Chapter 5
Analysis and Discussion

This chapter will discuss three experiments from the previous chapter. The analysis will follow the hypothesis of this project which is "The Self-Adaptive Evolutionary Algorithm should be faster in the performance of computing UIO sequences of finite state machines than the Genetic Algorithm". The analysis of the three experiments is explained below.

5.1 Analysis of computing UIOs of the FSMs in different lengths of the input sequences.

From the experiment 1, in the graph (Figure 4.1) and the box plots (Figure 4.2 and 4.3), the averages of the fitness values of the small FSM of the GA and the Self-Adaptive EA look unlikely not vary too much. While, in the graph (Figure 4.4) and the box plots (Figure 4.5 and 4.6), the averages of the fitness values of the large FSM between two programs look more different. Obviously, the Self-Adaptive EA can present the higher fitness values' averages at all running times when we observe in the various lengths of the input sequences (individuals) in both small and large FSMs. In addition, the results from the Self-Adaptive EA is quite more stable than the GA when running to compute UIOs of the small and large FSMs.

Moreover, there is the analysis by using the Wilcoxon Rank Sum Test. This test can analyse the distribution of the averages of the different lengths of the input sequences. In the small FSM, the p-value of the experiment is calculated at 0.0093240095 ($9.324 * 10^{-3}$). The p-value of the experiment is calculated at 0.003933 ($3.933 * 10^{-3}$) in the large FSM. Apparently, the p-values are lower than 0.05 so it means that the averages of the Self-Adaptive EA are better than the averages of the GA.

Hence, from this analysis, the different lengths of the input sequences can likely affect the fitness values' averages in both programs. The Self-Adaptive EA is likely better than the GA when observing in the small and large FSMs in experiment 1. This analysis also supports the hypothesis that The Self-Adaptive EA is really better in the performance of computing UIO sequences of finite state machines than the GA when we consider between two programs with the same FSMs.

5.2 Analysis of computing UIOs of the different artificial FSMs.

From experiment 2, this experiment focuses on computing UIOs of the several artificial FSMs. In Figure 4.7, the averages of the fitness values of the GA and the Self-Adaptive EA are likely different but it looks like not different too much. In the previous chapter, the Self-Adaptive EA can present the higher fitness values' averages at all running times when we observe in the different artificial FSMs. It can be seen that the number of states can affect the fitness values' averages because the fitness function is identified based on the number of states and the number of the leaf node when considering any same input sequences.

Furthermore, there is the analysis by using the Wilcoxon Rank Sum Test. This test can analyse the signification of the distribution of the averages of the different artificial FSMs between the GA and the Self-Adaptive EA. The p-value of this experiment is calculated at 0.28574985. The p-value is higher than 0.05 so it means that the averages of the Self-Adaptive EA are not better than the averages of the GA.

Hence, in basic condition of the analysis in experiment 2, if the number of states increases, the fitness values and the fitness values' averages also rise as well but they are not more than the number of states. The computation of UIOs of the different artificial FSMs likely affect the fitness values' averages in both programs and the Self-Adaptive EA is completely better than the GA. However, it cannot to be noted that the Self-Adaptive EA is likely better than the GA when we observed on computing UIOs of the different artificial FSMs because the results of both programs are not significant difference. Hence, this analysis is not strong enough to support the hypothesis of this project.

5.3 Analysis of computing UIOs of the real FSMs.

From the experiment 3, this experiment focuses on computing UIOs of the real FSMs. In Figure 4.10, the fitness values' averages of the GA and the Self-Adaptive EA are not different too much. However, the Self-Adaptive EA can present the higher fitness values' averages at all running times when we observe in the different real FSMs. Therefore, it can be seen that the number of states can affect the fitness values' averages because the fitness function is identified based on the number of states and the leaf node (UIOs). In addition, the real FSMs which contain some difficult transitions of the real FSMs can also impact the fitness values' averages in both programs. The complicated transitions refer the number of any bit-strings of input sequences which is read in each time to get any certain outputs and certain states. The vary output sequences also impact the UIOs of the real FSMs.

In the analysis by using the Wilcoxon Rank Sum Test. This test can analyse the distribution of the averages of the different real FSMs between the GA and the Self-Adaptive EA. The p-value of this experiment is calculated at 0.13750734. The p-value is higher than 0.05 so it means that the averages of the Self-Adaptive EA are not better than the averages of the GA because the fitness values' averages between the Self-Adaptive EA and the GA are not significantly different too much.

Therefore, from the analysis of experiment 3, if the number of states increases, the fitness values and the fitness values' averages also rise as well but their averages are not more than the number of states. The computation of UIOs of the real FSMs is unlikely to affect the fitness values' averages too much in both programs. Obviously, from this experiment, the Self-Adaptive EA is better than the GA when we observed on computing UIOs of the different real FSMs but it is not better and not different enough to note that the Self-Adaptive EA is really better than the GA when we consider by the Wilcoxon Rank Sum Test. Hence, it can be noted that this analysis cannot support the hypothesis that the Self-Adaptive EA is better in performance than the GA because the difference between the results of both programs is not significant enough.

From the previous research, there are many studies which used the GA, and the research' results present that the GA is effective for computing UIOs (Derderian, 2005; Guo, Hierons, Harman, & Derderian, 2004; Lehre & Yao, 2011). In the result of this work, it illustrates that the averages of the fitness values of the Self-Adaptive EA can get higher than the GA. Hence, it can be noted that the Self-Adaptive EA is also effective.