# Optimum Design of Passive Harmonic Filter by Using Game Theory Concepts

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## Abstract:

Passive harmonic Filters (PHF) are the simplest, cheapest, and the most effective way to reduce harmonics of the voltage and current waveforms. In designing the PHF, the main goals are to minimize the cost of the filters and reduce the total harmonic distortion of currents and voltages at the Point of Common Coupling (PCC) to the acceptable range which are defined by standards. In this paper, an important multi-objective optimization approaches namely Strength Pareto Evolutionary Algorithm (SPEA) has been used for tuning the PHF parameters. This approach is applied to IEEE 13 node test system with a six-pulse converter as a harmonic source. Another approach, called Nash GA, is based on non-cooperative game that gives an optimal point known as Nash equilibrium. This approach is also simulated on IEEE test system. The result of optimization shows lower THD and cost for optimal PHFs in comparison with the conventionally designed one. To make comparison, some results of these methods are compared and discussed.

**Keywords:** Game theory, Multi-objective optimization, Nash equilibrium, Non-dominated sorting genetic algorithm, Passive harmonic filter, Strength Pareto algorithm.

## 1. INTRODUCTION

In last years, power quality becomes a major issue for electric utilities and their customers, and indirectly to almost all manufacturers of equipment that depend on sinusoidal supply voltage waveforms. Harmonics cause distortions of the voltage and current waveforms, which have adverse effects on electrical equipment. Harmonics are one of the major power quality concerns.

To promote power quality, several methods such as the use of higher-pulse converters, the modification of electric circuit configurations, the choice of transformer connections, and the application of harmonic filters have been proposed. Among them, Passive Harmonic Filters (PHF) not only provides low impedance shunt paths for harmonic currents, but also gives reactive power compensation at the fundamental frequency [1], [2].

In a multi-bus system, how to tune and optimize PHF can be formulated as a nonlinear programming problem. Recently, the problem of optimal PHF planning has been studied by many researchers [1]-[5].

There are two major ways to design PHFs. First is conventional method and second is heuristic method.

In conventional design, PHF parameters are designed based on harmonic order, power system reactive power demand and system configuration. In this technique, you should have information system like harmonics value, system

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impedance and loads (see part IV). Furthermore, designer may not be able to tune filter properly. These all have encourage researchers to work on new design methods like the Genetic Algorithm [3], the hybrid optimization [5] and the PSO method [2].

In this paper, the new multi-objective approaches which have some excellent feature in comparison with aforementioned methods, has been presented. Two successful cooperative game theory based algorithms; SPEA [6] and NSGA-II [7] are employed to solve the problem. In these algorithms not a single solution is found, but instead a set of solutions that is called Pareto Optimal Set (POS) is obtained. Each Pareto set can be chosen as a favorite set of design parameters by the power system designers according to their own particular technical issues and contemplations.

Another multi-objective optimization approach which is used to design PHF is Nash GA [7]. The Nash GA's algorithm is based on non-cooperative game theory. This algorithm gives a single solution which is Nash equilibrium.

Game Theory, formulated mathematically by J. F. Nash in the early 50s and found its first applications in the economics. In particular it was applied to solve the problems concerning the decisions that have some effects on various and often competitive fields. These strategies may however been adopted also in the industrial design, and in particular they can be combined with evolutionary algorithms, in order to optimize a product following several criteria and objectives with the great advantage to save a lot of computational time, that is perhaps the first need in the industrial fields.

The structure of this paper is as follows: in section II power system model which is the IEEE 13 node test system and the three-phase six-pulse thyristor converter as a non-linear load are presented. In section III the optimization approaches and related game theory concepts are explained. Section IV describes conventional methodology of PHF designing. Section V shows simulation results and gives a comparison between CPHF and new ones. Section VI concludes the paper and section VII is appendix including symbols list and test system's information.

## 2. POWER SYSTEM MODEL

### 2.1. Power system case

IEEE 13 node test feeder is considered for evaluating the proposed designing approach. This feeder is very small and yet displays some very interesting characteristics. In this paper, the simplified system has been used.

For a small feeder this will provide a good test for the most common features of distribution analysis software's. This system is shown in Fig. 1 and its data is given in appendix. There is a non-linear load in feeder 634 that is a three-phase full-bridge converter. This converter feeds a RL load.

### 2.2. Three-Phase Full-Bridge converter

In industrial applications where three phase ac voltages are available, it is preferable to use three-phase converter circuits, because of their low ripple content in the waveforms and a higher power handling capability [8]. The three-phase six-pulse thyristor converter is shown in Fig. 2. This converter produces harmonics of orders 6k ± 1 for integer values of k [9].

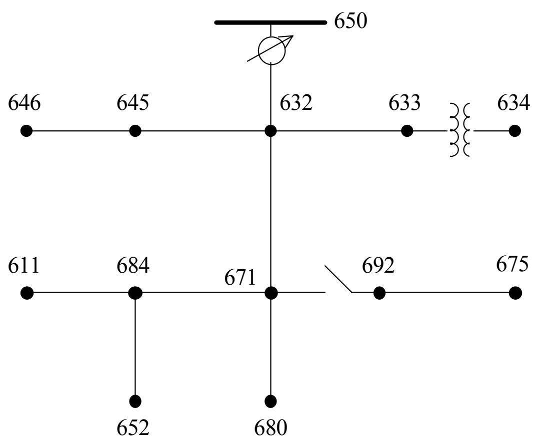


**Fig. 1: IEEE 13 Node Test Feeder**

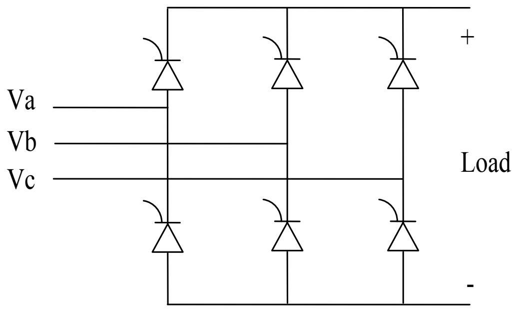

**Fig. 2: three-phase six-pulse thyristor converter**

## 3. OPTIMIZATION APPROACHES

Game theory concept is applicable for a multi-objective optimization problem in its own original status needless to any modification or combining the objectives. Of course it could be used together with an evolutionary method to reach optimum outcome.

Generally, a multi-objective optimization problem can be represented as:

Minimize:

$$g = f(x) = (f_1(x),\dots f_i(x),\dots f_k(x)) \tag{1}$$

Subjected to:

$$x = (x_1, x_2, \dots x_n) \in X \ \ \& \ \ y = (y_1, y_2, \dots, y_k) \in Y$$

### 3.1. Cooperative games: Pareto- front

Definition:

The vector $a$ in the search space dominates vector $b$ if:

$$\begin{aligned} &\forall_i \in \{1,2,\dots,k\}: f_i(a) \geq f_i(b) \\ &\exists_j \in \{1,2,\dots,k\}: f_j(a) > f_j(b) \end{aligned} \tag{2}$$

If at least one vector dominates $b$, then $b$ is considered dominated vector otherwise it is called non-dominated. Each non-dominated solution is regarded as an optimal in the sense of Pareto which is called Pareto optimal. Obviously, any Pareto optimal solution is comparatively the most optimal one in terms of at least one of the objective functions. The set of all non-dominated solutions is called Pareto Optimal Set (POS) and the set of the corresponding values of the objective functions is called Pareto Optimal Front (POF) or simply Pareto-front.

In a problem of minimizing two functions $f_1$ and $f_2$, the space variables have been defined as the set of rational strategies. In fact, when considering I and II as two players, each set of variables represents a combination of the strategies played by two players.

The Pareto front may be seen as the result of a cooperative game, in which the two players I and II try to minimize two functions simultaneously; in the other words, each strategy played by the players is paid by the fitness of the two functions, it means how much the solution satisfies the objectives of minimization of the two functions. Not a single solution, but instead a set of solutions called Pareto optimal front is found. This set is characterized by the fact that it is not available any solution such that both functions have a better fitness for any point of the front. Now a discussion for two successful evolutionary algorithms can be provided briefly.

### 3.2. Strength Pareto Evolutionary Algorithm (SPEA)

The SPEA which takes benefits of many features of some other approaches is used in this paper. Fig. 3 shows a flowchart of the approach which includes the following major steps [6]:

**SPEA Algorithm:**

1. Generate an initial population P and create the empty external non-dominated set P'.
2. Paste non-dominated members of P into P'.
3. Remove all solutions within P' which are covered by any other members of P'.
4. If the number of externally stored non-dominated solutions exceeds a given maximum N', prune P' by means of clustering.
5. Calculate the fitness of all individuals in P and P'.
6. Use binary tournament selection with replacement and select individuals from P and P' until the mating pool is filled.
7. Apply crossover and mutation operators as usual.
8. If the maximum number of generations is reached, then stop and, else go to step 2.

Fitness evaluation is also performed in two steps. Firstly, the individuals in the external non-dominated set P' are ranked. Then, the individuals in the population P are evaluated [6].

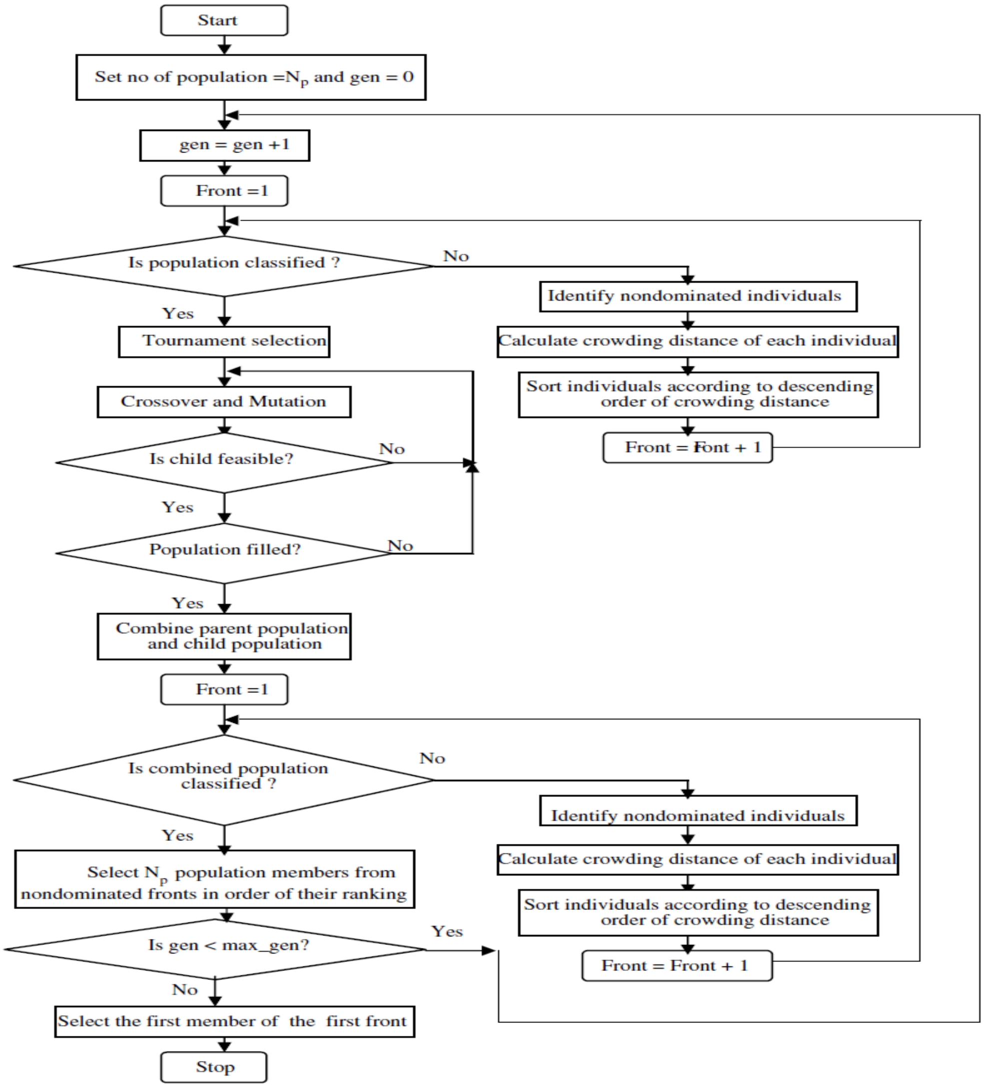


**Fig. 4: computational flowchart of NSGA-II [17]**

## 3.3. Non-dominated Sorting Genetic Algorithm (NSGA-II)

Non-dominated sorting genetic algorithm II (NSGA-II) is suggested in [7]. This paper has claimed that in the most of the problems, NSGA-II in comparison with SPEA is able to find much better spread of solutions and better convergence near the true Pareto optimal front. SPEA pay special attention to create a diverse Pareto optimal front. NSGA-II includes the following main steps:

**NSGA II Algorithm:**

1. Generate a random parent population P.
2. Sort P based on non-domination.
3. Assign fitness to P and create an offspring population Q using binary tournament selection with replacement, recombination and mutation.
4. Combine parent and offspring populations and form combined population R with size of 2N (except first period).
5. Sort R based on non-domination: R= $\{F_1, F_2 \ldots\}$.
6. Form new parent population according to non-domination and crowding distance sorting.
7. If the maximum number of generations is reached, then stop, else go to step 2.

The NSGA-II computational flowchart is shown in Fig. 4. More details of algorithm like non-dominated sorting and crowding distance sorting are given in [7].

### 3.4. Competitive games: Nash equilibrium

In a competitive game, two players act following different objectives; in particular, player 'I' have to choose his strategies in order to minimize his function $f_1$, while player 'II' have to minimize the function $f_2$. Of course, generally both functions depend on two domains, the strategies of one player influences the choices of the other one. The two players act simultaneously until an equilibrium which is Nash equilibrium is found. In that case, each player has minimized his own function with a common pair of strategies. The Nash equilibrium, also called strategic equilibrium, is a list of strategies, one for each player, which has the property that no player can unilaterally change his strategy and get a better payoff [10].

**Nash GA**

The idea is to bring together genetic algorithm and Nash strategy in order to make the genetic algorithm build the Nash equilibrium [11].

Let S=XY be the string representing the potential solution for a dual objective optimization problem. X corresponds to the subset of variables handled by Player 'I', and optimized along criterion 1.Y corresponds to the subset of variables handled by Player 'II' and optimized along criterion 2. Thus, as advocated by Nash theory, Player 'I' optimizes S with respect to the first criterion by modifying X, while Y is fixed by Player 'II'. Symmetrically, Player 'II' optimizes S with respect to the second criterion by modifying Y while X is fixed by Player 'I'.

The next step consists of creating two different populations, one for each Player. Optimization task of Player 'I' is performed by population 1 whereas optimization task of Player II' is performed by population 2. Let $X_{K-1}$ be the best value which is found by Player 'I' at generation K-1 , and $Y_{K-1}$ the best value found by Player 'II' at generation K-1. At generation $k$, Player 'I' optimizes $X_K$ while using $Y_{K-1}$ in order to evaluate S ($S=X_KY_{K-1}$). At the same time, Player 'II' optimizes $Y_K$ while using $X_{K-1}$ ($S=X_{K-1}Y_K$). After the optimization process, Player 'I' sends the best value $X_K$ to Player 'II' who will use it at generation K+1. Similarly, Player 'II' sends the best value $Y_K$ to Player 'I' who will use it at generation K+1. Nash equilibrium is reached when neither Player 'I' nor Player 'II' can further improve their criteria. Fig. 5 shows Nash GA's process.

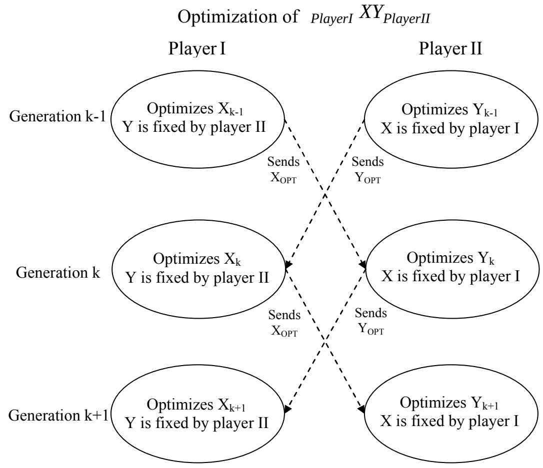


**Fig.5: Nash GA process [11]**

## 4. SINGLE TUNED PASSIVE FILTER DESIGN

Three-phase harmonic filters are shunt elements that are used in power systems for decreasing voltage distortion and power factor correction. Non-linear elements such as power electronic converters generate harmonic currents or harmonic voltages, which are injected into power system. The resulting distorted currents flowing through system impedance produce harmonic voltage distortion. Harmonic filters reduce distortion by diverting harmonic currents in low impedance paths. Harmonic filters are designed to be capacitive at fundamental frequency, so that they are also used for producing reactive power required by converters and for power factor correction [9].

There are different types of filters, but here, single-tuned passive filter (STPF) is used to mitigate harmonics. As it shown in Fig. 6, STPF filter is a series RLC circuit tuned to the frequency of one harmonic. Its impedance is given by:

$$Z = R + j(\omega L - \frac{1}{\omega C}) \tag{3}$$

Single-tuned filter designing methodology includes the following major steps [10]:

1. Calculate capacitor size ($C$) according to system call for reactive power.
2. Calculate inductor size ($L$), using equation 4.

$$L = \frac{1}{(2\pi f h)^2 C} \tag{4}$$

3. Calculate quality factor of filter ($Q$), using equation 5(optimum $Q$ which results in the

lowest harmonic voltage).

$$Q = \frac{\cos(\varphi_m) + 1}{2\delta \sin(\varphi_m)} \tag{5}$$

In which $\delta$ is often expressed as:

$$\delta = \frac{\Delta f}{f_n} + \frac{1}{2}(\frac{\Delta L}{L_n} + \frac{\Delta C}{C_n}) \tag{6}$$

4. Calculate $R$ using equation 7.

$$R = \frac{2\pi f h L}{Q} \tag{7}$$

Symbols description is given in appendix.

## 5. SIMULATION RESULTS

### 5.1. There is no filter

Table (1) gives current harmonics amount in bus 634 without any filter. This table includes harmonics of order 6k ± 1 while other harmonics are very low. THD is 27.7% that is high according to IEEE Std. 519-1992 [12] and should be reduced to its amount. In this paper a bank filter for the harmonics of 5, 7, 11, 13 orders has been designed, which have most contrast with [13]. As it was mentioned before, the simplest and cheapest way is to use STPF for each harmonic at PCC.

**Table (1): Magnitude of the PCC harmonics with no filter**

| Harmonic Order h | Harmonic Amount (%) |
|---|---|
| 1 | 100 |
| 5 | 20 |
| 7 | 13.3 |
| 11 | 8.66 |
| 13 | 6.64 |
| 17 | 5.15 |
| 19 | 4 |
| 23 | 3.3 |
| 25 | 2.57 |
| THD | 27.7 |

### 5.2. Passive filter design without optimization

A conventional STPF is designed using the method described in Section 4. According to Table (9), power system's call for reactive power is 1986 kVar.

If the capacitor temperature coefficient is 0.05% per degree Celsius, the inductor temperature coefficient 0.01% per degree Celsius, ambient temperature ±20◦C and frequency tolerance ±1%, then from equation 6, $\delta$ =0.016.

Having $\delta$ and $\varphi_m$ = 80, Quality factor $Q$, using equation 5 will be 37.24. Table 2 shows the results.

As it is seen from Table (2), THD and harmonics of current decrease noticeably using STPF and their amount are standard. But an estimation of filter cost is necessary.

**Table (2): Magnitude of the PCC harmonics with conventional STPF**

| Harmonic Order h | Harmonic Amount (%) |
|---|---|
| 1 | 100 |
| 5 | 3.16 |
| 7 | 1.29 |
| 11 | 0.35 |
| 13 | 0.35 |
| 17 | 0.54 |
| 19 | 0.61 |
| 23 | 0.55 |
| 25 | 0.54 |
| THD | 4.33 |

### 5.3. Passive filter design with optimization

In this case, filter cost and current THD at bus 634, are considered as the two objective functions, while $R$, $L$ and $C$ are designed using optimization variables. Optimization variables are quality factor $Q$ and total injected VAR of the filter $Q_c$. According to the previous part, limits of these variables are selected as follow:

$$1000kVar < Q_c < 5000kVar$$

$$10 < Q < 40$$

Objective functions are as follow:

$$Min\ : THD = f_1(R, L, C) = f_2(Q, Q_c) \tag{8}$$

$$Min : Cost = g_1(R, L, C) = g_2(Q, Q_c) \tag{9}$$

Where THD can be expressed as:

$$THD = \frac{\sum_{h=2}^{\infty} I_h^{\ 2}}{I_f} \tag{10}$$

The total cost of filter which is the sum of filter cost and power losses can be expressed as [14]:

$$C_{total} = (C_{PL} + C_F) \quad (11)$$

Where

$$C_{PL} = K_P \sum_{i=1}^{n_s} \sum_{h=1}^{n_h} I_{ih}{}^2 R_i \quad (12)$$

$$C_F = \sum_{i=1}^{n_b} \sum_{j \in F_s} K_{ij} Q_{ij} \quad (13)$$

And

$C_{PL}$ = he cost of total real power loss.

$C_F$ = the cost of installation of LC tuned filters.

$F_s$ = {5, 7, 11, and 13) is the filter order.

$n_h$ = the total harmonic order.

$n_s$ = the total number of system sections.

$n_b$ = total number of buses including filter.

$I_{ih}$ = the current for harmonic $h$ flowing in the $i^{th}$ section.

$R_i$ = the resistance of the $i^{th}$ section.

$K_p$ = the cost of per unit power loss, in $/ kWh.

$Q_{ij}$ = the size of the $j^{th}$ harmonic filter at bus $i$, in kVar.

$k_{ij}$ = the cost per kVar corresponding to the size $Q_{ij}$ in $/kVar.

The commercial three-phase capacitor sizes and the corresponding costs can be found in [15]. By using this reference, an average value for all of $k_{ij}$ which is 0.2 $/kVar has been used. The cost per unit power loss $K_p$ = 0.0192 $/KWh. In this study, cost of $L$ and $R$ isn't regarded.

Using this method, cost of conventional STPF is 1261$. Simulation is carried out using MATLAB SIMULINK environment. All three multi-objective optimization approaches employ genetic algorithm. Table (3) includes GA parameters of these algorithms.

Table (3): GA parameters

| Parameter | SPEA | NSGA-II | Nash GA |
|---|---|---|---|
| Generation number | 25 | 50 | 25 |
| Population size | N=60 & N'=15 | 15 | 30 |
| length of the chromosome | 20 | Same as SPEA | Same as SPEA |
| Selection | roulette wheel | Same as SPEA | Same as SPEA |
| Recombination | single-point crossover | Same as SPEA | Same as SPEA |
| Mutation | Discrete with probability of 0.035 | Same as SPEA | Same as SPEA |

For SPEA, a population of size 60 and an external population of size 15 has been used (this 4:1 ratio is suggested by developers of SPEA to maintain an adequate selection procedure for elite solutions [7]). For NSGA-II a population of size 15 (N=15) is used. So Pareto fronts of SPEA and NSGA-II will have same size. Meanwhile generation numbers are so adjusted that functions evaluations are 1500 for three methods, while other parameters are similar. As a result, there is equivalent context for comparison of the algorithms.

Fig. 7 illustrates the Pareto fronts of SPEA against the conventional design. As it was seen, almost all fronts have a better THD in comparison with conventional one, and have higher cost. Also one of fronts dominates conventional design (i.e. conventional one is not Pareto front). Fig. 8 shows the Pareto fronts of NSGA-II against the conventional design which is one of the fronts. A contrast between Figs 7 and 8 reveals that Pareto front of NSGA has better distribution than those of SPEA, but are worse in convergence to real Pareto front. The Pareto front given in Fig. 9 which is the result of superimposing Figs. 7 and 8 clearly shows the compromise between cost and THD in the best way. The front is quite informative and explains how much cost will be increased to reach a better THD. For the system under study, Fig. 6 shows rapid changes at the THDs around 2.7%. This means a little improvement in terms of THD that costs us a lot and vice versa. On the contrary, the front is almost constant at high THDs. This means even significant improvement in THD from 15% to 2.7% does not impose any significant extra cost. Based on the points discussed above, a designer can choice a favorite point based on the technical and economical requirements. Sometimes a THD less than 5% is needed to fulfill IEEE Standards [15].

Table (4) includes parameters of composed Pareto front. If a single-objective optimization program to be used to minimize THD, it quite likely reaches point 2 from Table (4) that is a highly expensive solution. Conversely, if just to try to minimize the cost only, the results would be point 1 which is not acceptable in terms of THD [16].

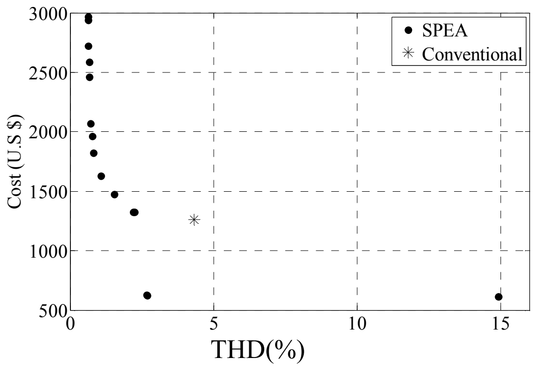


**Fig. 7: Pareto optimal front of SPEA versus conventional design**

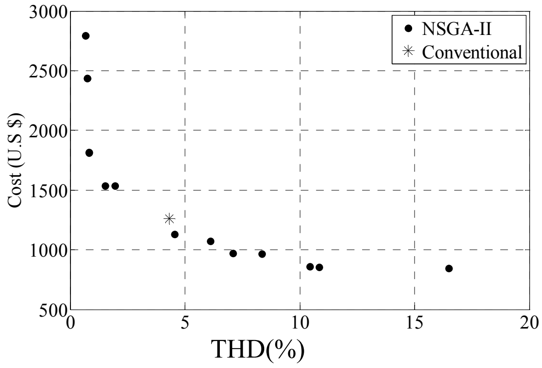


**Fig. 8: Pareto optimal front of NSGA-II versus conventional design**

**Table (4): Composed Pareto fronts parameters**

| Point | THD | Cost | $Q_c$ | Q |
|---|---|---|---|---|
| 1 | 14.9 | $6.13\times10^2$ | $1.02\times10^6$ | 39.7 |
| 2 | 0.625 | $2.97\times10^3$ | $4.95\times10^6$ | 36.2 |
| 3 | 2.70 | $6.22\times10^2$ | $1.04\times10^6$ | 37.9 |
| 4 | 2.67 | $6.27\times10^2$ | $1.04\times10^6$ | 38.1 |
| 5 | 2.25 | $1.33\times10^3$ | $2.21\times10^6$ | 34.5 |
| 6 | 0.706 | $2.07\times10^3$ | $3.45\times10^6$ | 16.5 |
| 7 | 0.679 | $2.46\times10^3$ | $4.10\times10^6$ | 29.7 |
| 8 | 1.54 | $1.48\times10^3$ | $2.46\times10^6$ | 36.5 |
| 9 | 1.08 | $1.63\times10^3$ | $2.71\times10^6$ | 36.2 |
| 10 | 0.639 | $2.72\times10^3$ | $4.54\times10^6$ | 36.2 |
| 11 | 2.21 | $1.33\times10^3$ | $2.21\times10^6$ | 29.5 |
| 12 | 0.782 | $1.96\times10^3$ | $3.27\times10^6$ | 34.4 |
| 13 | 0.628 | $2.94\times10^3$ | $4.90\times10^6$ | 30.4 |
| 14 | 0.669 | $2.58\times10^3$ | $4.31\times10^6$ | 29.7 |
| 15 | 0.815 | $1.82\times10^3$ | $3.03\times10^6$ | 24.4 |
| 16 | 1.53 | $1.54\times10^3$ | $2.56\times10^6$ | 17.8 |
| 17 | 0.815 | $1.81\times10^3$ | $3.02\times10^6$ | 18.1 |

As it mentioned above, there are two objectives; THD and filter cost and two optimization parameters; Qc and Q. So in the case of optimization with Nash GA, there are two players. Player ‘I’ optimizes THD and Player ‘II’ optimizes the cost. As for the repartition of the variables between the players (i.e. which player should optimize which variable), it depends on the structure of the problem [7]. Therefore, there are two cases. At the first case Player ‘I’ optimizes THD while he modifies Qc and Player ‘II’ optimizes cost while he modifies Q. In the second case Q and $Q_c$ for players has been replaced. The result is shown if Fig. 10. It seems that Nash GA 2 (i.e. case 2) have more rational choice, because it has selected a good THD with minimum possible cost whereas Nash GA 1 minimum possible THD with maximum cost. This proves the rationality of Nash GA. But there are two important points: a) the result of Nash GA may not be one of the Pareto fronts b) repartition of the variables between the players depends to relationship between objectives and variables and have an important role in final result.

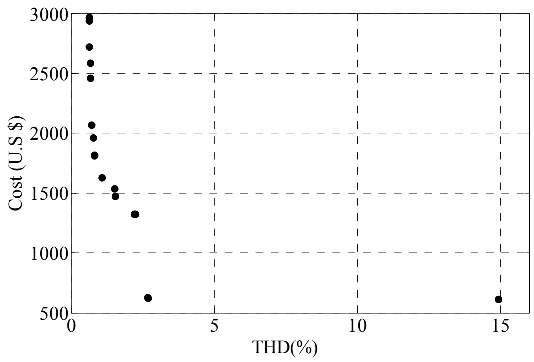


**Fig. 9: Composed Pareto optimal front**

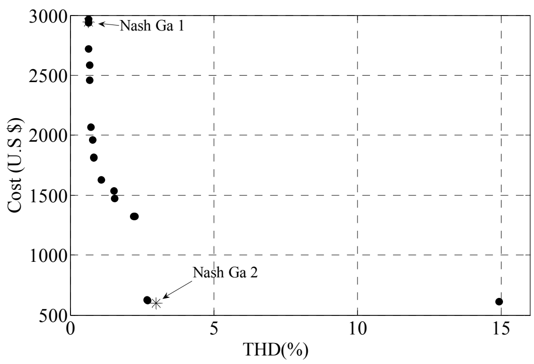


**Fig. 10: Composed Pareto optimal front versus Nash GA**

## 6. CONCLUSION

A new PHF design methodology i.e. Nash GA; which is a non-cooperative game theory based on multi-objective optimization approach, was proposed in this paper. SPEA and NSGA-II are two multi-objective evolutionary algorithms. These algorithms which employ cooperative game concepts were used for designing the PHF. A single tuned passive filter and a familiar distribution system were candidate of simulations. Minimization of the filter cost and THD were objectives. Nash GA presented a solution named Nash equilibrium while SPEA and NSGA-II produced a set of solution named Pareto front. Optimization results were compared with a conventionally designed filter and their capability were proved. Also Pareto fronts gave us good insight about THD and filter cost relationship. The Nash equilibrium was similar to the intellectual designed filter selected among Pareto fronts. These results proved rationality of Nash equilibrium and capability of the proposed algorithms in PHF designing and tuning.

## Appendix

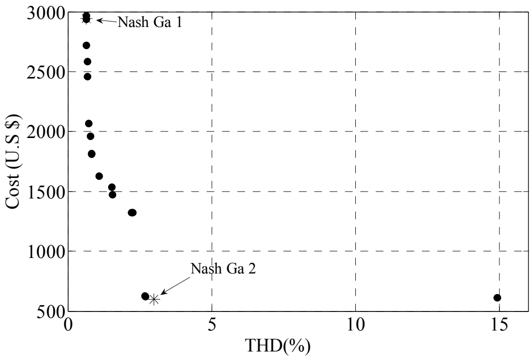


**Fig. 10: Composed Pareto optimal front versus Nash GA**

**Table (5): List of Symbols**

| Symbol | Description |
|---|---|
| $h$ | Harmonic order |
| $f$ | System frequency |
| $\varphi_m$ | Maximum phase angle of the network impedance |
| $\delta$ | Relative frequency deviation |
| $I_h$ | Harmonic component of current |
| $h$ | The harmonic number |
| $I_f$ | The fundamental current component, |
| $f_n$, $C_n$, $L_n$ | The nominal values of frequency, capacitance and |

**Table (6): Line Segment Data**

| Node A | Node B | Length(ft.) | Config. |
|---|---|---|---|
| 632 | 645 | 500 | 603 |
| 632 | 633 | 500 | 602 |
| 633 | 634 | 0 | XFM-1 |
| 645 | 646 | 300 | 603 |
| 650 | 632 | 2000 | 601 |
| 684 | 652 | 800 | 607 |
| 632 | 671 | 2000 | 601 |
| 671 | 684 | 300 | 604 |
| 671 | 680 | 1000 | 601 |
| 671 | 692 | 0 | Switch |
| 684 | 611 | 300 | 605 |
| 692 | 675 | 500 | 606 |

**Table (7): Transformer Data**

| | kVA | kV-high | kV-low | R % | X % |
|---|---|---|---|---|---|
| Substation: | 5,000 | 115 - D | 4.16 Gr. Y | 1 | 8 |
| XFM -1 | 500 | 4.16 – Gr.W | 0.48 – Gr.W | 1.1 | 2 |

**Table (8): Regulator Data**

| | | | |
|---|---|---|---|
| Regulator ID: | 1 | | |
| Line Segment: | 650 - 632 | | |
| Location: | 50 | | |
| Phases: | A - B -C | | |
| Connection: | 3-Ph,LG | | |
| Monitoring Phase: | A-B-C | | |
| Bandwidth: | 2.0 volts | | |
| PT Ratio: | 20 | | |
| Primary CT Rating: | 700 | | |
| Compensator Settings: | Ph-A | Ph-B | Ph-C |
| R - Setting: | 3 | 3 | 3 |
| X - Setting: | 9 | 9 | 9 |
| Voltage Level: | 122 | 122 | 122 |

**Table (9): Spot Load Data**

| Node | Load | Ph-1 | Ph-1 | Ph-2 | Ph-2 | Ph-3 | Ph-3 |
|---|---|---|---|---|---|---|---|
| | Model | kW | kVar | kW | kVar | kW | kVar |
| 634 | Y-Z | 160 | 110 | 120 | 90 | 120 | 90 |
| 645 | Y-Z | 0 | 0 | 170 | 125 | 0 | 0 |
| 646 | Y-Z | 0 | 0 | 230 | 132 | 0 | 0 |
| 652 | Y-Z | 128 | 86 | 0 | 0 | 0 | 0 |
| 671 | Y-Z | 385 | 220 | 385 | 220 | 385 | 220 |
| 675 | Y-Z | 485 | 190 | 68 | 60 | 290 | 212 |
| 692 | Y-Z | 0 | 0 | 0 | 0 | 170 | 151 |
| 611 | Y-Z | 0 | 0 | 0 | 0 | 170 | 80 |
| | TOTAL | 1158 | 606 | 973 | 627 | 1135 | 753 |

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