CHAPTER IV
THE PROPOSED ALGORITHM

4.1 The Procedure of the Proposed Algorithm

According to the previous chapter, initial population of GA that generated by random sampling has less uniformity properties, while sampling techniques can enhance the uniformity properties. Hence, in this research, we introduce the sampling techniques: Latin hypercube sampling (LHS), Faure sequence sampling (FSS), and Hammersley sequence sampling (HSS) in the step of generating initial population. The GA improved by LHS, FSS, and HSS are called LHS-GA, FSS-GA and HSS-GA, respectively. The procedure of proposed algorithms is shown in figure 4.1. The components and parameters in each step are the same as simple GA (as mentioned in the chapter 2)

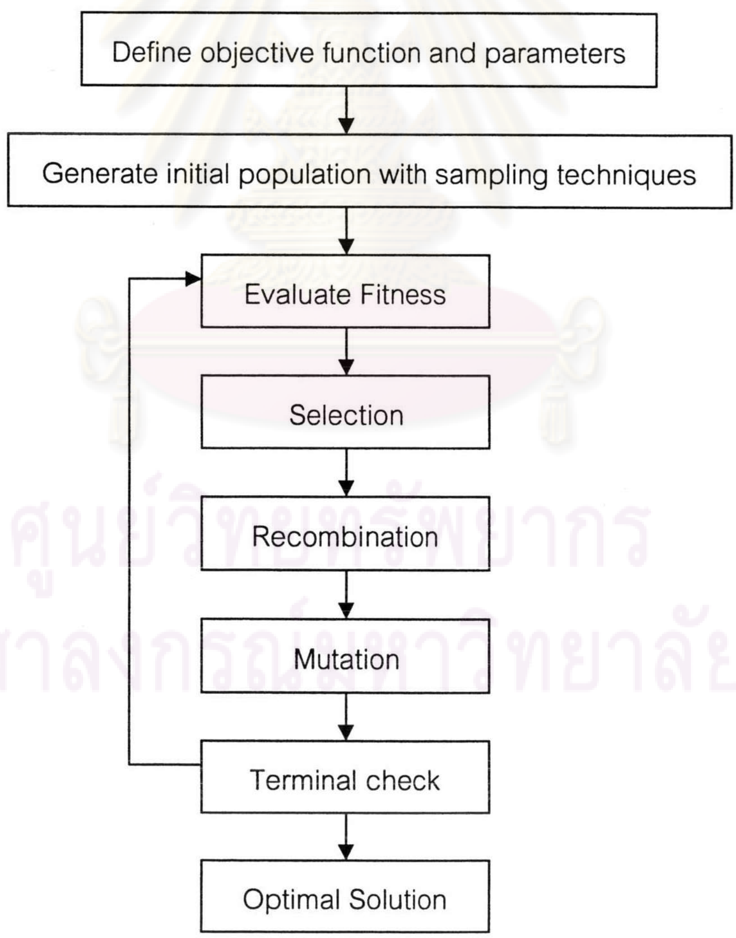

Figure 4.1 The proposed algorithm

4.2 Test Problems

In order to determine that our algorithms (LHS-GA, FSS-GA, and HSS-GA) have more efficient than simple genetic algorithm (SGA), several optimization problems have been used as test problems. The Matlab implementation of both our algorithms and simple GA has been tested with respect to efficiency and reliability by optimizing. Before algorithms start, many operators and parameters have to define as shown in the table 4.2. The six optimization problems are presented in the table 4.3.

Table 4.1 Operators and parameters used in each step for all of test problems

Step	Operator
Chromosome representation	Real-value chromosome
Selection	Roulette wheel selection
Crossover	Arithmetic crossover, $P_c = 0.6$
Mutation	Uniform Mutation, $P_m = 0.05$

Table 4.2 Test problems

Objective function	bound
$\min F_1(x) = 100(x_1^2 + x_2)^2 + (1 - x_1)^2$	$x \in [0,9]$
$\min F_2(x) = x_1 \sin(4x_1) + 1.1x_2 \sin(2x_2)$	$x \in [0,9]$
$\min F_3(x) = -e^A$ $A = 0.2(\sqrt{(x_1-1)^2 + (x_2-1)^2} + \cos(2x_1) + \sin(2x_2))$	$x \in [0,10]$
$\min F_4(x) = 1 + \sum_{n=1}^{N} \frac{x_n^2}{4000} - \prod_{n=1}^{N} \cos(x_n)$; $N = 5$	$x \in [-10,10]$
$\min F_5(x) = \sum_{n=1}^{N} \left(\lvert x_n \rvert - 10\cos(\sqrt{\lvert 10x_n \rvert}) \right)$; $N = 5$	$x \in [-10,10]$
$\min F_6(x) = 0.5 + \frac{\sin^2(\sqrt{x_1^2 + x_2^2} - 0.5}{1 + 0.1(x_1^2 + x_2^2)}$	$x \in [-5,5]$

4.2.1 Problem 1

$$\min F_1(x) = 100(x_1^2 + x_2)^2 + (1 - x_1)^2$$

$$x \in [0,9]$$

Number of population $= 20$

$F_1(x)$ is a two dimension problem. The characteristic of objective function of $F_1(x)$ is shown in figure 4.2. The graph shows this function is a one local optimum and this point is the global solution. Nevertheless, finding the global optimum may be slowly because the slope at the bottom of this function slightly decreases. For this reason, a good dispersion of initial population is critical to finding the global solution in term of speed of convergence.

The optimizing solutions of problem by using our algorithms and SGA are shown in Figure 4.3. This figure plots generation number versus minimum value of $F_1(x)$. It has been shown that LHS-GA, FSS-GA, and HSS-GA converge to the same solution at 7^{th} generation, while SGA converge to the other point. This means that our algorithms can provide the global solution: $F_1(0,0) = 0$, whereas SGA is unable to find the global solution in 25 generation. However, SGA tends to converge to the global solution for over 25 generation.

Hence, in this problem, we conclude that our algorithms provide the global optimum and succeed in reducing computational time.

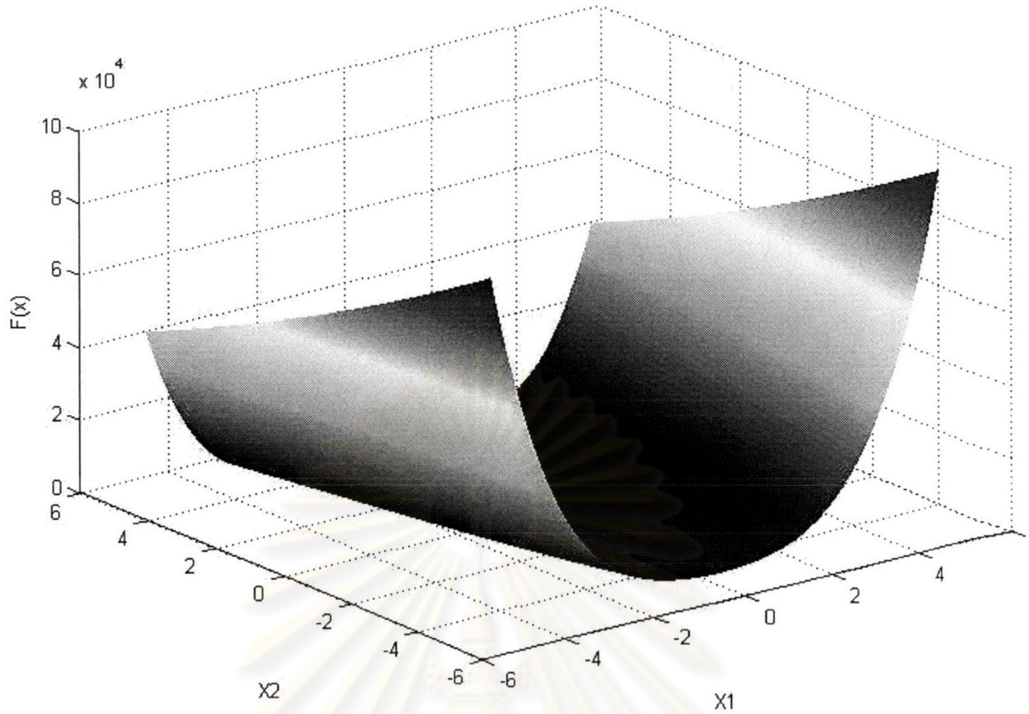

Figure 4.2 Graph of the function $F_1(x)$

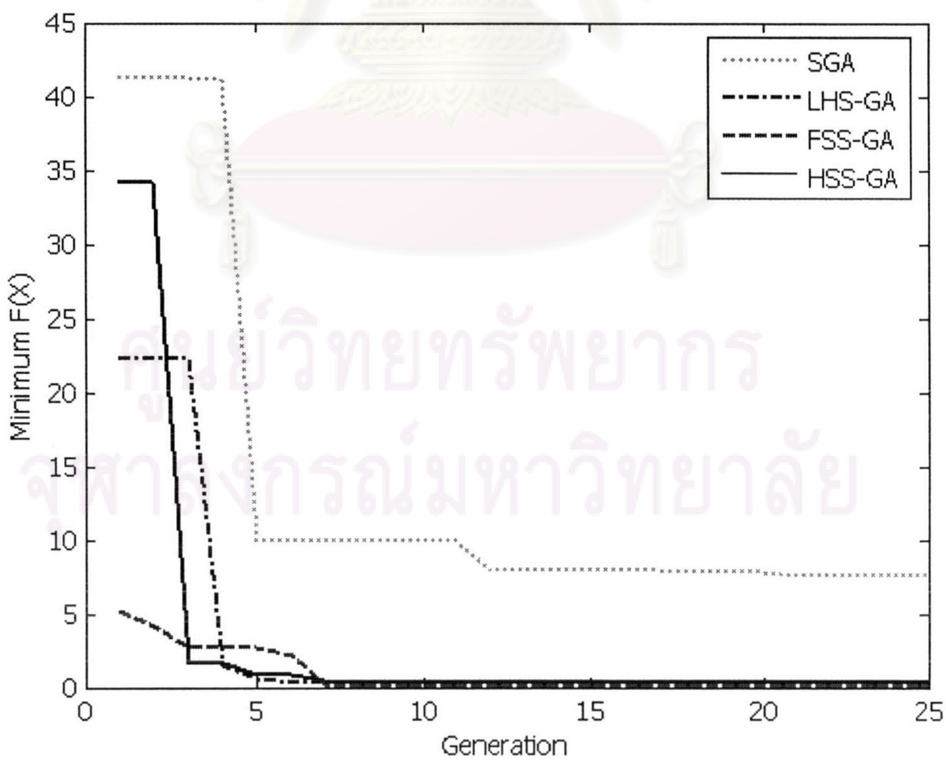

Figure 4.3 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_1(x)$

4.2.2 Problem 2

$$\min F_2(x) = x_1 \sin(4x_1) + 1.1x_2 \sin(2x_2)$$

$$x \in [0,9]$$

Number of population $= 50$

Problem 2, " $\min F_2(x) = x_1 \sin(4x_1) + 1.1x_2 \sin(2x_2)$ ", is a sinusoidal function in two dimensions. The characteristic of objective function of $F_2(x)$ is shown in figure 4.2. It has been noticed that $F_2(x)$ is a multimodal function, great number of local optimum. This problem is hard to find the global solution. Therefore, a good initial population plays an important role in seeking the global optimum.

The results of optimizing are illustrated in the figure 4.5. The figure show that the solutions of FSS-GA and HSS-GA converge to the same point at 10^{th} and 22^{nd} generation, respectively, whereas the solution of LHS-GA and SGA converge to the others. This means that FSS-GA and HSS-GA succeed in giving the global optimum: $F_2(9.039, 8.665) = -18.555$, while LHS-GA and SGA fail to provide the global solution because they trap into the local optimum. However, LHS-GA still enables solution to converge faster than SGA.

Thus, for the problem 2, we summarize that sampling technique can enhance the performance of GA. FSS-GA and HSS-GA provide a better solution than SGA, while LHS-GA dominates SGA in them of speed of convergence.

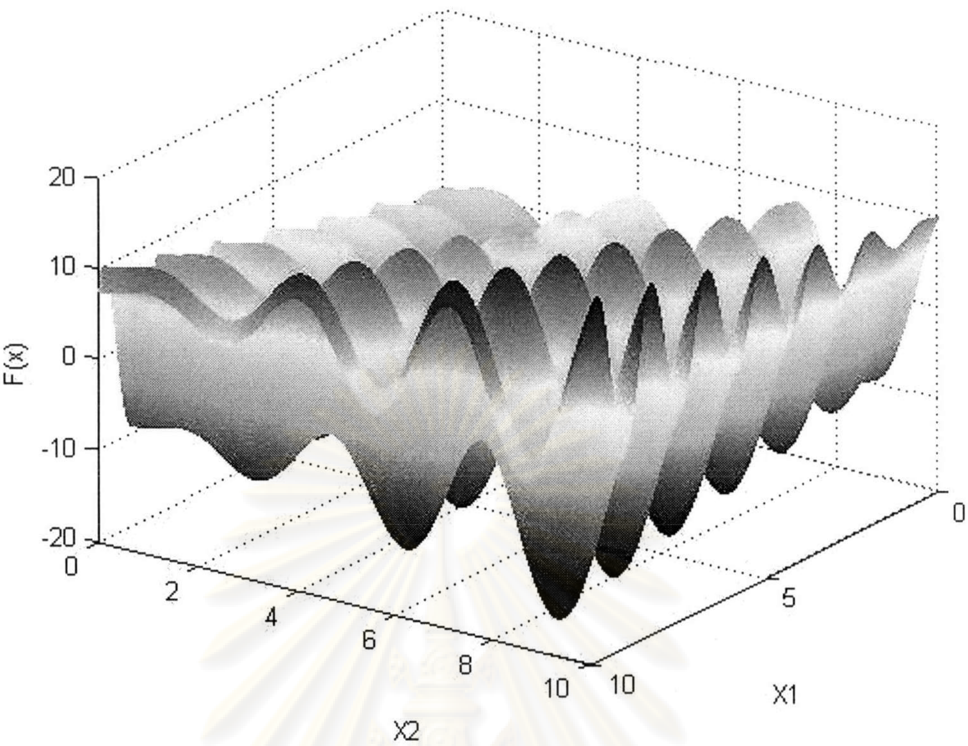

Figure 4.4 Graph of the function $F_2(x)$

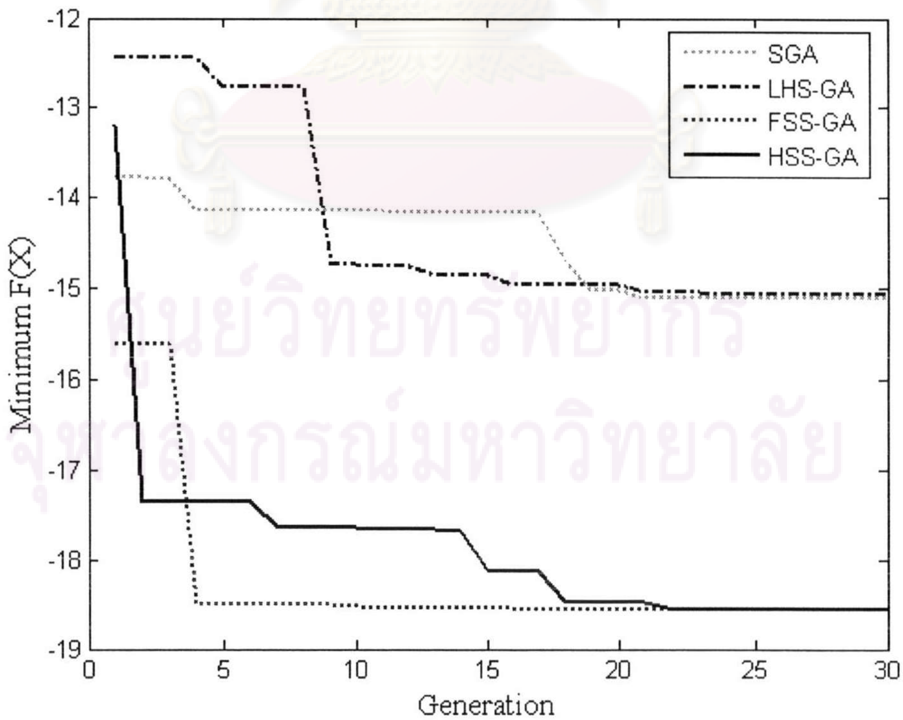

Figure 4.5 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_2(x)$

4.2.3 Problem 3

$$\min F_3(x) = -e^{A}$$

$$A = 0.2(\sqrt{(x_1-1)^2+(x_2-1)^2}+\cos(2x_1)+\sin(2x_2))$$

$$x \in [0,10]$$

Number of population = 50

Problem 3 is the exponential function on two dimensions. The characteristic of $F_3(x)$ is shown in figure 4.6. This graph plots the objective surface on the domain: $x_1, x_2 \in [0,10]$.

The results of optimization of the problem are shown in figure 4.7. The figure plots generation number versus minimum value of $F_3(x)$. It shows that

- SGA give the poor solution: $F(-3.009, 3.779) = -18.118$,
- LHS-GA provide $F(x) = -20.421$ at $x_1 = -3.150, x_2 = 3.938$,
- FSS-GA give the best solution: $F(-3.1802, -2.389) = -21.567$, and
- HSS-GA provide $F(x) = -21.496$ at $x_1 = -3.215, x_2 = -2.409$.

This means that FSS-GA and HSS-GA can provide an acceptable solution, and this solution is better than LHS-GA and SGA. Although, LHS-GA fails to provide the most promising solution, the solution from LHS-GA is still acceptable not the same as SGA.

Thus, for this problem, we summarize that our algorithms is more efficient than SGA, and low discrepancy sequences: FSS and HSS are appropriate technique to generate a good set of initial population.

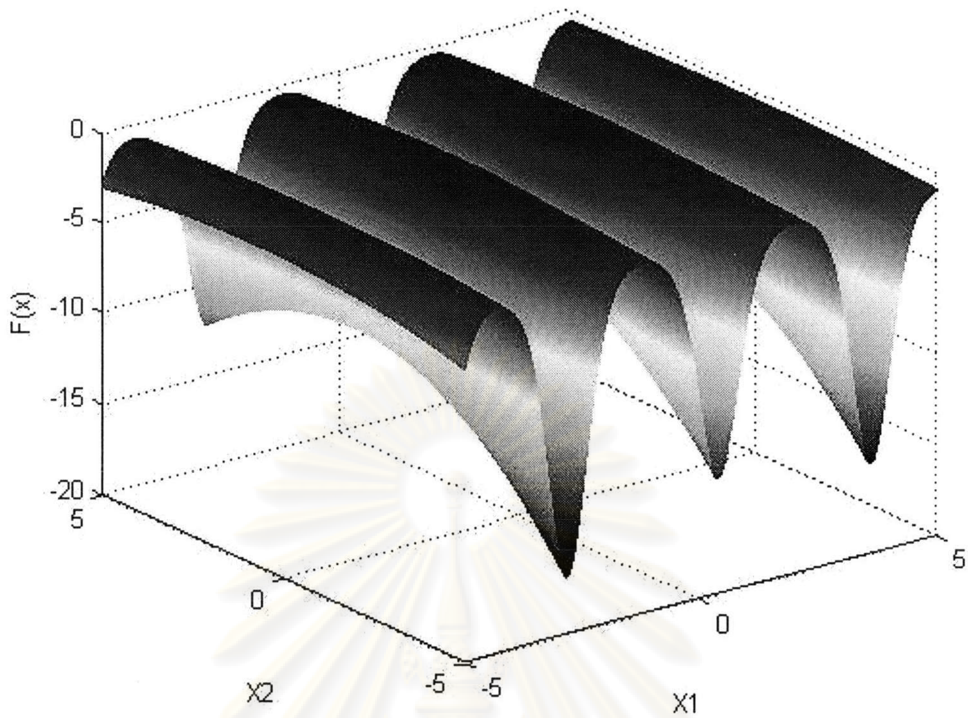

Figure 4.6 Graph of the function $F_3(x)$

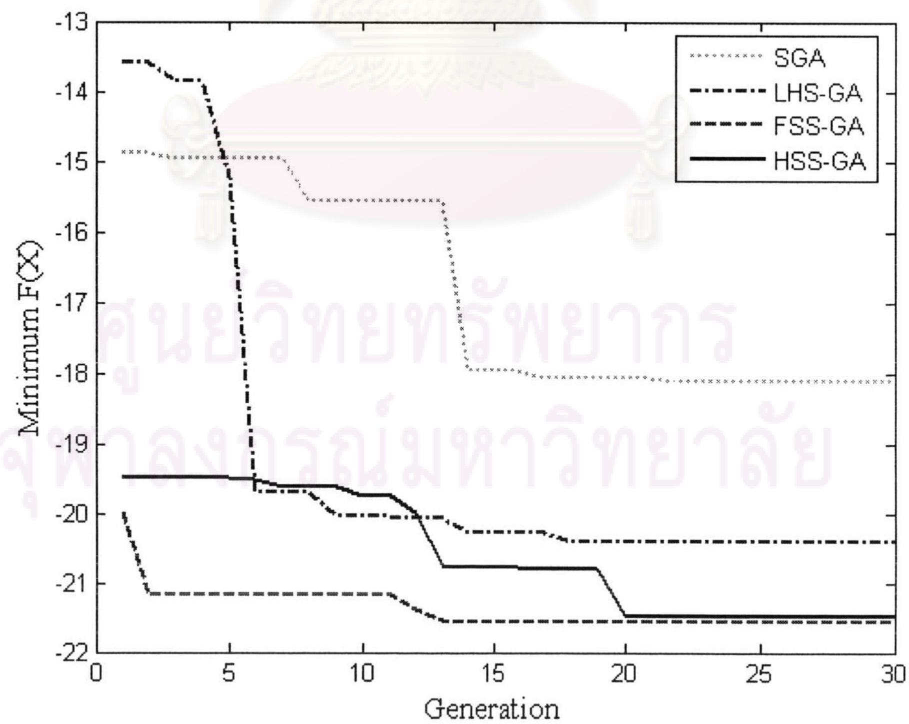

Figure 4.7 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_3(x)$

4.2.4 Problem 4

$$\min F_4(x) = 1 + \sum_{n=1}^{N} \frac{x_n^2}{4000} - \prod_{n=1}^{N} \cos(x_n)$$

$x \in [-10, 10]$

$N = 5$

Number of population = 100

This is an example of multimodal and high dimensions (5 dimensions) as shown in the figure 4.8. The graph plots the characteristic of this function in two dimensions. The function is very difficulty to seek the global result. Because of large domain, the number of initial population needs to use a lot of number.

The results of optimizing are shown in the figure 4.9. This graph plots generation number versus minimum value of $F_4(x)$. From this figure, the solutions of HSS-GA and FSS-GA converge to global minimum, $F(0,0,0,0,0) = 0$, at 11th generation and 16th generation, respectively. LHS-GA cannot provide the global solution in 25th generation. However, the solution from LHS-GA tends to converge to the global result at more 25th generation. On the other hand, SGA fails to provide acceptable result.

So, for this problem, we summarize that our algorithms are superior to the SGA in the ability of finding the global optimum, while FSS-GA and HSS-GA dominate the SGA in speed of convergence to the global optimum.

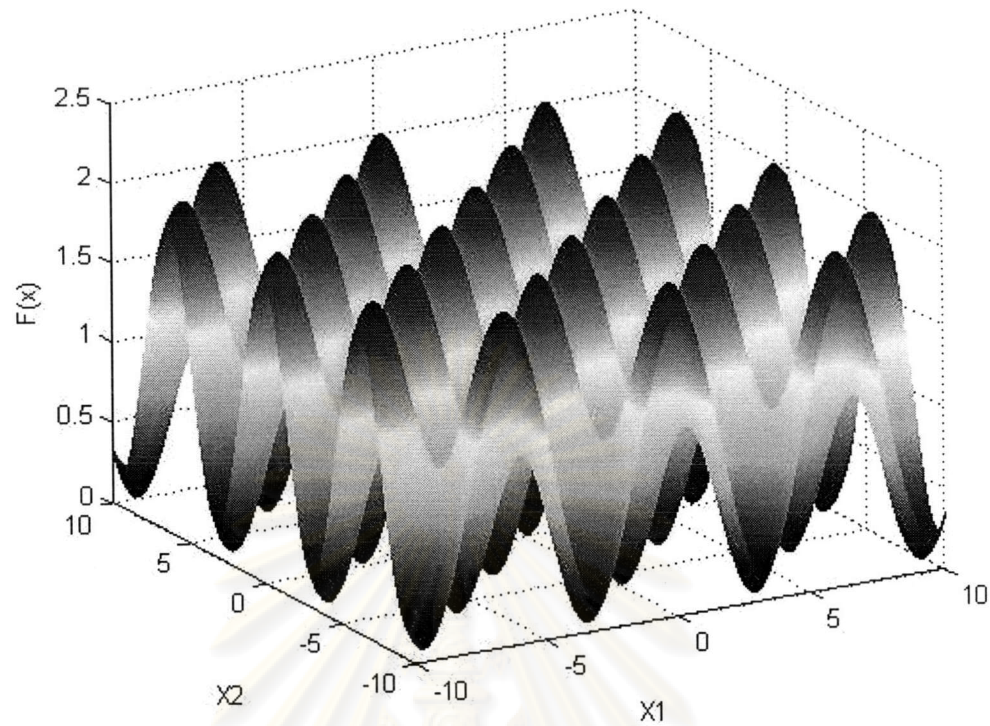

Figure 4.8 Graph of the function $F_4(x)$ in 2 dimensions

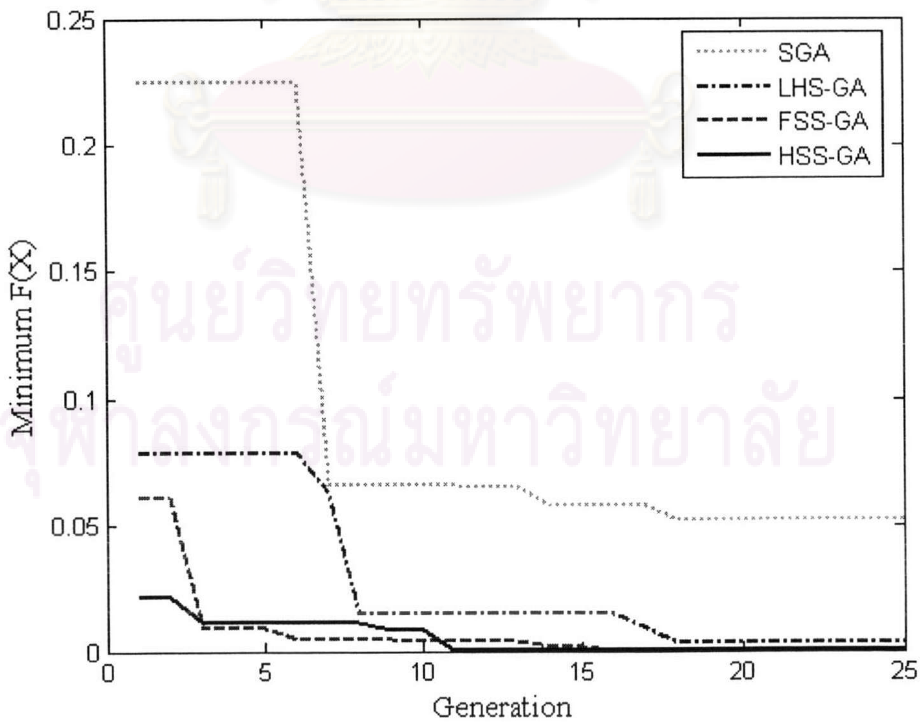

Figure 4.9 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_4(x)$

4.2.5 Problem 5

$$\min F_5(x) = \sum_{n=1}^{N} (|x_n| - 10\cos(\sqrt{|10x_n|}))$$

$x \in [-10,10]$; $N = 5$

Number of population = 100

$F_5(x)$ not only is a multimodal function but also have a large space. The characteristic of this function in two dimensions is illustrated in the figure 4.10. This problem is very difficulty to solve and to obtain the global solution.

The results of optimizing this function are shown in figure 4.11. The graph plots the generation number versus minimum value of $F_5(x)$. From this graph, it is shown that FSS-GA enables solution to converge to the global solution, $F(0,0,0,0,0) = -19.982$, at 20th generation, while the solutions from HSS-GA, LHS-GA, and SGA are not converge to the global minimum. However, HSS-GA still provides a better solution than LHS-GA and SGA in 25th generation.

Thus, for this function, we conclude that FSS is appropriate technique to generate initial population. FSS-GA succeeds in providing the global solution, whereas the others cannot.

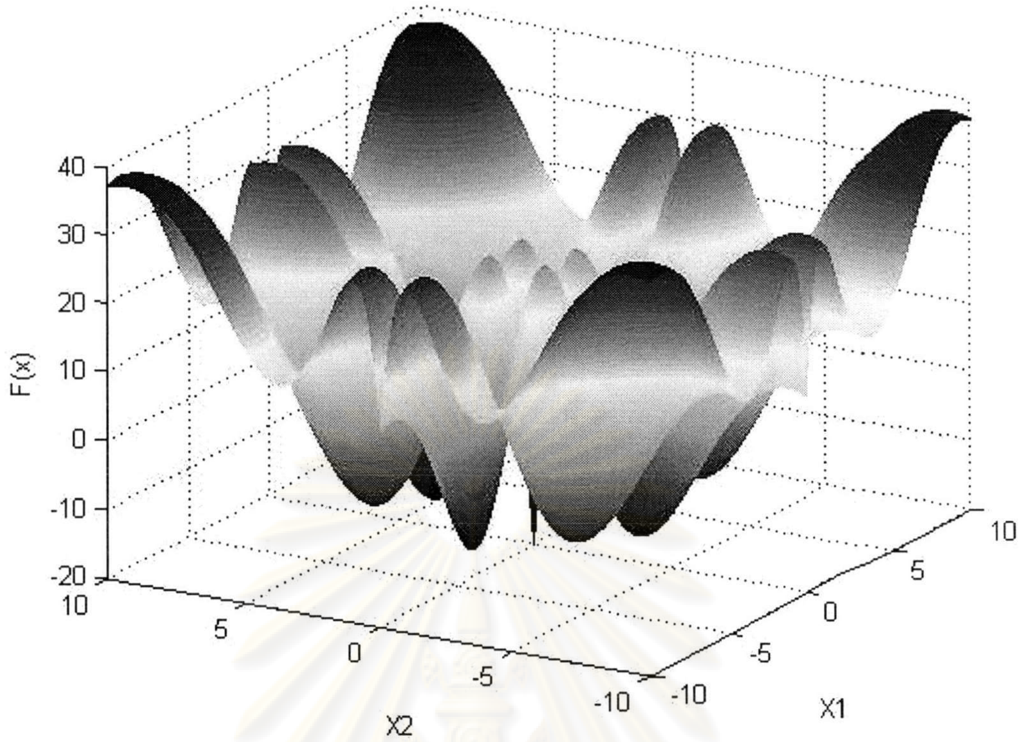

Figure 4.10 Graph of the function $F_5(x)$

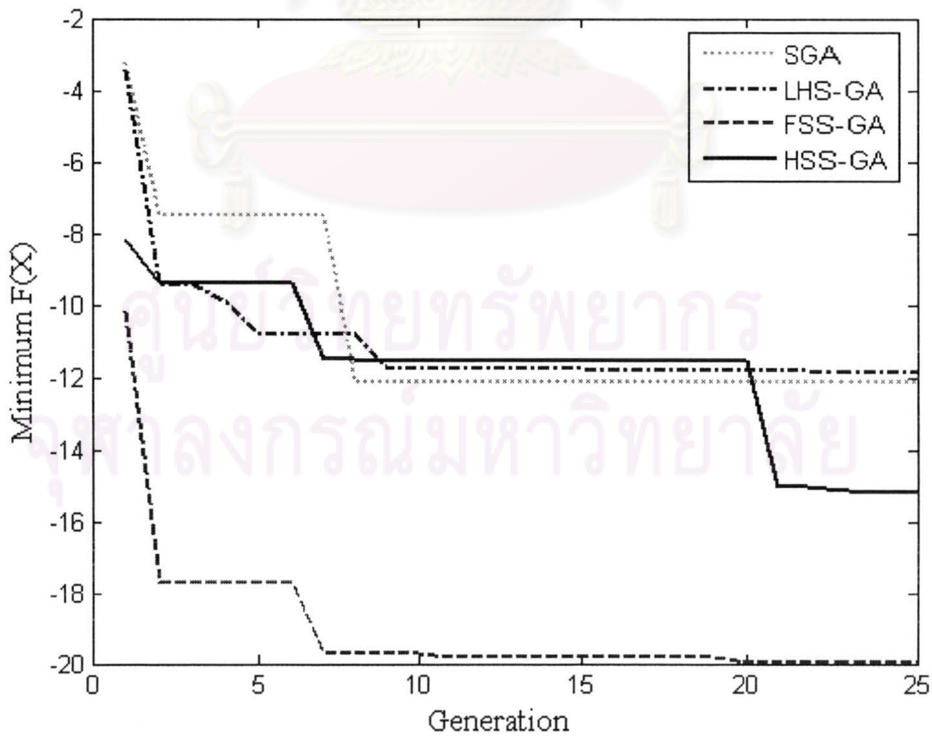

Figure 4.11 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_5(x)$

4.2.6 Problem 6

$$\min F_6(x) = 0.5 + \frac{\sin^2(\sqrt{x_1^2 + x_2^2} - 0.5)}{1 + 0.1(x_1^2 + x_2^2)}$$

$x \in [-5,5]$

Number of population = 20

The problem 6, " $\min F_6(x) = 0.5 + \frac{\sin^2(\sqrt{x_1^2 + x_2^2} - 0.5}{1 + 0.1(x_1^2 + x_2^2)}$ " is an example of multimodal function, and the characteristic of this problem is shown figure 4.12.

The results of optimizing this function are shown in figure 4.13. The graph plots the generation number versus minimum value of $F_6(x)$. It is shown that our algorithms can lead the solution to converge to the global result. The solution of LHS-GA, FSS-GA, and HSS-GA converge to global point $(F(x) = -0.9329)$ at 12^{th}, 14^{th}, and 16^{th} generation, respectively. In contrast, the solution of SGA not converges to the global solution.

Hence, for this problem, our algorithms have more performance than SGA in term of the ability of finding the global solution.

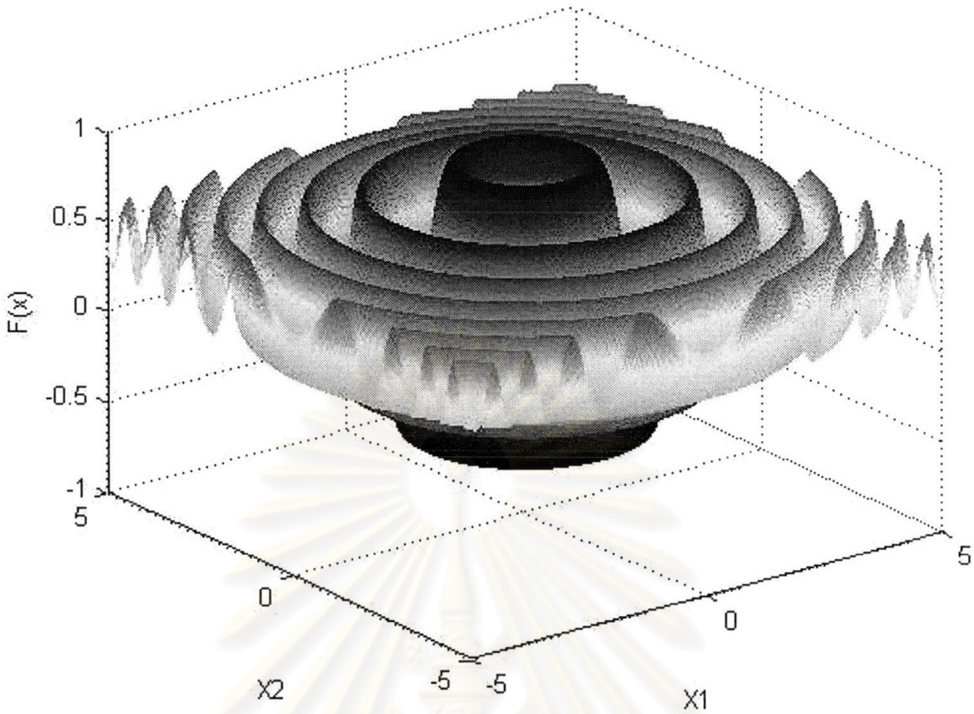

Figure 4.12 Graph of the function $F_6(x)$

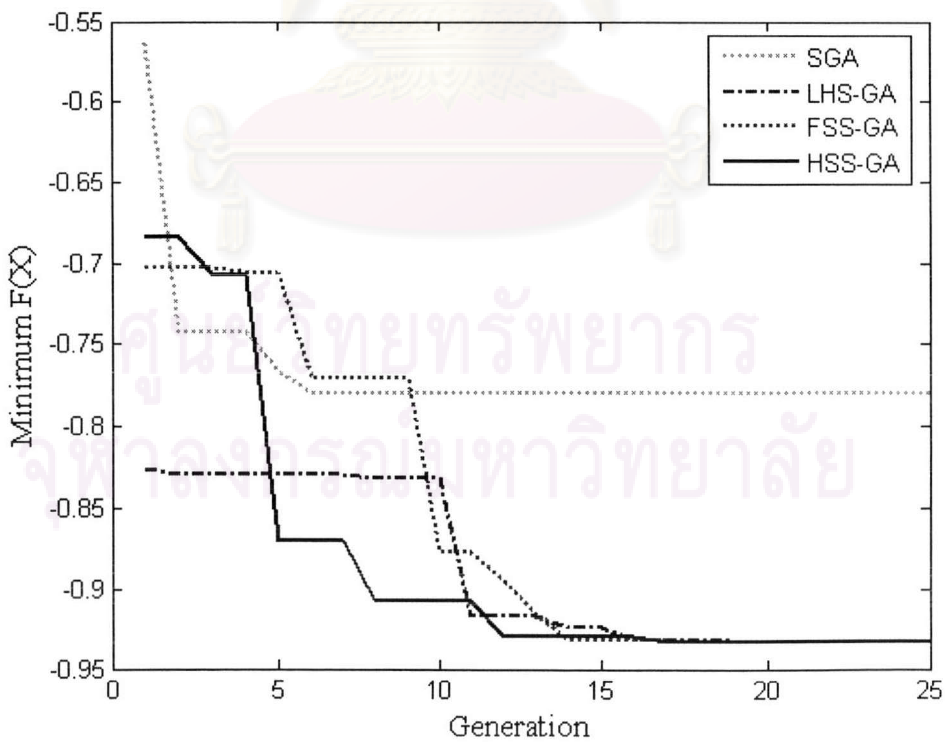

Figure 4.13 Comparison the performance of SGA, LHS-GA, FSS-GA, and HSS-GA: generation number versus minimum value of $F_6(x)$

4.3 Summary

In this chapter, we have introduced three new algorithms that is:

- LHS-GA: GA of which initial population generated by LHS,
- FSS-GA: GA of which initial population generated by FSS, and
- HSS-GA: GA of which initial population generated by HHS

The performance of our algorithms and SGA are compared in terms of solution quality and speed of convergence to the optimal point through six optimization problems. From the results, our algorithms outperform SGA in both terms. Hence, our algorithms are able to enhance the GA performance.