integer harmonics with the corresponding percentages of amplitudes.



(**a**) (**b**)

Figure 6. Voltage signal estimation and harmonic analysis of AFPMSG. (**a**) Superimposed estimated signal. (**b**) Integer–harmonic magnitude.



(**a**) (**b**)

Figure 7. Voltage signal estimation and harmonic analysis of UPS. (**a**) Superimposed estimated signal. (**b**) Integer−harmonic magnitude.

4.5. Real-Time Current Signal Harmonics Estimation of LEDs 214

Light Emitting Diodes (LED) lamps are non-linear load and are being extensively used in today's world due to their low energy consumption. LEDs consist of power electronic based circuitry which take non-linear current from the source which results in deterioration of supply voltage waveform due to inclusion of harmonics present in the current taken by LED [43]. The LED is 20 Watt with operating conditions of 90–260 V (AC), and compatible with both 50 and 60 Hz. Digital Oscilloscope is used to obtain the non-linear LED current waveform by considering 250 samples per cycle. WLS–MVO is tested for the said case study by taking 10 odd harmonics and 200 iterations. The output waveform is as shown in Figure 8 with a superimposed estimated signal.

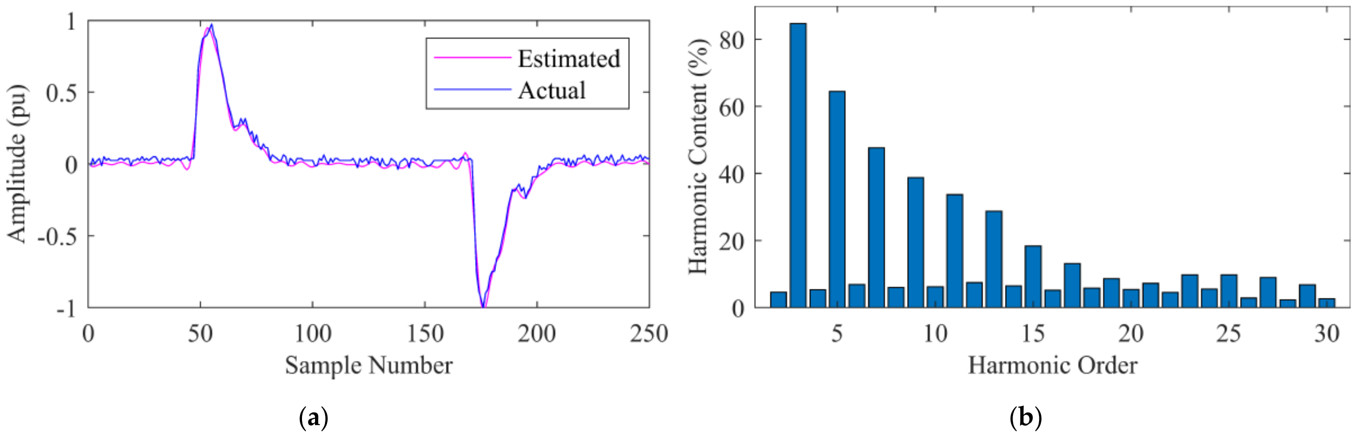


Figure 8. Estimation and harmonic analysis of current drawn by LED lamp. (**a**) Estimation with MAF. (**b**) Integer–harmonic amplitude using MAF.

5. Statistical Significance 224

The harmonics estimation problem involves the estimation of desired frequency components from a given distorted signal embedded with random noise to correctly estimate the amplitude and phase of the corresponding frequency component. The accuracy with which an optimization algorithm estimates the harmonics in the signal can be evaluated using some benchmark functions. Four performance indices are defined as (15–18), for which WLS–MVO has been evaluated and simulated as previously considered in the case studies. Statistical significance has been evaluated using statistical analysis software, SPSS (Statistical Package of Social Sciences). The harmonic estimation of current waveform of test case 1 is run 100 times using proposed WLS–MVO framework. The results are statistically evaluated through SPSS software. The lower and upper bounds of the results as shown in Table 4 are evaluated according to confidence internal. In this case, the confidence interval is 95%, which advocates the effectiveness of the proposed framework.

Table 4. Statistical significance of multiple test runs optimized by the proposed framework.

Parameter	Beta	Significance	95% Confidence Interval	
			Lower Bound	Upper Bound
Constant	0.9998	0	0.9998	0.9999
No of Test Runs	-2.39×10^{-6}	4.34×10^{-9}	-3.13×10^{-6}	-1.66×10^{-6}

To further validate the effectiveness of the proposed WLS–MVO for correct estimation of harmonics, boxplots considering the performance index RSS are plotted for the inter- and subharmonics for 100 simulation runs, as shown in Figure 9. In statistics, a boxplot gives the summary for a set of data (results), in terms of several parameters, which include minima, lower quartile, medium quartile (50th percentile), upper quartile, maxima, and outliers [44]. It is evident from the boxplots that the optimized solution lies between the minimum and maximum values having minimal outliers. Statistical tests using SPSS are also performed using linear regression to investigate the validity of results shown in Table 4. Hence, the statistical analysis justifies the effectiveness of the proposed WLS–MVO algorithm for correctly estimating the harmonic content in current and voltage waveforms with minimum computational time and with high accuracy compared to other optimization techniques reported in the literature.

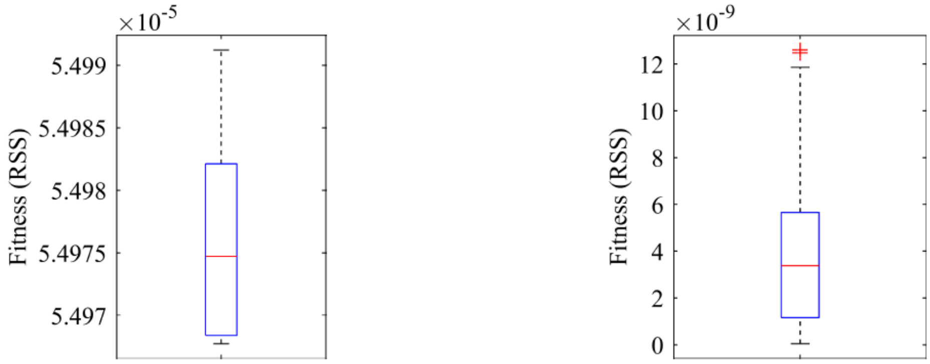


Figure 9. Boxplots for validation of proposed WLS–MVO for sub- and inter-harmonic estimation.

6. Conclusions

In this paper, the concept of hybridization is utilized to properly estimate real time harmonics present in noisy power signals. Thus, statistical approach is cascaded with meta-heuristic technique to suggest hybrid weighted least square multi-verse optimizer (WLS–MVO) for the proper estimation of harmonics. To validate the authenticity of the suggested technique, results are compared with previously developed techniques in terms of accuracy (PER, RSS, MSE) and computational time. Several theoretical and practical case studies are explored to validate the performance of the proposed approach. For the case study, integer harmonics are extracted from power signals at different uniform as well as Gaussian noise levels (40, 20, 10 dB). The results and discussion section clearly depict the effectiveness of WLS–MVO in harmonics estimation when compared to previously developed techniques. The application of WLS–MVO has been further extended to real-time current waveform of LEDs and voltage waveform of UPS and AFPMG. This variegated usage of the proposed WLS–MVO depicts the applicability of the algorithm for the solution of nonlinear and complex harmonic estimation problems.

Author Contributions: Conceptualization, U.W., A.H., M.M.A., F.S., M.S. and M.R.; methodology, U.W., A.H. and M.M.A.; software, U.W., A.H. and M.M.A.; validation, U.W., A.H., M.M.A., F.S. and M.R.; formal analysis, U.W., A.H. and M.M.A.; investigation, U.W., A.H. and M.M.A.; resources, U.W., A.H., M.M.A., F.S., M.S. and M.R.; data curation, U.W., A.H. and M.M.A.; writing—original draft preparation, U.W., A.H. and M.M.A.; writing—review and editing, M.M.A., F.S., M.S. and M.R.; visualization, M.M.A., F.S. and M.R.; supervision, M.M.A., F.S., M.S. and M.R.; project administration, M.M.A., F.S., M.S. and M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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