Shunt Active Power Filter Design using Genetic Algorithm Method

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Abstract: -This paper deals with the active power filter design controlled by using hysteresis technique. The genetic algorithm is used to design the controllers to minimize the %THD of the source current. The results are compared with that designed from Ingram and Round approach. The simulation results confirm that the genetic algorithm can provide the minimum %THD of the source current compared with the Ingram and Round method. The %THD also follows the IEEE std.519-1992.The design of the active power filter based on the genetic algorithm is flexible and can improve the performance of the filter.

Key-Words: - genetic algorithm, hysteresis control, harmonic elimination, active power filter

1 Introduction

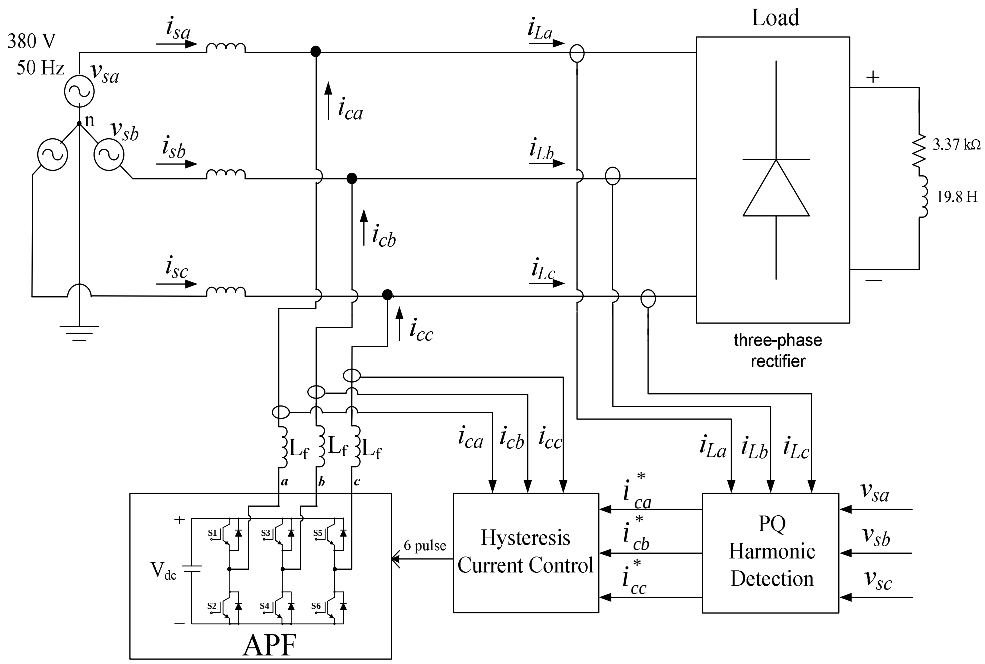

Fig.1 The power system considered

Power systems connected nonlinear loads can generate the harmonics into the systems. Theses harmonics cause a lot of disadvantages such as loss in transmission lines and electric devices, protective device failures, and short-life electronic equipments in the system [1]. Therefore, it is very important to reduce or eliminate the harmonics in the system. It is well known that the harmonic elimination via an active power filter (APF) [2] as shown in Fig.1 provides higher efficiency and more flexible compared with a passive power filter. In Fig.1, the three-phase bridge rectifier feeding resistive and inductive loads (R=3.37 kΩ and L=19.8 H) behaves as a nonlinear load into the power systems. An instantaneous reactive power theory (PQ method) [3] is used for a harmonic detection to calculate the reference currents for the active power filter. The APF is then controlled by a hysteresis method [4].

There are many approaches for the APF design using an artificial intelligence (AI) technique such as adaptive tabu search (ATS) [5], particle swarm optimization (PSO) [6], and genetic algorithm (GA) [7]. In this paper, the GA is used to search the appropriate parameters of the APF to minimize the %THD of the source current (i_s) after compensation. According to Fig.1, the APF parameters for GA searching are the DC bus voltage (V_{dc}), the filter inductance (L_f), and the hysteresis band (HB). The results of the APF design via GA are presented in this paper and are also compared with that designed from Ingram and Round approach [8].

The paper is structured as follows. The overview of compensating current control using the hysteresis method is addressed in section 2. The APF design using the Ingram and Round method and GA is fully presented in section 3 and section 4, respectively. The simulation results of the harmonic elimination including discussion are presented in section 5. Finally, section 6 concludes the advantages of GA approach to design the active power filter.

2 Control of compensating current using hysteresis method

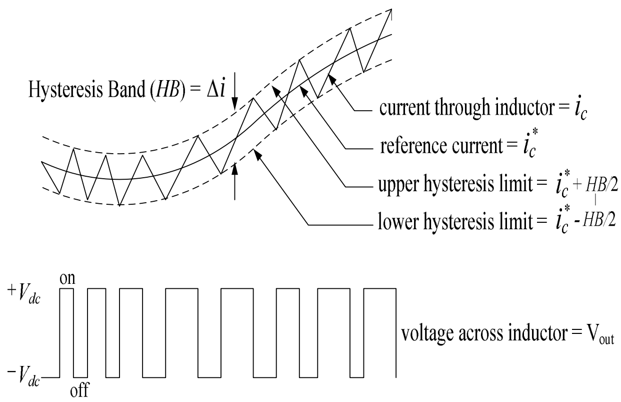

Fig.2 The compensating current control using hysteresis method

The compensating current control using the hysteresis approach is shown in Fig.2. According to Fig.2, the hysteresis band (HB) is the possible boundary of compensating current (i_c). This current swings between upper and lower hysteresis limits. The compensating current can be increased or decreased depending on the pattern switch of IGBT inside the APF. For example, when IGBT turns on, i_c will be increased. It is continually increased until reaching the upper hysteresis limit. At this state, IGBT will be automatically turned off to decrease the compensating current. If the current falls down to the lower limit, IGBT will be automatically turned on again to increase the compensating current. Therefore, the compensating current swings inside HB following the reference current i_c^*. The reference current can be identified by PQ harmonic detection as shown in Fig.1. Note that the upper and lower hysteresis limits are controlled by the hysteresis band.

3 The APF design using Ingram and Round method

In 1997, D.M.E. Ingram and S.D. Round presented the APF design controlled by hysteresis method. The details are explained as follows:

Step 1: Calculate the maximum value of di_c^*/dt by:

$$i_{h(\max)}(t) = A\sin(2\pi ft) \tag{1}$$

$$\max\left(\frac{d\,i_c^*}{dt}\right) = A2\pi f \tag{2}$$

where

$i_{h(max)}(t)$ is the maximum current for each harmonic components

A is the amplitude of the harmonic current

f is the frequency of the harmonic current

Step 2: Determine L_f by:

$$L_{f(\max)} = \frac{V_{dc} - V_s}{\max\left(\frac{d\,i_c^*}{dt}\right)} \tag{3}$$

where

V_s = the maximum voltage value of the source

Note that the maximum value of di_c^*/dt is from Step 1 and V_{dc} should be always designed higher than V_s [9,10].

Step 3: Determine HB by:

$$HB = \frac{2V_{dc}}{9L_f f_{sw}} \tag{4}$$

where

f_{sw} is the switching frequency.

4 The APF design using GA approach

4.1 The review of GA

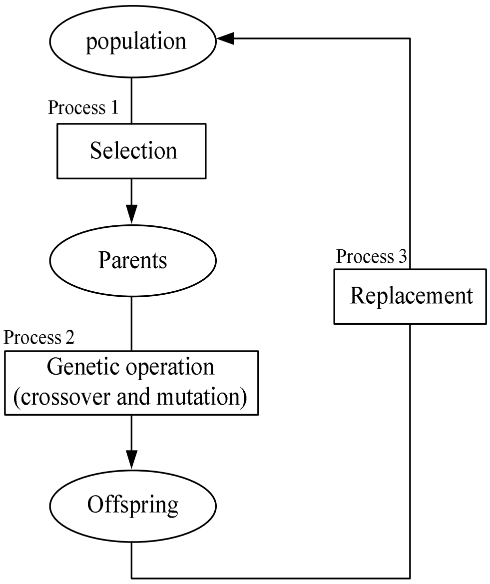

Fig.3 The process of GA

The concept of GA is depicted in Fig.3, there are three main processes for GA operations. The first is '*selection*'. This process will select the population in the searched system to be the parent for the next generation. The second process is '*genetic operation*' to search the better solutions for each generation by using the crossover and mutation techniques. The final process is '*replacement*'. The offspring from the genetic operation process will replace the previous population in which it may replace the whole of population or some part of population depending on the conditions in the algorithm. The more details of GA can be found in [11].

4.2 The selection of GA parameters for APF designs

The suitable GA parameters are necessary for applying this method to optimization problems. This is because the parameters in the GA algorithm are very important to the GA searching performance. Therefore, this section presents how to select the GA parameters for the APF design to achieve the best solution. The parameters needed to identify are a number of chromosome (*NC*), a genetic operation (*GO*), a crossover method (*CM*), a probability value of crossover (*PCM*), a mutation method (*MM*), and a probability value of mutation (*PMM*).The criterion of selecting these parameters for APF design is to minimize the fitness value, here is %THD.

4.2.1 *NC* selection

To find out the suitable *NC* values, we will vary these values from 10 to 60 with fixed other parameters (*GO* = stochastic uniform, *CM* = scattered crossover, *PCM* = 0.8, *MM* = Gaussian mutation and *PMM* = no need *PMM* for Gaussian mutation). The GA algorithm is then run in the computer 5 times for each *NC* values and the averaged %THD values ($\%THD_{averaged}$) can be calculated by:

$$\%THD_{averaged} = \frac{\sum_{i=1}^{N} \%THD_i}{N} \tag{5}$$

where

$\%THD_i$ = the minimum %THD value from i^{th} search (i=1, 2, …, N)

N = the times for searching (N is set to 5 in this paper)

The $\%THD_{averaged}$ for each *NC* values is given in Table 1. It can be seen that when the GA uses *NC* equal to 40, it can provide the minimum $\%THD_{averaged}$ value (0.9982%) compared with those of other *NC* values. In addition, the computation time for searching (the number of generation: *NG*) is considered. If *NG* is large, it means the GA uses a long time to achieve the answer. Otherwise, if *NG* is small, it means the GA performance is very good (very fast). As mentioned before, GA algorithm is run in the computer 5 times for each *NC* values. Therefore, the averaged *NG* value ($NG_{averaged}$) can be also calculated by:

$$NG_{averaged} = \frac{\sum_{i=1}^{N} NG_i}{N} \tag{6}$$

where i and N are the same meaning as Eq.(5)

From the results in Table 1, the *NC* value equal to 40 can provide the minimum $\%THD_{averaged}$. Fortunately, this *NC* value can also provide the minimum $NG_{averaged}$ equal to 38. It means that this *NC* value obtains the best answer with a fast computation time. Hence, the *NC* value equal to 40 is selected for APF design in this paper.

4.2.2 *GO* selection

Roulette, stochastic uniform, and tournament are selected for the testing *GO* parameters in this paper. In this section, we use the different *GO* approaches,

Table 1 *NC* testing results

testing / *NC* values	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
NC = 10 chromosomes						
%THD	1.0060	0.9749	1.0040	1.0080	1.0080	1.0001
NG	1288	306	396	1292	302	716
NC = 20 chromosomes						
%THD	0.9847	1.0100	1.0030	0.9984	1.0080	1.0008
NG	73	67	60	54	60	63
NC = 30 chromosomes						
%THD	0.9847	1.0100	1.0030	0.9984	1.0080	1.0008
NG	73	67	60	54	60	63
NC = 40 chromosomes						
%THD	0.9911	1.0030	1.0080	0.9928	0.9963	0.9982
NG	43	26	35	37	49	38
NC = 50 chromosomes						
%THD	1.0070	0.9952	0.9870	1.0100	0.9984	0.9995
NG	67	45	31	25	37	41
NC = 60 chromosomes						
%THD	0.9859	1.0060	1.0100	1.0050	0.9958	1.0054
NG	26	35	42	30	34	39

Table 2 *GO* testing results

testing / *GO* methods	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
GO using the roulette method						
%THD	0.9910	0.9980	0.9580	0.9850	1.0050	0.9870
NG	148	262	118	310	77	183
GO using the stochastic uniform method						
%THD	0.9650	1.0010	0.9880	0.9990	1.0050	0.9920
NG	200	102	423	447	1522	539
GO using the tournament method						
%THD	0.9760	1.0010	0.9980	1.0050	0.9940	0.9950
NG	60	95	289	603	81	209

while other parameters are fixed as follows: *NC* =40, *CM* = scattered crossover, *PCM* = 0.8, *MM* = Gaussian mutation and *PMM* = no need *PMM* for Gaussian mutation. *NC* value is given from Section 4.2.1. The testing results are given in Table 2. It shows that the roulette method provides the minimum $\%THD_{averaged}$ (0.9870%). Moreover, this method also obtains the minimum $NG_{averaged}$ equal to 183. It means that when GA uses the roulette method, the computation time is faster than stochastic uniform and tournament methods. Therefore, the roulette method is selected for APF design in this paper. Note that $\%THD_{averaged}$ and $NG_{averaged}$ for all testing can be calculated by using Eq. (5) and (6), respectively.

4.2.3 *CM* and *PCM* selections

There are three *CMs* of GA in this testing. These are single-point crossover, double-point crossover, and scattered crossover. The results by using these three different methods with fixed other parameters (*NC* = 40 from Section 4.2.1, *GO* = roulette method from Section 4.2.2, *PCM* = 0.8, *MM* = Gaussian mutation and *PMM* = no need *PMM* for Gaussian mutation) are shown in Table 3. The results show that the single-point crossover can provide the minimum $\%THD_{averaged}$ equal to 0.9836% with the minimum $NG_{averaged}$ equal to 57 generations.

For the *PCM* selection, we will vary this value from 0.1 to 1 with fixed other parameters (*NC* = 40 from Section 4.2.1, *GO* = roulette method from Section 4.2.2, *CM* = single-point crossover from

Section 4.2.3, *MM* = Gaussian mutation and *PMM* = no need *PMM* for Gaussian mutation). The testing results are given in Table 4. It shows that the single-point crossover with *PCM* equal to 0.7 obtains the answer ($\%THD_{averaged}$ = 0.9890% and $NG_{averaged}$ = 77 generations). Hence, the single-point crossover with *PCM* equal to 0.7 is selected for the APF design.

Table 3 *CM* testing results

CM \ testing	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
CM using the single-point						
%THD	0.9916	0.9727	0.9832	0.9698	1.0009	0.9836
NG	54	29	29	119	52	57
CM using the double-point						
%THD	0.9670	0.9830	0.9760	0.9960	0.9950	0.9840
NG	81	222	89	60	275	145
CM using the scattered						
%THD	0.9930	0.9800	0.9760	0.9960	0.9946	0.9879
NG	821	199	278	262	223	357

Table 4 PCM testing results

PCM values \ testing	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
PCM = 0.1						
%THD	0.9790	1.0090	0.9840	0.9945	1.0000	0.9933
NG	378	271	337	72	93	230
PCM = 0.2						
%THD	1.0060	0.9810	1.0030	1.0070	1.0090	1.0012
NG	237	116	137	618	188	259
PCM = 0.3						
%THD	0.9860	0.9925	0.9866	1.0060	0.9951	0.9972
NG	112	84	146	68	156	113
PCM = 0.4						
%THD	1.0040	1.0060	1.0030	1.0070	1.0070	1.0054
NG	45	109	96	364	177	158
PCM = 0.5						
%THD	0.9709	0.9935	1.0050	0.9954	1.0030	0.9935
NG	72	75	76	74	658	191
PCM = 0.6						
%THD	1.0050	1.0070	1.0040	1.0080	1.0090	1.0066
NG	43	56	56	81	165	96
PCM = 0.7						
%THD	0.9350	0.9900	1.0040	1.0070	1.0090	0.9890
NG	54	29	29	134	138	77
PCM = 0.8						
%THD	1.0030	1.0070	1.0080	1.0130	1.0050	1.0072
NG	41	63	59	1016	711	378
PCM = 0.9						
%THD	1.0080	0.9880	0.9868	0.9829	0.9897	0.9910
NG	76	68	65	665	106	196
PCM = 1.0						
%THD	1.0630	1.3270	1.0630	2.4260	1.115	1.3988
NG	500	500	505	507	504	503

Table 5 *MM* testing results

testing / *MM*	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
MM using the uniform						
%THD	0.9840	1.0090	0.9710	0.9920	1.0100	0.9930
NG	338	244	144	91	212	206
MM using the Gaussian						
%THD	1.0020	0.9810	0.9989	1.0020	0.9948	0.9901
NG	765	171	86	163	315	391

Table 6 *PMM* testing results

testing / *PMM* values	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	Averaged value
PMM = 0.01						
%THD	0.9980	1.0090	0.9828	0.9824	1.0380	1.0020
NG	505	1151	133	383	2252	885
PMM = 0.02						
%THD	0.9980	0.9693	1.0000	1.0570	1.0500	1.0148
NG	85	140	270	842	979	463
PMM = 0.03						
%THD	1.0070	1.0030	0.9978	1.0060	0.9965	1.0020
NG	392	630	447	183	120	354
PMM = 0.04						
%THD	0.9986	0.9932	1.0090	1.0040	0.9499	0.9909
NG	69	98	282	91	436	195
PMM = 0.05						
%THD	1.0010	1.0070	0.9900	0.9680	1.0090	0.9950
NG	94	220	274	468	571	325
PMM = 0.06						
%THD	0.9950	0.9850	1.0060	0.9711	0.9683	0.9850
NG	77	158	99	98	99	106
PMM = 0.07						
%THD	1.0080	1.0090	0.9864	1.0060	0.9929	1.0004
NG	157	82	335	510	108	238
PMM = 0.08						
%THD	0.9620	0.9930	1.0080	1.0180	1.0020	0.9966
NG	211	167	463	1219	76	427
PMM = 0.09						
%THD	0.9850	0.9730	0.9997	1.0090	0.9776	0.9886
NG	155	164	131	81	228	152
PMM = 0.10						
%THD	1.0070	0.9790	0.9884	1.0020	1.0010	0.9954
NG	301	103	116	277	61	172

4.2.4 *MM* and *PMM* selections

There are two *MMs* of GA in this testing; uniform mutation and Gaussian mutation, with fixed other parameters (*NC* = 40 from Section 4.2.1, *GO* = roulette method from Section 4.2.2, *CM* = single-point crossover with *PCM* = 0.7 from Section 4.2.3, *PMM* = 0.01 for only uniform mutation). The results for this testing are shown in Table 5. It shows that $\%THD_{averaged}$ from two different *MMs* is nearly the same. Therefore, $NG_{averaged}$ becomes more significant than $\%THD_{averaged}$ for this case. It can be seen from the results that although the uniform mutation provide the slightly greater $\%THD_{averaged}$ compared with Gaussian mutation, it can obtain significantly the minimum $NG_{averaged}$.

From the previous testing, the uniform mutation is selected. Therefore, the *PMM* selection needs to be considered. We will vary the *PMM* value of the uniform mutation from 0.01 to 0.1 with fixed other parameters (*NC* = 40 from Section 4.2.1, *GO* = roulette method from Section 4.2.2, *CM* = single-point crossover with *PCM* = 0.7 from Section 4.2.3, *MM* = uniform mutation from Section 4.2.4). The testing results are given in Table 6. It shows that the uniform mutation with *PMM* equal to 0.06 obtains the best answer ($\%THD_{averaged}$ = 0.9850% and $NG_{averaged}$ = 106 generations). As a result, the uniform mutation with *PMM* equal to 0.06 is selected for the APF design.

To conclude from all testing, the GA parameters for APF design in the paper are summarized as follows:

-*NC* equal to 40 chromosomes

-*GO* using the roulette method

-*CM* using the single-point crossover with *PCM* equal to 0.7

-*MM* using the uniform mutation with *PMM* equal to 0.06

The APF design using GA with the parameters from this section is described in Section 4.3 and the results is given in Section 5.

4.3 The APF design using GA

In section 2, the APF is controlled by using hysteresis method. In this paper, the GA is applied to determine the appropriate APF parameters. The parameters for searching are DC bus voltage (V_{dc}), the inductor filter (L_f), and the hysteresis band (*HB*). The block diagram to explain how to search the parameters of APF using GA method is depicted in Fig. 4. It can be seen in Fig.4 that GA will search the APF parameters in which %THD of the compensated current on supply side is defined as the cost value for GA tuning. This value can be determined from the objective function as shown in Fig. 4. The GA will try to search the best APF parameters to achieve the minimum %THD also following on the IEEE std. 519-1992.

According to Fig. 4, the steps of searching APF parameters by using GA are as follows:

Step 1: Define the boundary of parameters. In this paper, the upper and lower limits of V_{dc}, L_f, and *HB* are set to 312-700 V, 0-10 H, and 0-0.02 A, respectively.

Step 2: Define the population encoding scheme for GA. In this paper, the chromosomes for the population encoding scheme are set to be the real value [12].

Step 3: Set the population size equals to 40 chromosomes.

Step 4: Define the initial population by random within the search space of parameters.

Step 5: Define the maximum number of generation for searching, here is set to 1000.

Step 6: Define the selection process, here set to roulette. The uniform mutation (probability = 0.06), the single-point crossover (probability = 0.7), and the whole population replacement are selected.

Note that the more details of GA can be found in [12].

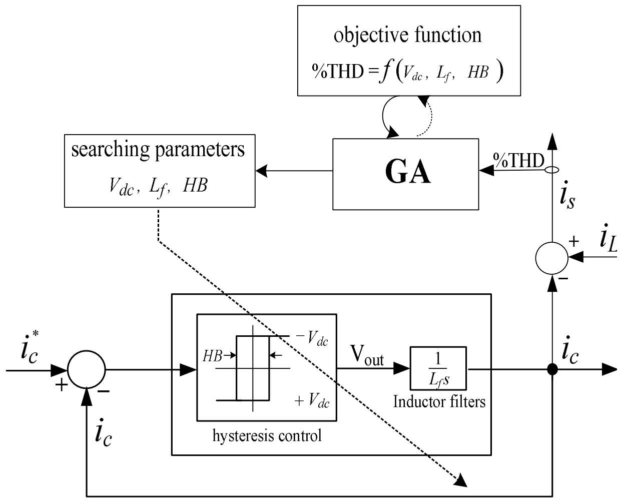

Fig.4 The GA approach for APF design

The system in Fig.1 is operated with APF controlled by hysteresis method. The APF parameters are designed by using GA. The objective of GA method is to minimize %THD of compensated currents and this value has to follow on IEEE std. 519-1992. The GA can search the APF parameters to achieve smaller %THD for each round of searching as shown in Fig.5. In this paper, the maximum number of generation is set to 1000 in which GA can provide the %THD equal to 0.9885%. In Fig.5, it can be seen that %THD is equal to 0.9940% during generation = 439-519. This is as the local solution for this problem. However, GA can escape the local solution to achieve the better %THD (0.9885%). The parameter values of APF from GA search compared with Ingram and Round method are given in Table 7. In addition, the results in Fig.5 also show the convergence of GA for this problem.

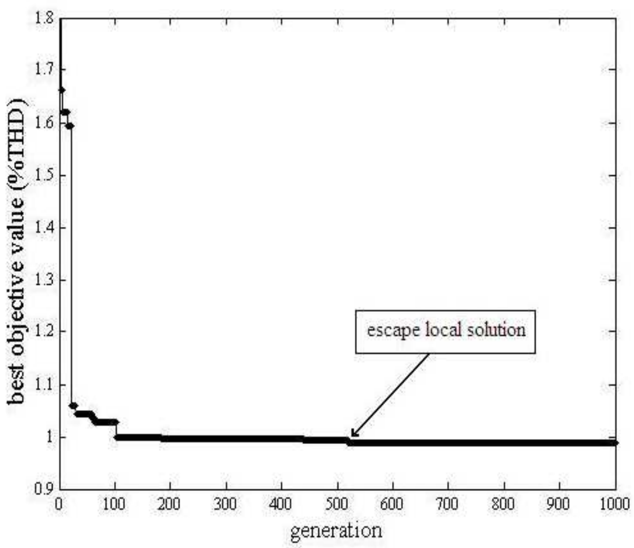

Fig.5 The convergence of %THD

5 Simulation results and discussion

The simulation results of the system in Fig.1 with the APF parameters from GA searching are depicted in Fig.6. The compensating current from APF (i_{ca}) injects into the system at t=0.04 s. It can be seen that the source current after compensation (i_{sa}) is nearly sinusoidal waveform. %THD of this current is equal to 0.9885% that is satisfied under IEEE Std. 519-1992, while %THD before compensation is 25.45%.

The simulation results for Ingram and Round method are illustrated in Fig.7. From Fig.7, the source current after compensation is nearly sinusoidal waveform the same as the results in Fig.6. However, %THD for this method is 1.5019% that is greater than the one from GA method (0.9885%). Hence, GA method can provide the smaller %THD compared with Ingram and Round method. The results show that GA approach is very useful and more convenient for APF design.

Table 7 The comparison between GA method and Ingram and Round method

APF parameters	APF design method	
	GA	Ingram and Round
V_{dc} (V)	620	600
L_f (H)	0.39	0.50
HB (A)	0.00043	0.0088
%THD before compensation	25.45 %	
%THD after compensation	0.9885 %	1.5019 %

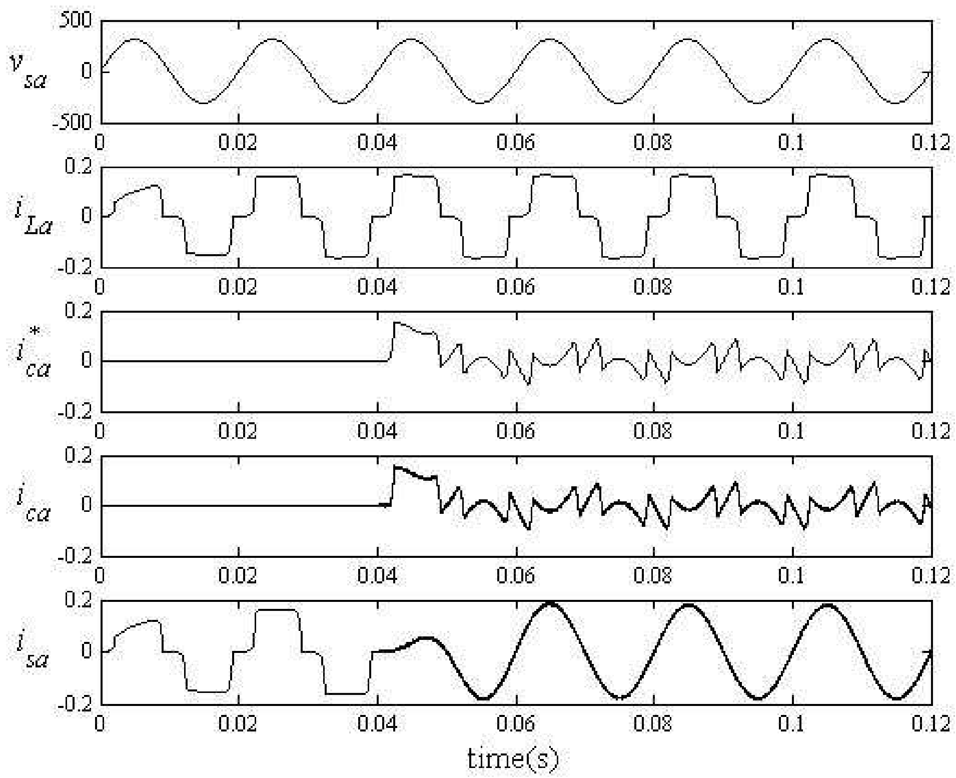

Fig.6 The simulation results for GA method

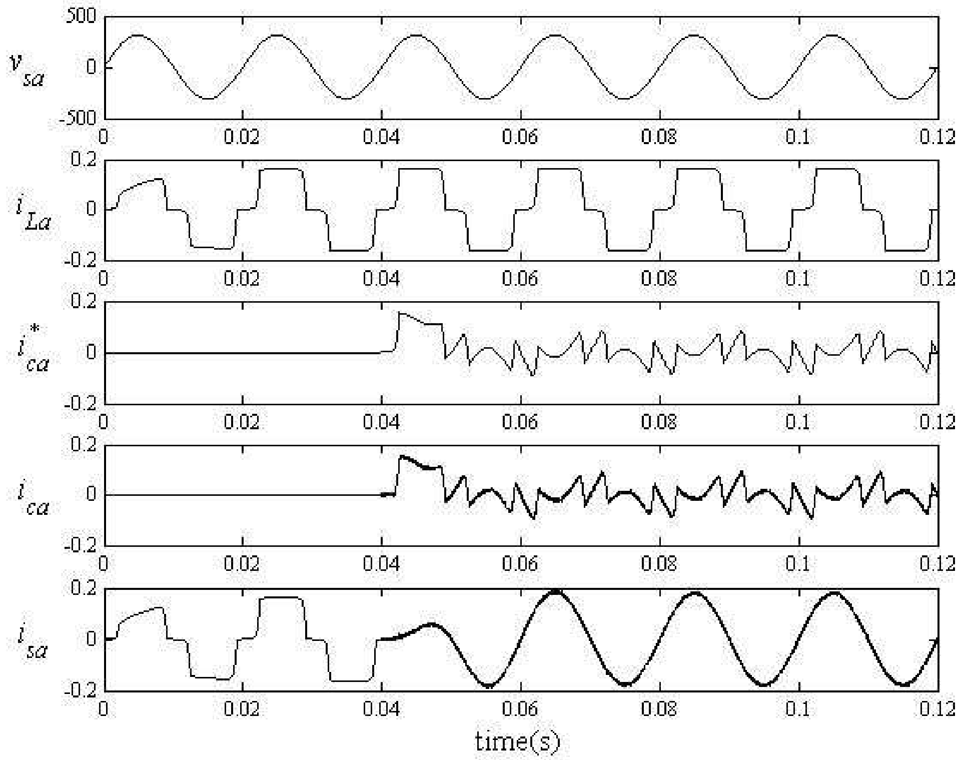

Fig.7 The simulation results for Ingram and Round method

There are many researches for the harmonic mitigation approaches using artificial intelligent (AI) such as genetic algorithm (GA) [13], adaptive linear neural network (ADALINE) [14], and fuzzy logic [15]. Therefore, for the future work, AI techniques will be applied to obtain the better results for harmonic elimination compared with the reported method in this paper.

6 Conclusion

This paper presents the application of GA for the design of APF controlled by hysteresis method. The results confirm that GA can provide the minimum %THD of the source current after compensation. In addition, %THD is also satisfied under IEEE Std. 519-1992. Moreover, the mathematical model of APF is not necessary for GA approach. Hence, the GA approach for APF design is very useful and flexible.

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References:

[1] IEEE Std. 519-1992 ,IEEE Recommended practices and requirement for harmonic control in electrical power system.

[2] Zhuo F. , Yang J., Hu J., and Wang Z., Study on Active Power Filter used in Three-Phase Four Wire System, *IEEE Power Electronics and Motion Control Conference,*vol.3, 2000, pp. 1037-1040

[3] Peng F. Z. and Lai J-S, Generalized instantaneous reactive power theory for three-phase power system, *IEEE Trans. Instrum. Meas.*,vol.45, no.1, 1996, pp. 293-297

[4] Zeng J. , Yu C. ,Qi Q. , Yan Z., Ni Y., Zhang B.L.,Chen S., and Wu F. F., A Novel Hysteresis Current Control for Active Power Filter with Constant Frequency, *Electric Power Systems Research 68*, 2004, pp.75- 82

[5] Narongrit T., Areerak K-L. and Srikaew A. Design of an Active Power Filter using Adaptive Tabu Search, *Proceedings of the 8th WSEAS Int.Conf. on Artificial Intelligence.,* 2009, pp:314-318

[6] Kennedy J. and Eberhart R., Particle Swarm Optimization, In *Proceedings IEEE Internatio-*

nal Conference on Neural Networks Australia, vol 4, 1995, pp. 1942-1948

[7] Cupertino F., Marinelli M. Zanchetta P.and Sumner M., Modelling and Design of Shunt Active Power Filters using Genetic Algorithms, *EPE*, 2005 ,pp.1-9

[8] Ingram D.M.E. and Round S. D., A Novel Digital Hysteresis Current Controller for an Active Power Filter",*IEEE Transaction*, 1997,pp. 744-749

[9] Benchaita L., Saadate S. and Nia A.S., A Comparison of Voltage Source and Current Source Shunt Active Filter by Simulation and Experimentation, *IEEE Trans*., Vol. 14, No. 2, 1999, pp.642-647

[10] Tsang K.M. and Chan W.L., Design of single- phase active power filter using analogue cascade controller, IEE,Vol.153, No. 5 2006, pp. 735-741

[11] Wright A. H., Foundations of Genetic Algorithms, *chapter Genetic Algorithms for Real Parameter Optimization*, 1991, pp. 205-218.

[12] Man, K.F. Tang, K.S. and Kwong S., Genetic algorithms: conceptsand applications [in engineering design], *IEEE Transactions, Industrial Electronics,* vol: 43, 1996, pp. 519-534

[13] S.G. Seifossadat, M. Razzaz, M. Moghaddasian and M. Monadi, Harmonic Estimation in Power Systems Using Adaptive Perceptrons Based on a Genetic Algorithm, *WSEAS Transactions on Power Systems*, Vol. 2, Issue 11, 2007, pp.239-244.

[14] Y. Han, Mansoor, G. Yao, L-D. Zhon and C. Chen, Harmonic Mitigation of Residential Distribution System using a Novel Hybrid Active Power Filter, *WSEAS Transactions on Power Systems*, Vol. 2, Issue 12, 2007, pp.255-260.

[15] A. Ghasemi, S.S. Mortazavi and R. Kianinezhad, Fuzzy Logic Controlled Adaptive Active Power Filter for Harmonics Minimization and Reactive Power Compensation under Fast Load Variation, *WSEAS Transactions on Power Systems*, Vol. 3, Issue 5, 2008, pp.300-309.