Hybrid Genetic Algorithm-Particle Swarm Optimization Based Approach for Optimal Sizing and Placement of a Passive Filter

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Abstract: This work presents a hybrid Genetic Algorithm-particle swarm optimization based technique for optimal placement and sizing of a passive power filters to reduce harmonics distortion and mitigate the total active power losses in distribution lines with linear and nonlinear loads. The problem was formulated as a nonlinear multi-objective optimization problem with equality and inequality constraints using hybrid Genetic Algorithm with practical swarm optimization. Recommendations by IEEE standards 519-1992 and 18-2002 are considered as the main constraints in this study. Based on the minimum total harmonic distortion and active power losses as the main optimization criteria the optimal solutions were selected. The proposed approach is validated on the IEEE 14 bus system and on a real power system. The results confirmed that proposed method provides robust, effective and high-quality solutions for large power systems.

Keywords: Passive filter, harmonic mitigation, Genetic algorithm, Particle swarm optimization, optimal harmonic power flow.

1. Introduction

The expansion of harmonic currents in electrical systems had risen recently due to various factors, including solid-state power conversion devices, traction drives, industrial variable speed drive systems, A/D converters, and increased utilization of arc welders. Additionally, important sources of harmonic currents in power systems include electrical equipment like fluorescent lamps, large induction motors, near-saturated power transformers, and computer system installations. Presently, nonlinear devices constitute a growing portion of the electrical load in industrial and commercial power systems. When a sinusoidal supply feeds a combination of linear and nonlinear loads, the total supply current will inevitably contain harmonics. The introduction of harmonic currents and the resulting harmonic voltages can lead to power quality issues, impacting the performance of consumers connected to the electric power network, [1]. Nonlinear devices produce harmonics in line currents, leading to increased conductor heating. This elevated temperature can exceed the rated capacity of cables not designed for harmonic currents, causing potential problems. The effects of harmonics in power distribution systems include aging, reduced capacity of components, malfunctioning protection and measurement devices, a lower power factor, and a consequent decrease in power system efficiency due to increased losses.

To mitigate these issues, industrial standards and recommended practices for power systems have been established. However, power systems must still endure harmonic flow as complete elimination is not possible. Consequently, as non-linear loads in power systems continue to grow, there is a growing need for more effective methods to counteract the harmonic effects both among sources and on the power system itself. Extensive efforts have been made in analyzing, simulating, and developing passive and active filters, hardware for identification, classification, and mitigation of power system harmonics. Consequently, there is a growing interest for the application of passive and active filters to mitigate the harmonic effects generated by these loads. Proper consideration of the sizing and placement of passive filters is crucial to prevent the amplification of harmonic currents and voltages, which can occur due to potential resonance at specific harmonic frequencies. Various research studies, such as [1-5], utilize genetic algorithms to determine the optimal size and location of shunt capacitors in radial distribution systems, taking into account harmonic distortion limits imposed by nonlinear power electronic devices. In [6], the non-dominated sorting genetic algorithm (NSGA-II) is employed to identify the optimal placement of passive filters. Another innovative approach proposed in [7] involves the use of fuzzy dynamic programming to decide the optimal size and location of compensation shunt capacitors for distribution systems with harmonic distortion. A method for determining optimal or near-optimal locations and sizes of single-tuned passive harmonic filters within existing capacitor buses in a power system is introduced in [8]. Additionally, [9] presents a novel method towards passive filter placement, and [10] utilizes a whale optimization algorithm for filter placement. The methodology of the present study is based on harmonic flow simulation in the Alternative Transient Program (ATP/EMTP) and employs the NSGA-II optimization algorithm simulated on MATLAB® to identify the optimal placement of passive filters. Although the method presented in [11] accounts for both harmonic current sources from nonlinear loads and the presence of background voltage harmonics, the objective functions are notably complex. This complexity, particularly at lower levels, leads to challenges in filtering due to conflicting requirements. In [12], a C-type filter is used to reduce harmonic distortion, improve system performance and compensate reactive power. In order to improve the load power factor, also considering economic factors. In [13], a method for designing an L compensator in time-variant, non-sinusoidal systems, is proposed. It examines the realistic representation of implementing the equivalent system impedances, source voltage harmonics, and the equivalent load impedance, the proposed method shows a high level of complexity. The work in [14] introduces a method that combines sequential neural-network approximation with orthogonal arrays (SNAOA) to reduce harmonic distortion using passive harmonic filters. While the method yields satisfactory results, it requires a substantial amount of real data to effectively train the neural network. In [15], the proposed technique aimed to allocate and sizing single tuned passive filters in power distribution systems. The objective is to minimize total harmonic distortion. The method employs the standard genetic algorithm (GA) without any modifications.

In the time where most reviewed research emphasizes using a single optimization technique with one or two objective functions, this often doesn't result in finding the global minimum or optimal solution due to the common problem of getting stuck in local minima. The proposed method suggests a hybrid approach. It involves selecting a wide-ranging population for one optimization technique while keeping the population relatively close and locally separated for the other optimization technique. The proposed method can continually search for a global minimum while also exploring local minima solutions.

This work aims to introduce a novel approach to passive filter sizing and allocation, utilizing optimization techniques to enhance the filter's impact on reducing harmonics distortion and active power losses. As the filter comprises multiple branches in shunt, the distribution of reactive power among these branches will be optimized. The proposed passive filter design incorporates a hybrid GA-PSO algorithm.

The choice of this algorithm, among others, is based on its combination of the unique individual generation functions of both GA and PSO, mimicking social behaviors such as animal breeding and survival of the fittest. This integration enhances the overall efficiency of the algorithm's results. While the PSO algorithm excels in efficient local searches, the GA serves as a potent tool for global searches, albeit with less power in local search. Hence, a hybrid algorithm is employed to capitalize on the strengths of both approaches.

1.1 Passive Filters

Passive filters come in two primary configurations: Shunt passive filters and Series passive filters. They are employed to either divert harmonic currents away from the line or impede their transmission between different parts of the system by tuning the elements to resonate at specific harmonic frequencies. Fig. 1 depicts various common filter configurations. Comprising inductance, capacitance, and resistance elements, passive filters typically utilize a single-tuned "notch" filter, which is both commonly used and cost-effective for many applications. Besides mitigating harmonics, notch filters also contribute to Power Factor (PF) correction [2].

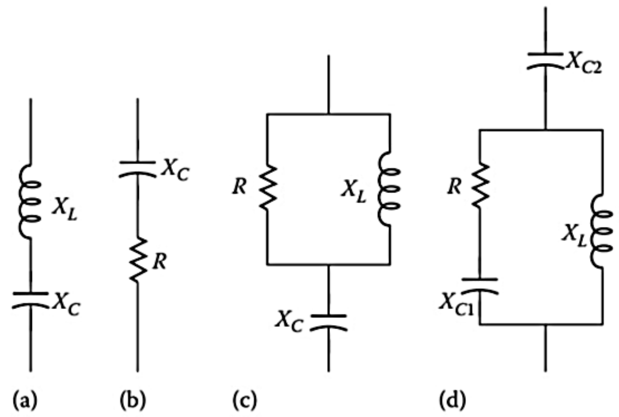

Figure 1: (a) Single tuned filter (b) 1st order high pass filter (c) 2nd order high pass filter (d) 3rd order high pass filter, [9].

The application of a series filter is constrained when it comes to blocking multiple harmonic currents since each harmonic requires a dedicated series filter tuned to that specific harmonic. This setup can lead to considerable losses at the fundamental frequency. Therefore, in centralized filter design, the use of shunt filters is more suitable than series filters. This preference arises from the expected outcome of multiple harmonics due to the diverse nature of nonlinear elements in the system.

Shunt passive filters rely on three key design parameters: the tuning harmonic orders (h), the quality factor (Q), and the impedance of the filter at the fundamental frequency. The tuning of harmonic orders is contingent upon the nonlinear behavior of the system. The quality factor, denoting the ratio of reactance to resistance at the fundamental frequency, typically ranges between 50 and 150 for a single-tuned filter, [5]. The filter reactance, X_L, and resistance, R, can be calculated by $X_L = \frac{X_C}{h^2}$ and $R = \frac{h\,X_L}{Q}$, respectively. Where, X_C is the filter capacitance, h is frequency order, and Q is the filter quality factor.

The fundamental steps in the design process of passive filters can be condensed into a few key stages. Initially, the tuned frequency for the filter is chosen. Once this frequency is established, the capacitor bank size and resonant frequency can be calculated. The maximum value for the filter reactive power Q_f is determined by the total fundamental reactive power. The filter reactance X_f, representing the difference between the capacitive reactance, X_C, and the inductive reactance, X_L, can be determined by $X_f = X_C - X_L = V/Q_f$. Where V is the line to line voltage. So, the filter capacitive reactance, capacitor and inductor values can be calculated by, [9], $X_C = h^2 X_L = \frac{X_f\,h^2}{h^2-1}$, $C = \frac{1}{X_C \omega_o}$, and $L = \frac{X_L}{\omega_o}$.

1.2 Objective Function

The objective function selected to be minimized for this optimization problem is the branches active power losses (P_{loss}) and the total harmonic distortion (THD) that can be calculated according to the following:

$$P_{loss} = \sum_{h=1}^{max} \sum_{i=1}^{N-1} P_{loss(i,i+1)}{}^{h} \quad (1)$$

$$P_{loss(i,i+1)}{}^{h} = (R_{i,i+1}{}^{h}((V_i{}^{h} - V_{i+1}{}^{h}) * Y_{i,i+1}{}^{h})^2) \quad (2)$$

$$THD = \frac{\sqrt{(\sum_{h=2}^{max} |V_i{}^{h}|^2)}}{|V_i{}^{1}|} \quad (3)$$

These two optimization objectives were employed in the optimization problem. THD served as the primary objective function in the section executed by PSO. Conversely, THD was transformed into a constraint in the section where GA was employed, with the minimum P_{loss} being the objective function. Throughout this problem, the aim was to determine the optimal configuration of certain control variables (e.g., single-tuned filter location, size, and tuned frequency) while adhering to specified equality and inequality constraints.

The Newton-Raphson method was utilized in this optimization problem to compute the total fundamental reactive power and to uphold the equality constraints associated with the fundamental active and reactive power at bus i within its specified tolerance. At harmonic frequencies, the power system was reconfigured, taking into account the passive filter, the nonlinear load, and the frequency effect at all the buses, as follows:

$$Y_{l,i}^{h} = \frac{P_{l,i}}{|V_i{}^{1}|^2} - j\frac{Q_{l,i}}{h|V_i{}^{1}|^2} \tag{4}$$

$$Y_{c,i}^{h} = hY_{c,i}^{1} \tag{5}$$

$$Y_{f,i}^{h} = \frac{1}{Z_{f,i}{}^{h}} \tag{6}$$

$$Y_{i,i+1}^{h} = \frac{1}{R_{i,i+1} + jhX_{i,i+1}} \tag{7}$$

The impedance for single tuned filter is

$$Z_{f}^{h} = R + j\omega L + \frac{1}{j\omega C} \tag{8}$$

Efficient simulation is essential for large systems, prompting the recommendation to employ decoupled harmonics power flow for system parameter calculations. In the case of the i^{th} bus, where $P_{nl,i}$ and $Q_{nl,i}$ denote the nonlinear active and reactive power at the fundamental frequency, the nonlinear current can be computed using the provided equations.

$$I_{nl,i}^{1} = \left[\frac{P_{nl,i} + jQ_{i,nl}}{V_i^{1}}\right]^{*} \tag{9}$$

$$I_{nl,i}^{h} = c(h)I_{nl,i}^{1} \tag{10}$$

1.3 Constraints

The fundamental active and reactive power at bus (i) is considered as constraints during this optimization method and it can be calculated by:

$$P_{G,i} - P_{l,i} = \left|V_i^{(1)}\right| \sum_{j=1}^{N} \left|V_i^{(1)}\right| \left|Y_{i,j}^{(1)}\right| \cos\left(\emptyset_{i,j}^{(1)} - \delta_i^{(1)} + \delta_j^{(1)}\right) \tag{11}$$

$$Q_{G,i} - Q_{l,i} = \left|V_i^{(1)}\right| \sum_{j=1}^{N} \left|V_i^{(1)}\right| |Y_{i,j}^{(1)}| sin\,(\emptyset_{i,j}^{(1)} - \delta_i^{(1)} + \delta_j^{(1)}) \tag{12}$$

Where: i=1…N is the bus number, $P_{G,i}, P_{l,i}, Q_{G,i} and Q_{l,i}$ are the generated and load active and reactive power respectively. $Y_{i,j}^{(1)}$ is the fundamental admittance between bus i and j $\emptyset_{i,j}^{(1)}, \delta_i^{(1)} and\ \delta_j^{(1)}$ are the admittance phase angle and the voltage angle at bus i and j at the fundamental frequency.

1.4 Optimization Techniques

This study proposes a combination of two global optimization algorithms, GA and PSO, to solve nonlinear optimization problems. The rationale behind this lies in both algorithms working with an initial population of solutions, making the integration of their search capabilities a sensible strategy. The subsequent sections outline the steps and flowchart of the GA, PSO and the hybrid GA-PSO optimization techniques.

1.4.1 Particle Swarm Optimization

Swarm behavior can be replicated through a set of straightforward rules, allowing for the modeling of schools of fish and flocks of birds. Even with individual agents following simple behavior rules, the collective behavior of the entire swarm can become intricate. Agents make decisions based on both their own experiences and the experiences of others, contributing to the fundamental elements that underlie PSO.

Each agent is aware of its personal best value (p_{best}) and its corresponding x, y position, akin to individual experiences. Additionally, each agent is informed about the best value within the group (g_{best}) among the p_{best}, resembling knowledge about how neighboring agents have performed. Agents seek to modify their positions based on its current position, velocity, p_{best} and g_{best}. This modification is conceptually represented by the notion of velocity, where the velocity of each agent can be adjusted using a specific equation.

$$V_i^{k+1} = wv_i^k + c_1 rand_1 * \left(g_{best_i} - S_i^k\right) + c_2 rand_2 * (g_{best} - S_i^k) \quad (13)$$

where, V_i^K is velocity of agent i at iteration k, w is weighting function, c_j is weighting coefficients, rand is a random number between 0 and 1, S_i^K is current position of agent i at iteration k, p_{besti} is p_{best} of agent i, and g_{best} is g_{best} of the group. Namely, velocity of an agent can be changed using three vectors. The velocity is usually limited to a certain maximum value [16-23].

The following weighting function is usually utilized:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \quad (14)$$

where, w_{max} is initial weight, w_{min} is the final weight, $iter_{max}$ is maximum iteration number, and iter is the current iteration number.

The three velocity vectors convey the following implications: The initial term represents the agent's previous velocity. The second and third terms are employed to adjust the agent's velocity. Without these latter terms, the agent would persist in moving in the same direction until reaching a boundary. In essence, this implies an exploration of new areas, making the first term synonymous with diversification in the search process.

The current position (searching point in the solution space) can be modified by the following equation:

$$S_i^{K+1} = S_i^k + V_i^{k+1} \quad (15)$$

The general process flow of PSO can be outlined as follows:

Step 1: Initialization of each agent's initial conditions. Initial search points (s_i^0) and velocities (v_i^0) for each agent are typically randomly generated within the allowable range. The current search point is set as pbest for each agent. The best-evaluated value of pbest becomes gbest, and the corresponding agent number is stored.

Step 2: Evaluation of each agent's search point. The objective function value is computed for each agent. If the value surpasses the current pbest of the agent, the pbest value is updated with the current value. If the best value of pbest is superior to the current gbest, gbest is updated with the best value, and the corresponding agent number is stored.

Step 3: Modification of each search point.

Step 4: Checking the exit condition. If the current iteration number reaches the predetermined maximum iteration number, the process exits; otherwise, it returns to Step 2. Figure 2 provides a visual representation of the overall flowchart of PSO [21, 22].

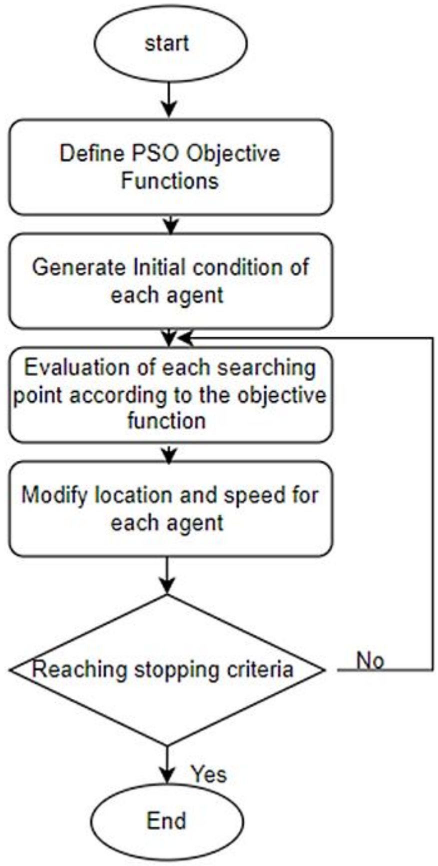

Figure 2: PSO Searching Flowchart

Based on, [21-25], the following parameters were deemed suitable, and their values are found to be independent of specific problem characteristics:

$c_i = 2{:}0$ $\quad$ $w_{max} = 0{,}9$ $\quad$ $w_{min} = 0{,}4$

The values are also proved appropriate for power system problems.

1.4.2 Genetic Algorithm

Unlike traditional optimization techniques that start with a single candidate and iteratively seek the optimal solution using static heuristics, the Genetic Algorithm (GA) approach employs a population of candidates to simultaneously and adaptively explore various areas within a solution space, [3, 4].
While some heuristic search methods rely on local search, such as hill climbing, others opt for a nonconvex optimization approach that accepts cost-deteriorating neighbors. GA stands out as one of the most popular methods extending beyond simple local search. Genetic algorithms operate on a population of individuals, where each individual represents a potential solution. Following the generation of an initial population, either randomly or heuristically, the algorithm evolves the population through sequential and iterative application of three operators, culminating in the formation of a new generation at the end of each iteration, [4]:

- Selection.
- Crossover.
- Mutation.

2. Material and Method

In the realm of heuristic optimization, a robust method for tackling complex nonlinear equations involves the combination of particle swarm optimization (PSO) and genetic algorithms (GA). This hybrid approach, known as GA-PSO, synergizes the strengths of PSO and GA by incorporating PSO mechanisms for generating individuals in a new generation, alongside the traditional crossover and mutation procedures observed in GA, [8].
In the following section the proposed hybrid GA-PSO optimization technique will be defined in steps as well as in a flowchart shown in Fig.3.

2.1 GA-PSO Optimization Technique Steps:

Step 1:

1. Input line data at the fundamental harmonic (i.e: branches impedance).
2. Input the fundamental active ve reactive bus power bus voltages amplitude and phase bus code (slack, load or generating bus).
3. Insert Sbase , maximum number of iteration= 1000 and the accuracy = 0.001.
4. Generate Ybus , Jacobian Matrix.
5. Use Newton Raphson method to calculate the power solution at the fundamental frequency.
6. Calculate active ve reactive power at the slack bus for the fundamental frequency.
7. Calculate the reactive power required by the filter that is the total fundamental reactive power.

Step 2

1. Input harmonic current spectrum and its frequency order.
2. Enter active and reactive power for the non linear load and its position.
3. Calculate I1 for the non linear load.
4. Calculate Ih using C(h) and I1 for the non linear load.
5. Calculate Ih and Vh at all buses.

Step 3

1. Give a first assumption for the filter size and tuned frequency.

Step 4

1. Input PSO parameters (c_i =2:0 w_{max} =0,9 w_{min} =0,4).
2. Define objective functions (minimum P_{loss} and THD).
3. Define constrains (fundamental power equation).
4. Generate initial filter position and tuned harmonic order for each agents.
5. Evaluate the searching point for each agents.
6. Modification for each searching agents.
7. Maximum iteration number reached.

Step 5

1. Input GA parameters.
2. Use the PSO output and generate a random value for the filter size and set the frequency order for each chromosome in the population.
3. Calculate the power equations in at the fundamental frequency then recalculate V_h
4. Evaluate the objective functions of minimum active power losses with the constraints of not exceeding THD limits for each chromosome in the population.
5. Maximum Number of Iterations.
6. If not, selection, crossover and mutation.
7. New Population.
8. Print filter size, position and set frequency.

2.2 The Hybrid GA-PSO Test on the IEEE 14 Bus System and on a Real Electrical Network

To explore the optimal placement and dimensions of a passive filter within a power system, aiming to reduce total harmonic distortion to the IEEE standard-defined legal limits, minimize active power losses in branches, and improve the system power factor using a hybrid optimization technique integrating PSO and GA; two tests had been done. In the following sections the details of the tested systems were identified.

2.2.1 The IEEE 14 Bus System

The 14-bus IEEE standard system was selected as the basis for the optimization study. The optimization task involved addressing the passive filter design and allocation problem. The GA-PSO hybrid optimization technique previously defined was applied to assess solutions for the IEEE 14-bus system. This undertaking aimed to evaluate the effectiveness, robustness, and quality of the proposed technique.

The IEEE 14-bus system comprises four generation buses, one slack bus, and nine load buses, all operating at the same voltage level (1kV). The characteristics of each bus, including its type, rated voltage amplitude and angle, active and reactive power for loads and generators, as well as reactive power limits, are detailed in Table 1. The single line diagram for the IEEE 14 bus is represented using ETAP program as shown in Fig.4.

In the assumption that the system is initially free from harmonics, a nonlinear load was introduced to serve as the harmonic source in the system. Specifically, a nonlinear load in the form of an IEEE typical 6-pulse rectifier was added to bus number 10. This load contributes 18.75 MW and 16.53 Mvar of active and reactive power, respectively. The harmonic spectrum associated with this load is depicted in Fig.5.

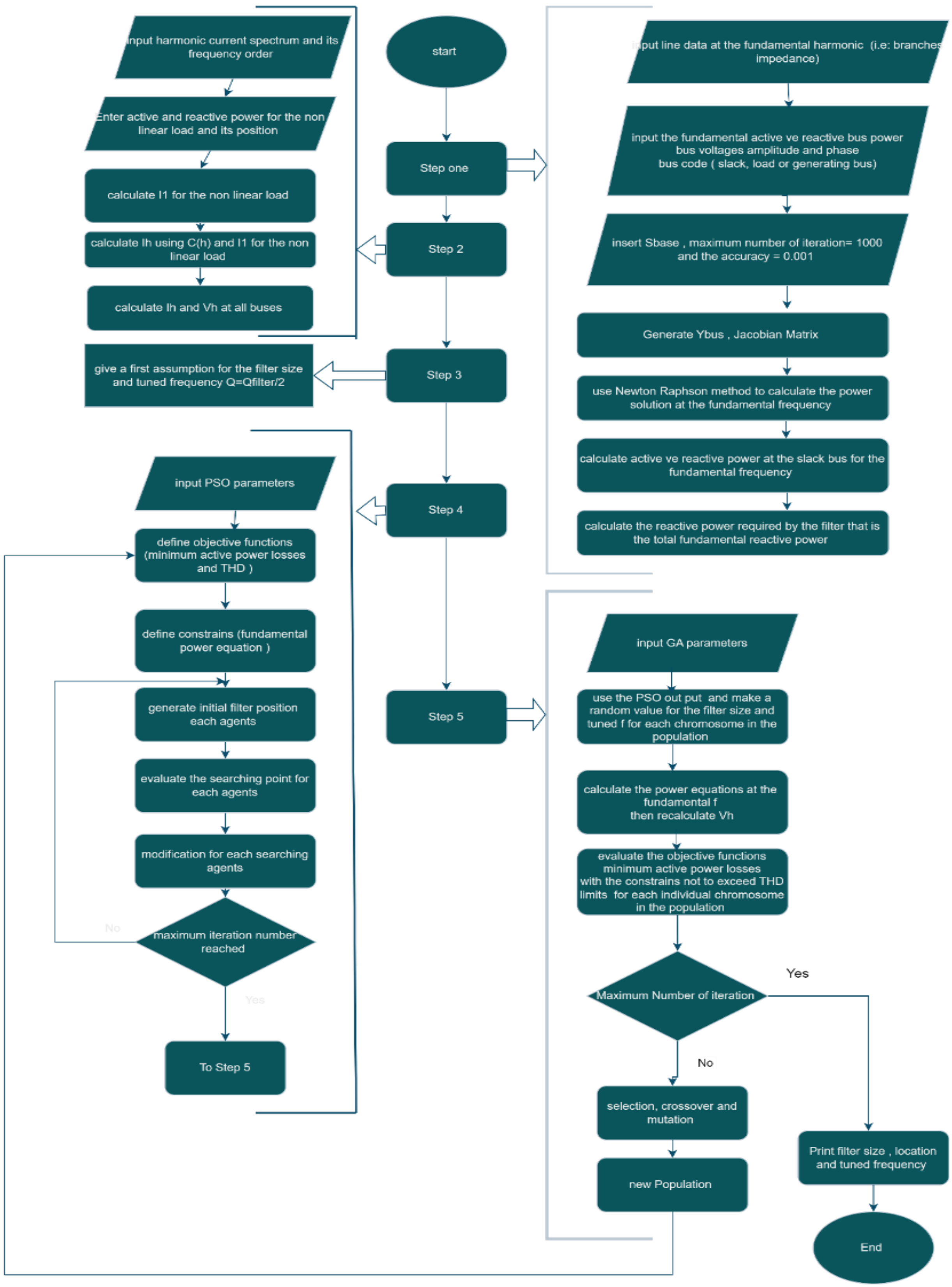

Figure 3: Hybrid GA-PSO Flowchart

Table 1: Generation Bus Information for IEEE 14 Bus System.

Generation Bus			Voltage		Generation		Mvar Limits	
ID	kV	Type	% Mag.	Angle	MW	Mvar	Max	Min
Bus1	1.000	Voltage Control	109.0	0.0	0.000		1.000	-1.000
Bus 1 H_1	1.000	Swing	106.0	0.0				
Bus 2 H_2	1.000	Voltage Control	104.5	0.0	29.145		29.145	-29.145
Bus 3 H_3	1.000	Voltage Control	101.0	0.0	0.000		23.400	0.000
Bus 6 L_6	1.000	Voltage Control	107.0	0.0	0.000		12.200	-6.000

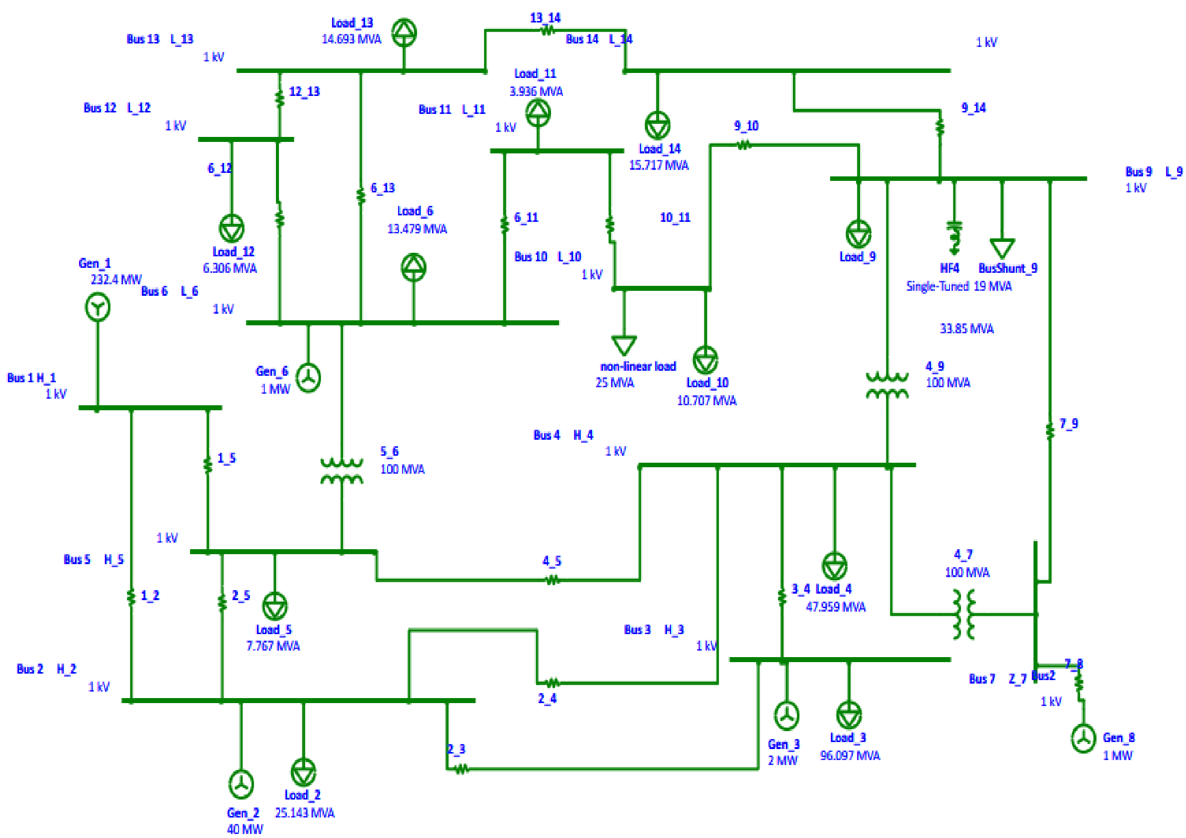

Figure 4: IEEE 14 Bus System Single Line Diagram

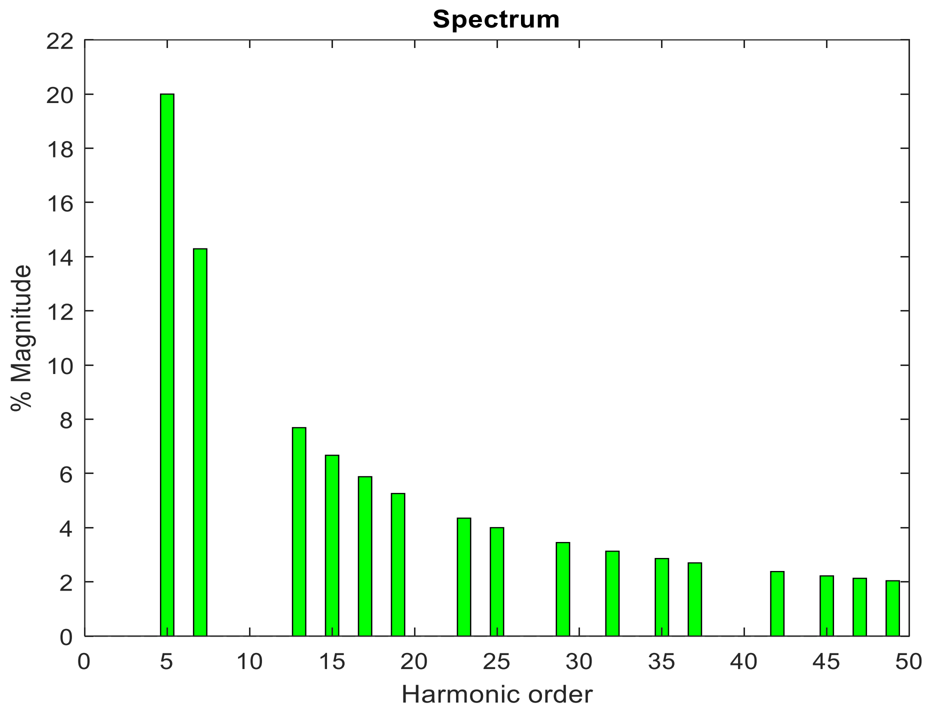

Figure 5: Nonlinear Load Harmonic Spectrum

The harmonics orders are [5 7 13 15 17 19 23 25 29 32 35 37 42 45 47 49]. The harmonic current can be determined using Eq.10 where C(h) represents a fraction of the fundamental current components or it is defined based on real values from its power spectrum. The coefficients C(h) for different harmonic orders (h) are specified as follows:

C(h)=[0.20.0286 0.0313 0.0345 0.04 0.0435 0.0526 0.0588 0.0667 0.0769 0.1429 0.0270 0.0238 0.0222 0.0213 0.0204]

In this work, optimization algorithms were employed to determine the optimal locations and sizes for one and two single-tuned filter. The results obtained were then compared with those obtained without any filters. Prior to the initiation of the optimization algorithm, the total reactive power for the filters was calculated using the Newton-Raphson power flow analysis method, resulting in a value of 73.299 Mvar, representing the total fundamental reactive power.

The THD at each bus of the system before the filter installation is illustrated in Fig.6. It is evident that the THD has surpassed IEEE limits at buses 10 and 9, and that the THD at buses 1 and 14 is very close to the IEEE limit. Bus 9 exhibits the highest THD value at 5.61%.

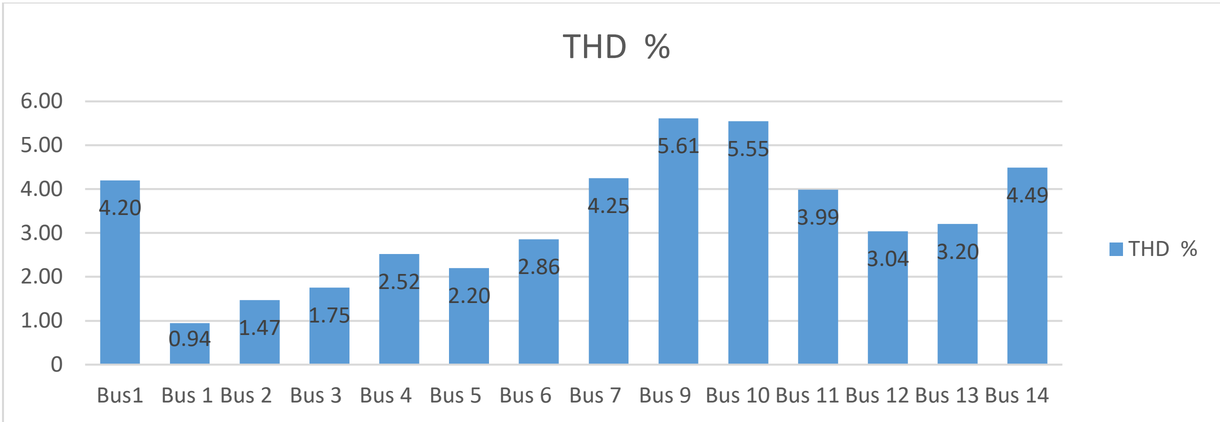

Figure 6: THD for the IEEE 14 Bus System without Installing Passive Filter.

2.2.2 The Second Case Study a Real Electrical Network that is Tubas District Electricity Company:

The Tubas District Electricity Company (TDECO), a publicly limited company, was established on 2006 with a capital of $3,491,320. It operates in Tubas city, a small governorate covering an area of 402 km^2 in the Middle East of Palestine. In 2002, the company commenced its operations by providing electricity to its initial 23 member shareholders, comprising municipal and village councils. Over the years, the company expanded its services to include electricity departments in municipalities and local authorities, serving a total of 15,000 customers by 2011.
With the goal of supplying electricity to 20,000 customers with a daily consumption rate of 25 mega-volt amperes, the company relies on two connection points receiving electricity from the Israeli company. The primary feeding point is located in Tayasir, delivering more than 20 MW, while the secondary point is in Al-Jalamah.
The electrical network in Tubas comprises 674 buses, 267 transformers, 408 cables and transmission wires, including 33 underground cables. To visualize and analyze this network, a single-line diagram was created using ETAP software, capturing the network's structure and components. The single-line diagram is illustrated in Fig.7.

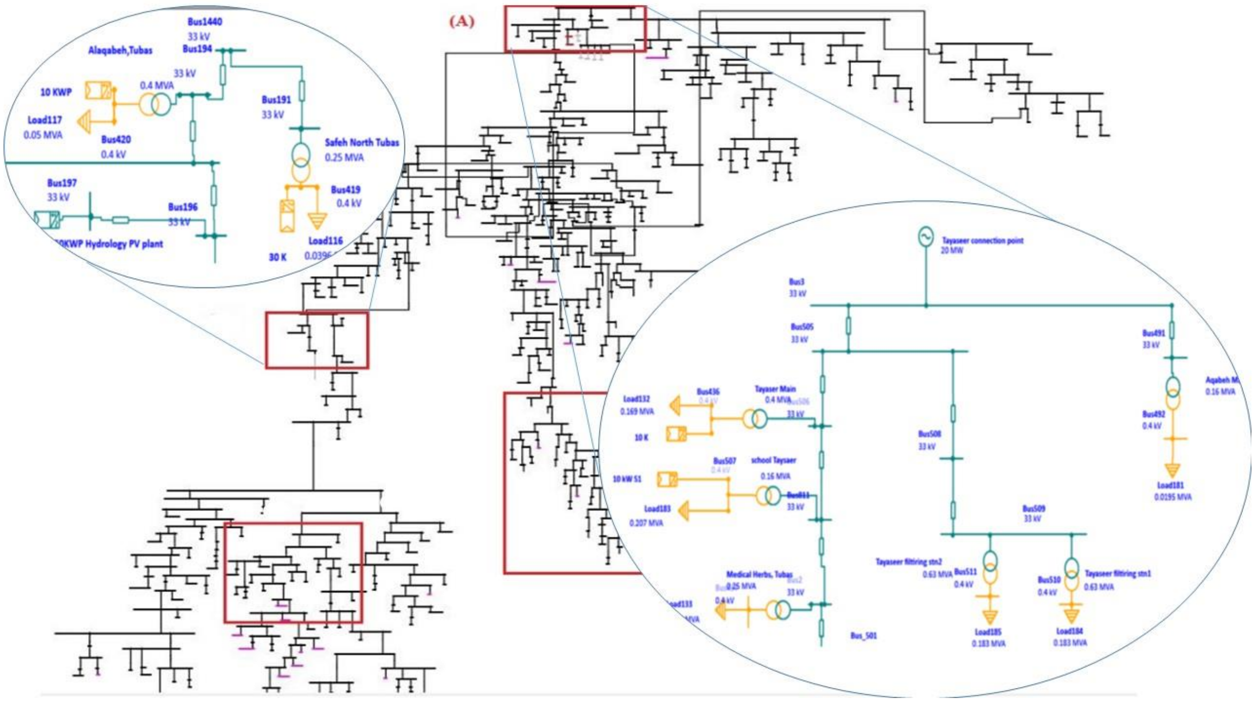

Figure 7: TDECO Single Line Diagram

For the TUBAS network, the total reactive power used to determine the filter sizes was 6 Mvar, calculated through the Newton-Raphson power flow analysis method before initiating the optimization algorithm. This value represents the total fundamental reactive power.

To assess the impact of passive filters on the network's behavior, a nonlinear load was introduced to one of the buses. Given the absence of specific harmonic distortion data, except for its exceedance of legal limits in multiple buses and the main feeding point, a nonlinear load was added to the bus with the maximum PV system, considering photovoltaic systems as potential sources of harmonics. At Bus 5, where the largest PV system with 5 MWp is installed (the biggest PV system in the network exceeding 19 MWp), a nonlinear load in the form of an IEEE typical 6-pulse rectifier was added. This load contributes 3.3 MW and 3.7 Mvar of active and reactive power, respectively.

The Total Harmonic Distortion (THD) at each bus of the system before installing the filters is illustrated in Fig.8. It is evident that the THD has exceeded IEEE limits at buses 459, 550, 565, and 717, and that the THD at buses 163, 164, 168, and 716 is very close to the IEEE limit. Bus 549 exhibits the highest THD value at 6.34%.

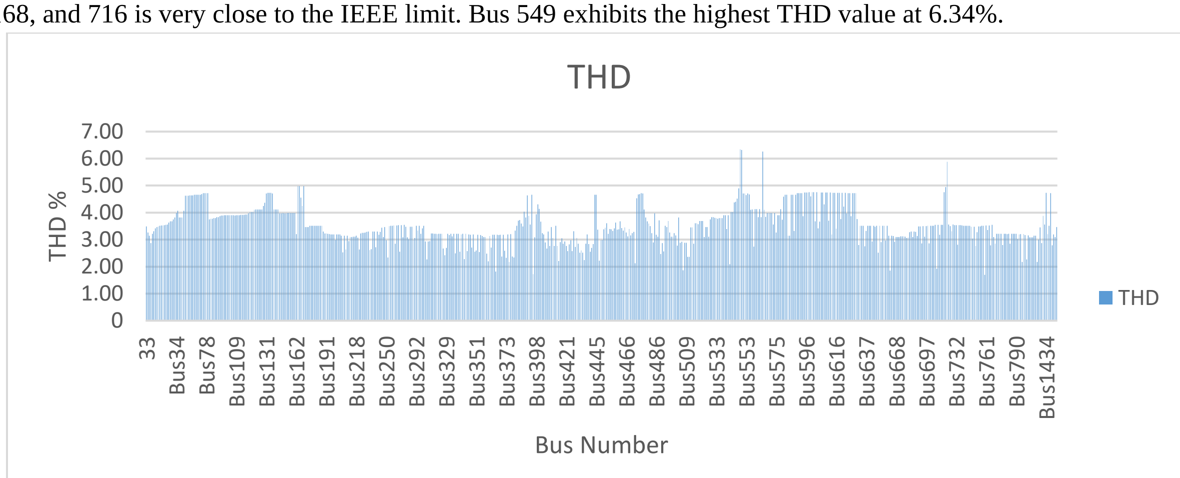

Figure 8: THD for the TDECO Buses before Installing Passive Filters.

3. Results and Discussion

3.1 IEEE 14 Bus System Test Results

The effect of installating a single passive filter with a capacity of 21.6 Mvar at bus number 9, on the 14 bus IEEE system, could be notice over the THD as shown in Fig.9 as well as over the power factor improvment and active power loss reduction. The maximum THD has seen a reduction of 27.6%, decreasing from 5.61% to 4.06%. Additionally, the total active power losses at branches have experienced a 2.4% reduction, decreasing from 46.3 MW to 45.2 MW. It is noteworthy that these reductions could further enhance if more than filter is installed. The results of installing one and two single tunde filter is summrized in Table 2.

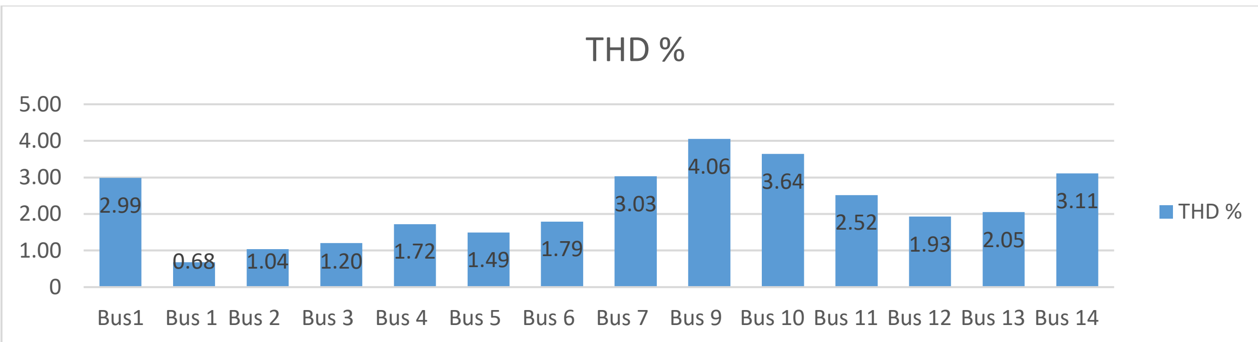

Figure 9: THD for the IEEE 14 Bus System after Installing Passive Filter with 21Mvar Capacity

Table 2: IEEE 14 Bus System Original Case and after Installing One and Two Single Tuned Passive Filters.

Objective Function values with the Design parameters	Original case (without Filters)	One filter solution	Two filter solution	
			Filter 1	Filter 2
Filter size Mvar	-	21.6	37	32
Active power losses MW	46.3	45.2	42.6	
THD%	5.61	4.06	4.4	
Filter Location	-	9	10	13
Tuned Frequency	-	7.04	7.12	7.14
Filter Inductance (mH)	-	2.9	3.96	4.56
Filter capacitance (μF)	-	65529	47509	41089
Filter Resistance (mΩ)	-	97.4	134	113.5
Q Factor		66	66	90
Power factor at the main connection point	96.4	97.6	99.06	

3.2 The Second Case Study Tubas District Electricity Company Test Results

The Total Harmonic Distortion (THD) after installing a single passive filter with a capacity of 5 Mvar at bus number 165 in the TUBAS network is illustrated in Fig.10. Notably, the maximum THD has undergone a reduction of 48% decreasing from 6.34% to 3.0%. Additionally, the active power losses at branches have experienced a 8% reduction, decreasing from 1.63 MW to 1.4 MW. Moreover, the power factor at the main connection point has increased by 11% rising from 61.7 to 68.5.

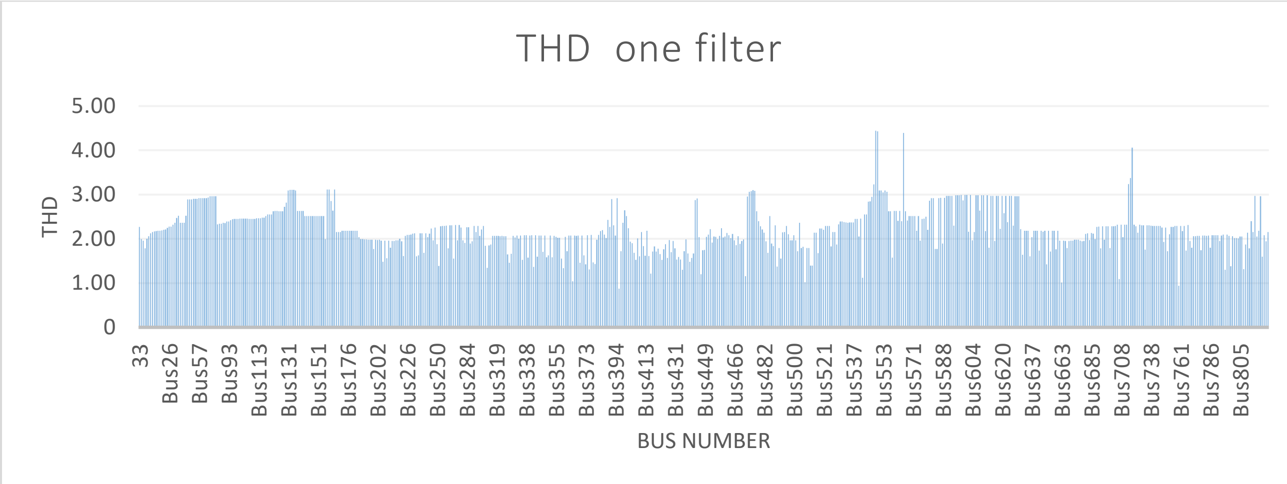

Figure 10: THD for the TDECO Buses after Installing One Passive Filters

The impact of installing two passive filters, with capacities of 1.62 Mvar and 2.8 Mvar, at bus numbers 163 and 717 in the TUBAS network is illustrated in Fig.11. The results indicate a significant improvement in system performance: The maximum THD has been reduced to 4.4%, representing a reduction of 30.6% compared to the original THD of 6.34%. Active power losses at branches have been reduced by 5.5%, decreasing from 1.63 MW to 1.54 MW.
The power factor at the main connection point has increased by 14.3%, rising from 61.7 to 72%. These improvements highlight the effectiveness of strategically placing passive filters in the network to mitigate harmonic distortions, decrease active power losses, and enhance power factor. The result of installing one and two single tuned passive filters is summarized in Table 3.

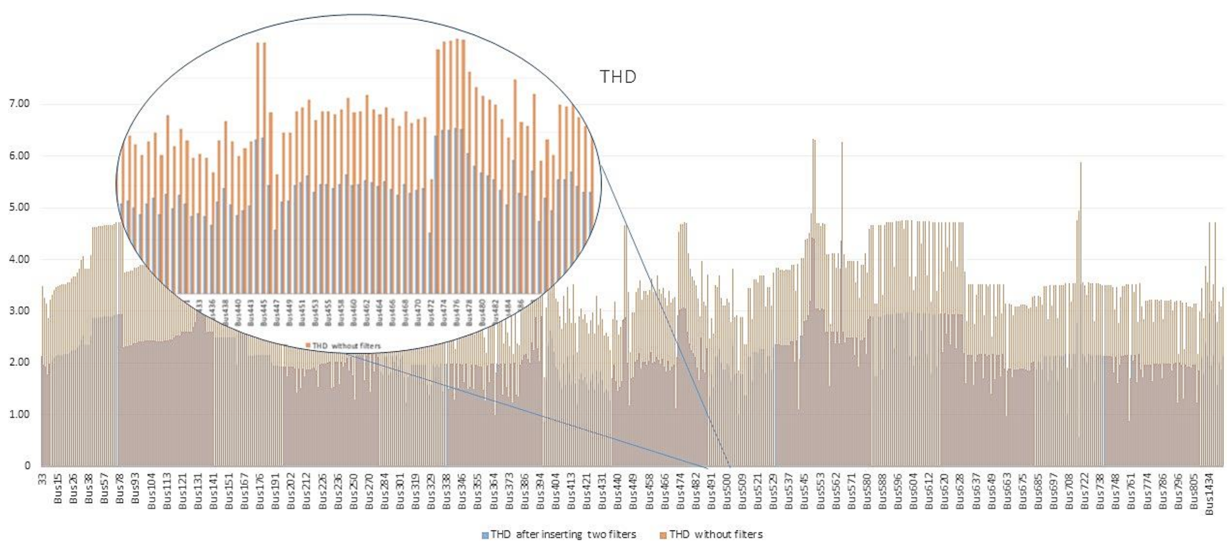

Figure 11: THD for the TDECO Buses before and after Installing Two Passive Filters

Table 3: TDECO Original Case and after Installing One and Two Single Tuned Passive Filters.

Objective Function values with the Design parameters	Original case (without Filters)	One filter solution	Two filter solution Filter 1	Filter 2
Filter size Mvar	-	5	1.62	2.8
Active power losses MW	1.63	1.4	1.54	
THD%	6.34	3.0	4.4	
Filter Location	-	165	163	717
Tuned Frequency	-	5.125	5.14	5.26
Filter Inductance (mH)	-	2.9	7.1 µ	0.016
Filter capacitance (μF)	-	65529	53978	23077
Filter Resistance (mΩ)	-	97.4	0.124	0.26
Q Factor		66	99	102
Power factor at the main connection point	61.7	68.5	72	

GA and PSO optimization methods were used to select the position of two single tuned passive filter for this system. Using PSO decreasing the THD by 30.6% and reducing the active power losses by 4.3% while enhancing the power factor by 17%, while using GA decreasing the THD by 27.4% and reducing the active power losses by 8.6% while enhancing the power factor by 17.7% as summarized in Table 4. In one hand, the heuristic optimization methods used on this research shows satisfied results, on the other hand the hybrid GA-PSO methods shows a robust effective and high-quality solutions specially for large systems.

Table 4: TDECO Original Case and after Installing Two Single Tuned Passive Filters Using PSO and GA.

Objective Function values with the Design parameters	Original case (without Filters)	PSO		GA	
		Filter 1	Filter 2	Filter 1	Filter 2
Filter size Mvar	-	1.6	2.4	1.2	2.4
Active power losses MW	1.63	1.56		1.49	
THD%	6.34	4.41		4.6	
Filter Location	-	163	722	163	716
Tuned Frequency	-	5.13	5.29	5.39	5.26
Q Factor		100	99	99	101
Power factor at the main connection point	61.7	72.29		72.6	

4. Conclusion

The results achieved through the hybrid GA-PSO approach align with the predefined objective functions, focusing on minimizing active power losses, and comply with the IEEE standard for Total Harmonic Distortion limits, serving as specified constraints met within this proposed methodology. The results shows that the THD could be reduced to a proximately 50% of its initial value. The reduction on the active power loss had a lower reduction percentage and that's due to the large number of buses in the time where the algorithm had restricted by allocating two filters as a max.

Comparative analysis between the outcomes of the hybrid GA-PSO approach and those of GA or PSO reveals that the hybrid GA-PSO method offers efficient, and high-quality solutions for extensive systems, whereas PSO demonstrates exceptional solutions for smaller systems. The accuracy and efficiency of the hybrid GA-PSO approach are successfully validated through the utilization of ETAP and MATLAB programs, illustrated effectively by both the standard IEEE 14 and the real system of Tubas Electric Company. Irrespective of the objective function's structure, the suggested hybrid GA-PSO approach can be easily and promptly applied to any other distribution system featuring linear and/or nonlinear loads.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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