CHAPTER 3

HARMONIC ELIMINATION SOLUTION
USING GENETIC ALGORITHM

3.1 INTRODUCTION

Recent advances in computation, and the search for better results for complex optimization problems, have stimulated the development of a family of techniques known as Evolutionary Algorithms (EA). EA are stochastic based optimization techniques that search for the solution of problems using mathematical models that simulate the biological evolution process. These algorithms provide an alternative for obtaining global or near global optimal solutions, particularly in the presence of non-continuous, non-convex and wide solution spaces.

Specifically, these algorithms are population based techniques, which explore the solution space randomly by using a population of candidate solutions instead of the single solution estimate used by most classical techniques. The success of EA lies in the capability of finding solutions with random exploration of the solution space rather than performing exhaustive exploration. This results in a faster optimization process with less computational resources while maintaining the capability of finding global or near global solutions.

Genetic Algorithm (GA) is an effective optimization method for solving complex problems. This method has no limit on the optimization space. Therefore, it is insensitive to the local optimum points and finds
absolute optimum point in all cases if calculation time is not limited. The GA is applied in many industries for control processes. In this chapter, a GA based method has been proposed for solving the complex equations in a SHE-PWM problem. Thus, the issue of an intelligent guess for initial point has been eliminated. The maximum harmonics elimination has been optimized using the GA method.

Selective harmonic elimination programmed pulse width modulation has been used to achieve certain function optimization for the output voltage of the power electronic converters/inverters. Optimization of the function often needs to solve a complex non-linear equation or a set of equations. Therefore, online switching angles calculation is almost impossible. In addition the final solution depends highly on the initial point. This step could even lead to a non-optimum solution in certain cases.

### 3.2 GENETIC ALGORITHM

Genetic algorithm is one of the main paradigms within evolutionary algorithms, which uses an analogy of nature. GA are a part of evolutionary computing, which is a rapidly growing area of artificial intelligence. These are search algorithms based on the mechanics of natural selection and natural genetics. It is an example of iterative search procedure that uses random choice as a tool to guide a highly explorative search through a coding of a parameter space and the reliability is improved by the principle of natural genetics. GA mimic the evolutionary process in nature, which is based on Darwin’s theory called “the survival of the fittest”, only the fittest individuals likely to survive and reproduce. In GA, instead of trying to optimize a single solution, works with a population of candidate solutions that are encoded as chromosomes. These chromosomes are having separate genes that represent the independent variables for the problem at hand. Algorithm begins with a set of solutions called population. New combinations of genes are generated
from previous ones by exchanging segments of genetic material among chromosomes (known as “crossover”). In every generation, a new set of artificial creatures (strings) are created using bits and pieces of the fittest of the old and an occasional new part is tried for good measure. This is motivated by a hope, that the new population will be better than the older one. A fitness function must be provided for evaluating each string. Each solution is associated with a fitness value, based on the fitness function, to reflect how good it is. Solutions which are selected to form new solutions (offspring) are reproduced according to their fitness.

GA is not guaranteed to reach the global optimum, but they are generally good at finding a better solution during an acceptable amount of time. However, when combining with other techniques it can also deal the problems with constraints. It is so robust that it can be applied to a wide range of problem areas. GA can also be hybridized with other special technique to solve difficult problems to get good performance in the result.

3.2.1 GA Parameters

The performance of GA mainly depends upon its parameters and their characteristics. In this section a brief introduction about GA parameters are given.

**Initialization:** Creating the initial population provides the starting point of the genetic algorithm. This is done by randomly generating chromosomes which are adopted in this work.

**Fitness function:** The fitness function is the most crucial aspect of GA, along with the coding scheme used. A general rule to construct a fitness function is that it should be able to reflect the value of a chromosome realistically. However, the “real” value of a chromosome is usually not good enough for
guiding a genetic search. When coming up with a combinatorial optimization problem, where there are many constraints, most points in the search space represent invalid chromosome. In this case, a better fitness function should be defined in terms of how good it is to lead us towards valid chromosomes.

**Population and generation:** In genetic algorithm, population is one which contains group of strings which may be coded or non-coded. Each string is unique and is generated randomly and mapped to a unique feature. The width of each string depends on the number of bits. Usually the population size is assumed between 10 to 20. Evaluation of all strings in a population is considered as one complete generation. It encapsulates all the fundamental operations like reproduction, crossover and mutation. The newly mutated strings form the next generation.

**Genetic operators:** While the variety of genetic operators is quite large, only few operators are useful in solving general problems. In general, GA works with randomized operators like reproduction, crossover, mutation, deletion, inversion etc, which are direct descendants of natural mechanisms. Among these operators crossover and mutation are the most important operators. The performance of GA is mainly influenced by these two operators.

a) **Reproduction:** Reproduction is usually the first operator applied on a population. It is otherwise called as selection operator. This operator, of course, is an artificial version of natural selection. Reproduction is a process in which individual strings are copied according to their objective function values. Copying strings according to fitness functions means that strings with a higher value have a higher probability of contributing one or more offspring in the next generation. In natural populations fitness is determined by a creature’s ability to survive predators, pestilence and
subsequent reproduction. The reproduction operator is implemented in algorithm form in a number of ways that is Elitist selection, Fitness-proportionate selection, Roulette-wheel selection, Scaling selection, Tournament selection, Rank selection, Generational selection, Steady-state selection and Hierarchical selection. Some of these methods are mutually exclusive, but others can be used in combination.

b) **Crossover and Mutation**: These are two basic operators of GA where performance of GA depend on them very much. The type and implementation of operators depends on the encoding and also on the problem. A crossover operator is mainly responsible for the search of new strings, even though a mutation operator is also used for this purpose carefully. A simple crossover proceeds in two steps, that is first members of the newly reproduced strings in the mating pool are mated randomly and secondly each pair of strings are allowed for crossover at some specific site which are generated randomly. The various types of crossover are single point crossover, two point crossover, multiple point crossover, uniform crossover and flexible crossover. The next process followed by crossover is mutation. The implementation of mutation in algorithm form is very simple. It is just an exchange of bits from “zero” to “one” and vice versa. Here the mutation probability rate ranges from 0.001 to 0.05 for every bit of the total string length. It is an operator which restores lost genetic materials and helps to escape from local optima’s trap by maintaining the diversity in the search space. In this thesis work, two point crossover with crossover probability of 0.8 and mutation probability of 0.05 are adopted.
3.2.2  **Strengths of GA**

**Parallelism:** The first and most important point is that GA is intrinsically parallel. Most other algorithms are serial and can only explore the solution space to a problem in one direction at a time, and if the solution they discover turns out to be sub-optimal, there is nothing to do with. However, GA has multiple offspring; they explore the solution space in multiple directions at once. If one path turns out to be a dead end, they can easily eliminate it and continue work on more promising avenues, giving them a greater chance in each run for finding the optimal solution. Due to the parallelism that allows them to implicitly evaluate many schemes at once, genetic algorithms are particularly well suited for solving problems where the space of all potential solutions are too vast to search exhaustively in any reasonable amount of time.

**Multiple solutions:** Another area in which genetic algorithms excel is their ability to manipulate many parameters simultaneously. Many real world problems cannot be stated in terms of a single value to be minimized or maximized, but must be expressed in terms of multiple objectives, usually with tradeoffs involved, one can only be improved at the expense of another. GA are very good at solving such problems in particular, the use of parallelism enables them to produce multiple and equally good solutions to the same problem, possibly with one candidate solution optimizing one parameter and another candidate optimizing a different one and a human overseer can then select one of these candidates to use.

3.2.3  **Drawbacks of GA**

Although genetic algorithms have proved to be an efficient and powerful problem solving strategy, they are not a universal remedy. GA does have certain limitations; however, it will be shown that all of these can be
overcome and none of them bear the validity of biological evolution. Some of the drawbacks that would happen while applying the genetic algorithm are given in this section.

**Fail to attain peak point:** Since GA operators are working under stochastic search and recombined with random cut section, generally it locates the regions of the search space, which contains the global optimum, but not the true global optimum solution. This issue is solved by blending with some other optimization technique that is local search, tabu search etc. to improve and locate the exact global optimal solution.

**Termination criteria:** In GA generally iteration process is ended if all the population has the same chromosomes that are convergence or if it reaches the fixed number of generation whichever happens earlier. If the search space is large, convergence of GA will lead to local optima. Because the algorithm is looking for the repetition of chromosomes instead of the new breeding and it restricts the exploration. Since GA is a stochastic search technique, exploration and exploitation will yield the best result.

### 3.2.4 Improvement in GA

Since the GA has some drawbacks such as more computational time to converge the result, die-out of best solution by reproduction of species in next generation, repeated analysis for duplicated chromosomes and failure to locate the global optima especially for solving complicated problems, some modifications has been introduced as given below.

**Elitism:** In this method, when creating a new population by crossover and mutation, there is a big chance of loosing the best chromosome. Elitism addresses the problem of loosing good solutions during the optimization process due to random effects. Elitism is the method that first copies the best
chromosome to the new population. One way to deal with this problem is to combine the old population and the offspring that is the mating pool after variation and to apply a deterministic selection procedure instead of replacing the old population by the modified mating pool. Elitism rapidly increases the performance of GA, because it prevents the loss of the best found solution. The concept of elitist approach without any local refinement cannot be used at all times unless an enhanced solution is encountered in the next generation.

**Memory table:** During the genetic operations and iterations, duplicate or repetitive occurrence of chromosomes in each generation is possible and it leads to unnecessary repeated and lengthy calculations. So it takes more computational time for analytical problems especially for eigen value analysis. To avoid this repetitive calculation a memory table is used for storing the design variables and the corresponding solutions. When the GA encounters a design variable, which has been stored in the memory table, then it will take the corresponding solution from the table instead of repeating the calculation. This concept of memory table reduces more CPU time.

### 3.3 HARMONIC ELIMINATION USING GENETIC ALGORITHM METHOD

It is proposed that the function given in equation (2.25) is minimized using genetic algorithm. Due to quarter wave symmetry of the output voltage, the even harmonics are absent and only odd harmonics are present. The amplitude of the $n^{th}$ harmonic $b_n$ is expressed only with the switching angles $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \ldots \alpha_N$. The Fourier coefficients of the SHE-PWM switching pattern for a three phase line to neutral are given by the equation (2.21). In selective harmonic elimination, $b_n$ is assigned with desired value for fundamental component and equated to zero for the harmonics to be eliminated. Equation (2.21) has N variables ($\alpha_1$ to $\alpha_N$) and a set of solution
are obtained by equating N-1 harmonics to zero and assigning a specific value to the fundamental amplitude $\alpha_1$, through the equation (3.1).

\[
f_i(\alpha) = \frac{4}{\pi} \left[ -1 - 2 \sum_{i=1}^{N} (-1)^i \cos(\alpha_i) \right] - M = \varepsilon_i
\]

\[
f_2(\alpha) = \frac{4}{5\pi} \left[ -1 - 2 \sum_{i=1}^{N} (-1)^i \cos(5\alpha_i) \right] = \varepsilon_2
\]

\[
\vdots
\]

\[
f_N(\alpha) = \frac{4}{n\pi} \left[ -1 - 2 \sum_{i=1}^{N} (-1)^i \cos(n\alpha_i) \right] = \varepsilon_N
\]

where, the variables $\varepsilon_i, \varepsilon_N$ are the normalized amplitude of the harmonics to be eliminated. The objective function of SHE-PWM technique is used to minimize the harmonic content in the inverter load voltage is given in equation (3.2).

\[
F(\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_N) = \varepsilon_1^2 + \varepsilon_2^2 + \ldots + \varepsilon_N^2
\]

For quarter wave symmetric pulse pattern, the N switching angles are limited within $\frac{\pi}{2}$. This constraint is given by the equation (3.3).

\[
0 < \alpha_1 < \alpha_2 < \alpha_3 < \alpha_4 < \alpha_5 \ldots \alpha_N < \frac{\pi}{2},
\]

In this GA approach, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and $\alpha_5$ solutions are expected with elimination of 5th, 7th, 11th, and, 13th harmonics. Non-linear transcendental equations are thus formed after solving these equations, $\alpha_i$ through $\alpha_N$ are computed. Triplen harmonics are eliminated in a three phase balanced system and these are not considered in Fourier coefficients calculation. It is evident that N-1 harmonics are eliminated with N number of switching angles. The implementation of GA is given below.
Step 1: Initialization

The initial population (P\textsubscript{in}) of ‘m’ chromosomes is generated with randomly selected initial individual switching angles. The generated switching angles are distributed uniformly between their minimum and maximum limits by satisfying the equation (3.3). Each chromosome is coded as binary string which is mapped into a real number.

Step 2: Fitness of the candidate solutions

The Fitness function value (FV) in this case attempts to minimize the objective function using the given equation (3.4). Fitness function value is calculated for each chromosome in the population.

\[
FV = \frac{1}{1 + f_i(\alpha)}
\]  \hspace{1cm} (3.4)

where, \( f_i(\alpha) \) is calculated using the equation (3.1).

When the switching angles violate the minimum and maximum value, the penalty factor is introduced to avoid violation. The alpha limit violation is dealt with the violation coefficient value using equation (3.5).

\[
Vio\_coeff = (1 + [\alpha_{i+1} - \alpha_i]) \times \rho
\]  \hspace{1cm} (3.5)

where, \( \rho \) is the penalty factor,

\( \alpha_i \) is the \( i^{th} \) value of switching angle \( \alpha \).

In such cases, the objective function is calculated by multiplying the \( Vio\_coeff \) value. After computing the fitness function value of each individual chromosome, the parents undergo genetic operation of selection, crossover and mutation. After the evaluation of the initial randomly generated
population, GA begins to create new generation. The process of selection and mating of individuals continues until a new generation is reproduced.

**Step 3: Selection**

Chromosomes from the parent population are selected in pairs with a probability proportional to their fitness to replicate and form offspring chromosomes. This selection scheme is known as Roulette Wheel selection. Each chromosome selects a percentage of Roulette Wheel equal to its normalized fitness value. The chromosomes that will be copied are selected with rates proportional to their fitness.

**Step 4: Crossover**

In accordance with the crossover rate, randomly chosen pairs of parent chromosomes from the population produced after reproduction undergo crossover to produce offspring. A random cut point is selected for fixed length chromosomes, the cut point between the first and the last gene of the present chromosomes. For variable length chromosomes, the cut point is between the first and the last gene of the present chromosome with minimum length.

**Step 5: Mutation**

In accordance with the mutation rate, some chromosomes from the population produced after crossover will undergo mutation. Random genes are selected and altered from 0 to 1 or vice versa. In this way, the old population is replaced with the improved population generated through step 2 to step 5.
Figure 3.1 General flow diagram for genetic algorithm
Step 6: Elitism

The crossover and mutation for the two chromosomes are repeated until all the chromosomes of the parent generation are replaced by the newly formed chromosomes. The best chromosome of the parent generation and the best chromosome found in all of the previous generations are copied intact to the next generation, so that the possibility of their destruction through a genetic operator is eliminated. The general process for optimization using the genetic algorithm is shown in Figure 3.1.

Step 7: Termination Criteria

The above procedure from the step 2 to step 6 is repeated until the maximum iteration count is reached.

3.4 SIMULATION RESULTS

After solving the five non-linear functions of equations with N=5 variables (3.3) simultaneously using MATLAB 7.0 optimization toolbox, five variables (switching angles $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and $\alpha_5$) were obtained. This process was repeated for the various modulation indices from 0.1 to 1.3 and simulations were carried out on a Pentium IV 2.4 GHz, 512–MB RAM processor. The coding to solve SHE-PWM problem using genetic algorithm was written using MATLAB 7.0. The control parameters used by Shi and Hui (2005) are fixed as the initial control parameters for genetic algorithm method. Population size determines the number of chromosomes in the population. The population size depends on the nature and the complexity of the problem. In this work, the proposed algorithm was tested for various population sizes. Finally, the selected population size is equal to 20. Crossover rate determines the frequency with which the crossover operator is applied to the chromosomes of the population, so that a new population is
generated. The higher the crossover rate, the more individuals are introduced in the new population. The crossover rate is usually in the range between 0.6 and 1.0. In this algorithm, crossover selected is equal to 0.8 after a considerable number of trials. Mutation rate determines the probability that a gene’s value in a chromosome would be changed. Mutation introduces new areas of the unexplored search space. However, the mutation rate should not be too high, because it increases the randomness in the search. The mutation rate is usually less than 0.1 and in this algorithm it is selected as 0.05 after too many trial runs. After too many trial runs, the numbers of generation are selected as 100 for standard genetic algorithm method. The Table 3.1 shows different values of switching angles $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and $\alpha_5$ for the various values of modulation index M.

**Table 3.1  Values of switching angles for various values of M using genetic algorithm**

<table>
<thead>
<tr>
<th>M</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\alpha_3$</th>
<th>$\alpha_4$</th>
<th>$\alpha_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.81859</td>
<td>11.9199</td>
<td>48.2256</td>
<td>60.1452</td>
<td>71.854</td>
</tr>
<tr>
<td>0.2</td>
<td>0.81559</td>
<td>21.0152</td>
<td>38.6713</td>
<td>61.51</td>
<td>78.81</td>
</tr>
<tr>
<td>0.3</td>
<td>2.0465</td>
<td>21.929</td>
<td>37.301</td>
<td>62.415</td>
<td>78.2028</td>
</tr>
<tr>
<td>0.4</td>
<td>3.6974</td>
<td>22.838</td>
<td>35.484</td>
<td>64.696</td>
<td>75.995</td>
</tr>
<tr>
<td>0.5</td>
<td>2.912</td>
<td>22.38</td>
<td>36.395</td>
<td>63.602</td>
<td>76.98</td>
</tr>
<tr>
<td>0.6</td>
<td>4.094</td>
<td>23.293</td>
<td>35.0317</td>
<td>65.149</td>
<td>75.785</td>
</tr>
<tr>
<td>0.7</td>
<td>4.7292</td>
<td>23.5668</td>
<td>33.8503</td>
<td>65.7859</td>
<td>75.0554</td>
</tr>
<tr>
<td>0.8</td>
<td>11.6484</td>
<td>23.2051</td>
<td>30.6631</td>
<td>46.135</td>
<td>51.4204</td>
</tr>
<tr>
<td>0.9</td>
<td>10.9203</td>
<td>23.2051</td>
<td>29.694</td>
<td>46.135</td>
<td>50.3771</td>
</tr>
<tr>
<td>1</td>
<td>9.46433</td>
<td>22.8382</td>
<td>27.4815</td>
<td>46.6796</td>
<td>48.9898</td>
</tr>
<tr>
<td>1.1</td>
<td>9.0974</td>
<td>22.4774</td>
<td>27.0229</td>
<td>45.5847</td>
<td>47.2528</td>
</tr>
<tr>
<td>1.2</td>
<td>8.7363</td>
<td>22.1102</td>
<td>26.1172</td>
<td>45.04</td>
<td>46.209</td>
</tr>
<tr>
<td>1.3</td>
<td>8.7363</td>
<td>22.1102</td>
<td>26.1229</td>
<td>45.5847</td>
<td>46.9031</td>
</tr>
</tbody>
</table>
Figure 3.2 shows the trajectory of calculated switching angles $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, and $\alpha_5$ with respect to the modulation index varies from 0.1 to 1.3 for the SHE-PWM switching pattern using GA.

Over the whole range of possible modulation index values, the trajectories of these angles are neither smooth, nor with a predictable trend. In this approach, the trajectories of the angles are almost smooth for $\alpha_2$ and $\alpha_3$ over the whole range of possible modulation indices. There is an abrupt fall of $20^\circ$ for $\alpha_4$ and $\alpha_5$ and rise of about $5^\circ$ for $\alpha_1$ for the modulation index 0.7. All five switching angles are smooth after $M=0.8$. All these characteristics bring unpredictability to traditional algorithms that require precise initial values to guarantee convergence. In this approach GA is widely used because of discrete nature of harmonics to be eliminated.

![Trajectory of switching angles](image)

**Figure 3.2** Trajectory of calculated switching angles of SHE-PWM switching pattern using GA
Having obtained the switching angles through MATLAB optimization tool box, the proposed system of VSI is developed using PSIM software.

![Power circuit of voltage source converter/inverter drive system](image)

**Figure 3.3 Power circuit of voltage source converter/inverter drive system**

The power circuit for voltage source converter drive system is given in Figure 3.3. The circuit uses three 230V single phase AC supply sources which was connected to the primary winding of the three phase star/delta transformer. DC voltage was obtained using six pulse voltage source rectifier. The six pulse voltage source rectifier was developed using six diodes as bridge. This rectifier was connected to voltage source inverter through the inductor and capacitor which were acting as a DC link between the rectifier and inverter. The load to the proposed VSI was a three phase squirrel cage induction motor.

The calculated switching angles $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and $\alpha_5$ are used to construct the required SHE-PWM switching pattern and are shown in Figure 3.4. SHE-PWM pulse pattern was constructed with the help of switching angles between $0^0$ and $90^0$ and quarter wave symmetry method was applied to construct the full pulse pattern.

The harmonics were observed in the output line-to-line voltage and load current. The output line-to-line voltage waveform for the modulation
index, $M=0.9$ with RL load is shown in Figure 3.5. The values of resistance and inductance for R-L load used in this method are $5 \, \Omega$ and $50 \, \text{mH}$ respectively.

**Figure 3.4** SHE-PWM switching pattern for 5th, 7th, 11th and 13th harmonics elimination

**Figure 3.5** Inverter output voltage for RL load
The Harmonic spectrum of output voltage with RL load is shown in Figure 3.6.

![Output Voltage harmonics Spectrum for RL Load](image)

**Figure 3.6** Harmonics spectrum for inverter output voltage for RL load (after eliminating 5\textsuperscript{th}, 7\textsuperscript{th}, 11\textsuperscript{th} and 13\textsuperscript{th} harmonics using GA) at M=0.9

![Load Current for RL Load](image)

**Figure 3.7** Load current waveform for RL load
The waveform for the load current with RL load and its harmonics spectrum is shown in Figures 3.7 and 3.8 respectively. This current waveform was observed from a single phase of a three phase system, and is similar to a sinusoidal waveform even though the inverter output voltage is non-sinusoidal.

![Load Current Harmonics Spectrum for RL Load](image)

**Figure 3.8** Load current harmonics spectrum for RL load

![Line to Line Output Voltage for Induction Motor Drive](image)

**Figure 3.9** Output line-to-line voltage with induction motor drive at M=0.9
The output line-to-line voltage waveform for the modulation index, M=0.9 with induction motor drive load is shown in Figure 3.9. The parameter values of the induction Motor are $R_s=0.294 \ \Omega$, $L_s=0.0039 \ \text{H}$, $R_r=0.156 \ \Omega$, $L_r=0.00074 \ \text{H}$, $L_m=0.041 \ \text{H}$, poles=6, power=5 HP and torque=40 N-m. The induction motor was loaded with the maximum torque of 40 N-m which is considered to be the partial load. The harmonic spectrum of the output voltage with induction motor drive load for M=0.9 is shown in Figure 3.10.

![Output Voltage Harmonics Spectrum for IM Drive](image)

**Figure 3.10 Output voltage harmonics spectrum for induction motor drive at M=0.9**

Even though it is known that the output voltage of VSI is independent of the load, the $V_{ab}$ figure with induction motor load is given in order to show that the similar pattern of voltage wave was obtained for both R-L and induction motor load. The waveform for the load current with induction motor drive and harmonics spectrum for load current are shown in Figures 3.11 and 3.12 respectively.
The total harmonic distortion is calculated in PSIM software with a THD block which uses a 2\textsuperscript{nd} order filter to extract the fundamental frequency.
The equation for the calculation of THD with voltage as the variable is given by, \( THD = \frac{\sqrt{V_{rms}^2 - V_1^2}}{V_1} \)

where \( V_{rms} \) is the total RMS value of the input voltage and \( V_1 \) is the fundamental component. Simulation is carried out to obtain the steady state THD behaviour of inverter line voltage in each and every instant of time. The THD of the line-to-line voltage is shown in Figure 3.13. The measured THD value of the line voltage is 73.23%.

![THD with RL load](image)

**Figure 3.13 THD of output voltage (using GA method)**

The main parameters that are involved in induction motor load are torque and speed. While implementing induction motor in PSIM software, the value of speed and torque are set as 1000 rpm and 40 N-m respectively. Figure 3.14 shows the speed and torque of the induction motor load with respect to time using genetic algorithm method. It is observed from Figure 3.13 that the induction motor takes 1.48 seconds to reach the set speed and torque using this approach.
Figure 3.14  Speed and Torque versus time (using GA)

3.5  EXPERIMENTAL RESULTS

A low power laboratory voltage source inverter prototype based on the power MOSFET (IRF460) three phase bridge module is shown in Figure 3.3 was developed and tested to verify the feasibility and the validity of the theoretical and the simulation findings. The laboratory setup was powered by the three phase 440 V, 50 Hz AC power supply. Approximately 100 V DC voltage was obtained from the three phase power converter circuit. Ripple of the DC voltage was reduced by the capacitive filter and this DC voltage is the source voltage for the three phase inverter circuit. The gate pulse for the MOSFET switches are generated using ATMEL microcontroller board with the help of pre-calculated PWM switching pattern. The switching pattern is created with the help of KEIL C software and embedded to the microcontroller with the help of ATMEL parallel programmer circuit. The microcontroller AT89C51 is a low power, high performance CMOS 8-bit microcomputer with 4kB of erasable programmable read only memory. By
combining a versatile 8 bit CPU with Flash on a versatile chip, the AT89C51 is a powerful microcomputer which provides a highly flexible and cost effective solution to many embedded control applications.

The switching gate pulses generated by the microcontroller are obtained from the port 1 and port 2. The clock frequency of crystal used in this model is 12 MHz. The output pulses from the microcontroller are amplified to a voltage of 15 V using an emitter follower circuit connected by SL100 transistors. This amplified output from the amplifier is given as the input to the driver or isolator IC. The driver circuit can also be called as the isolator circuit because it is used for the isolation of the gate signal from the common ground of the microcontroller and source of the MOSFET switches. It is also a protection device which protects microcontroller from the over current caused by power circuit.

A digital real time oscilloscope (Portable Energy & Harmonics Analyzer) ALM30 was used to display and capture the output waveforms and using the feature of the Fast Fourier Transform (FFT), the spectrum of each of the output voltage was obtained. Figures 3.15 and 3.16 shows the experimental results, where the line-to-line voltage with RL load is given in the Figure 3.15 and the harmonics spectrum of the line-to-line voltage with RL load is given in the Figure 3.16. The values of resistance and inductance used for experimental hardware circuit are 10 Ω and 100 mH respectively. The result shows that the lower order harmonics up to the 13th are fully eliminated using genetic algorithm approach.
Figure 3.15 Experimental results: Line-to-line voltage with RL load

Figure 3.16 Experimental results: Harmonic spectrum of line-to-line voltage with RL load
Figure 3.17  Experimental results: Line current with R-L load

Figure 3.18  Experimental results: Harmonic spectrum of line current with RL load

Figures 3.17 and 3.18 shows the experimental results, where the line current with RL load is given in the Figure 3.17 and the harmonics spectrum
of the line current with RL load is given in the Figure 3.18. Figures 3.19 and 3.20 shows the experimental results, where the line-to-line voltage with induction motor load is given in the Figure 3.19 and the harmonics spectrum of the line-to-line voltage with induction motor load is given in the Figure 3.20. The ratings of induction motor used for the experimental purpose are 415 V, 50 Hz, 3 Amps, 1440 rpm and 2 HP. The load current was observed in the no load condition of induction motor. The THD value of line-to-line voltage measured from the experimental results are 55.3% for R-L load and 50.3% for induction motor load using GA approach. The experimental line current wave and its harmonic spectrum are given in Figure 3.21 and 3.22 for induction motor load. The THD value of line current measured from the experimental results are 21.2% for R-L load and 6.6% for induction motor load using this approach.

Figure 3.19  Experimental results: Line-to-line voltage with induction motor load
Figure 3.20 Experimental results: Harmonic spectrum of line-to-line voltage with induction motor load

Figure 3.21 Experimental results: Line current with induction motor load
The harmonics spectrum Figures 3.6, 3.16 for R-L load and 3.10, 3.20 for IM load shows that all 5th, 7th, 11th and 13th harmonics of line-to-line voltage are eliminated for the modulation index value 0.9. These are the characteristic lower order harmonics to be eliminated for the six pulse converter. In this method, 5 (N) variables are used to eliminate 4 (N-1) non-triplen harmonics for three phase VSI using GA approach. The harmonic spectrum of line current with R-L load and induction motor shows that the reduction of harmonics in the line current in greater extent using genetic algorithm approach.

3.6 DISCUSSION

Masswood and Wei (2005) have suggested a method to eliminate 5th and 7th order harmonics using a dual transformer. But in this method, 5th, 7th, 11th and 13th harmonics are eliminated without using a dual transformer. Sayyah et al (2006) have suggested a method to minimize the total harmonic
distortion by suppressing 5\textsuperscript{th} and 7\textsuperscript{th} harmonics. But selective harmonic elimination method suppresses harmonics up to 13\textsuperscript{th} using genetic algorithm is proved in this approach.

The simulation results presents that GA has great potential in solving not only the required switching angles, but also optimization of non-linear converter switching characteristics. MATLAB 7.0 solutions coupled with PSIM6.1 implementation results were verified and analyzed in order to yield good output voltage and current waveforms. The novelty of the approach is elimination of lower order harmonics of VSI feeding induction motor drive without using dual transformer. The genetic algorithm technique is used to find the required switching angles without initial guessing or assumptions. This method suppresses harmonics up to 13\textsuperscript{th} in voltage source inverter feeding induction motor drive. This highlights the SHE-PWM method, which provides a clean power converter environment and meets most accepted standards.

3.7 CONCLUSION

In this chapter, the GA is used to calculate the best possible switching angles in a SHE-PWM. The proposed method is insensitive for setting the initial points. The simulation results verify the ability of GA for the calculation of optimum switching pattern. The minimum computational time taken by the GA method is 8.28188 seconds. The average computational time taken by the GA method over 30 different trial run of the algorithm is 11.26773 seconds. The percentage of THD by the simulation results for both RL and IM load using this algorithm are 73.23\%. The percentage of THD obtained from the experimental results for RL load is 55.3\% and 50.3\% for IM load. ‘N’ switching angles are calculated to eliminate ‘N-1’ non-triplen characteristic harmonics (i.e 5\textsuperscript{th}, 7\textsuperscript{th}, 11\textsuperscript{th} and 13\textsuperscript{th}) from VSI line voltage using GA method.
This method is considered to be the basic method among all evolutionary algorithms used in this thesis. Dual transformer and twelve pulse rectifier are avoided to eliminate $5^{th}$ and $7^{th}$ lower order harmonics using standard GA. High capacity dual transformer connections are also avoided to eliminate the lower order harmonics using genetic algorithm. The elimination of higher order harmonics greater than 13 are dealt in the next chapters.