terms of the convergence, the speed and the robustness.

- Convergence

MSCTS algorithm has better convergence for more complex problems. The convergence of MSCTS algorithm is evaluated by *Max_value, Min_value* and *E_relative*.

On the one hand, MSCTS algorithm can get more precise values. From TABLE 3, as for the test functions which have little variables, just like the *Branin, Gold price, Shubert* and *Hartmann34*, MSCTS and SCTS algorithm can both achieve the theoretical optimum solution in tests. However, when the number of variable of test function are more, like the *Brown1, Brown3, F5n, F10n* and *F15n*, the calculated optimum solution by MSCTS algorithm is much closer to the theoretical optimum solution than by SCTS algorithm.

On the other hand, MSCTS algorithm can be better in avoiding the local optimum. A test function is solved by an optimization algorithm, which repeats many times. The optimization algorithm is trapped by the local optimum if almost function values with the calculated optimization solution are same, and not the theoretical optimum value. However, if the calculated optimum values of the test function with little variables near the theoretical optimum value can be achieved, there is little possibility that algorithm is trapped by the local optimum.

- Speed

MSCTS algorithm can quickly solve all test functions. *AIT* and *Time* are used to evaluate the speed of these algorithms. From TABLE 3, for the same test function, the number of actual iteration times of MSCTS algorithm is 3 to 17 times as many as that of SCTS algorithm. Especially for Shubert which has many sharp peaks, the number of actual iteration times of MSCTS algorithm is 17 times as many as that of SCTS algorithm. The runtime of MSCTS algorithm is 3 to 9 times as many as that of SCTS algorithm. The larger the number of variables in test function can be resolved rapidly by MSCTS algorithm, which is a great improvement of MSCTS algorithm.

- Robustness

MSCTS algorithm can be applied in many fields than SCTS algorithm. The practicability of the MSCTS algorithm can also be described by *E_relative*. According to TABLE 3, SCTS algorithm cannot resolve the more complicated functions (like *Brown3, F5n, F10n* and *F15n*). However, little *E_relative* values were gotten by MSCTS algorithm. MSCTS algorithm can deal with practical problems in science and engineering efficiently.

VI . Conclusion

In order to improve the convergence, speed and robustness of SCTS algorithm, MSCTS algorithm is proposed and modified at neighborhoods selection and setting range. The multidimensional normal distribution function is used to instruct the generation of the neighborhoods. The current optimal solution is taken as the mean value and the difference vector of the objective function as the standard deviation in the multidimensional normal distribution function.

The performance of MSCTS and SCTS algorithm are tested by 9 typical test functions respectively which results are contrasted and evaluated by 5 performance indexes. There are several conclusions based on the results and analysis.

It not only improves the convergence and robustness of MSCTS algorithm, but also the application range is expanded wildly because the neighborhood selection is guided by the change of the objective function at the current optimal solution. MSCTS algorithm works very well especially for complicated problem.

Due to different setting of neighborhood range at different stages, the calculating speed of MSCTS algorithm increase remarkably. The fastest optimizing speed of MSCTS algorithm can be improved to 17 times.

The problem of MSCTS algorithm is that the found optimum solution may go beyond solution space because the neighborhood selection is based on "3σ principle" of multidimensional normal distribution. In order to ensure the effectiveness of the optimum solution, the location of optimum solution should be judged by Point location in MSCTS algorithm.

VII. Acknowledgment

We would like to thank R.T Zheng for his help to our development of this MSCTS algorithm. We also want to thank Yu Wu, who did much about testing our MSCTS algorithm, and all of people offered help to our study and writing this article. We would like to thank anonymous reviewers for their constructive comments and suggestions on this paper.

References

[1] Fred Glover, "Tabu Search-Part I", ORSA Journal on Computing, vol. 1, no. 3, Summer 1989.

[2] Fred Glover, "Tabu Search-Part II", ORSA Journal on Computing. vol. 2, no. 1, Winter 1990.

[3] Vahid Mansourkhaki, "Application of Tabu Search for Metabolic Flux Analysis Based on Labeling Balances", UMI Microform, 1439935, 2006.

[4] Wen-Hsing Liu, "Tabu Search Heuristics for the Dynamic Facility Layout Problem", UMI Microform, 1429106, 2005.

[5] Eugenia D áza, Javier Tuya, Raquel Blancoa, Jos é Javier Dolado, "A tabu search algorithm for structural software testing", Computers & Operations Research, 35 (2008) 3052 – 3072, 2007.

[6] Eugeniusz Nowicki, Czestaw Smutnicki, "A fast tabu search algorithm for the permutation flow-shop problem", European Journal of Operational Research, 91 (1996) 160-175

[7] Whei-Min Lin, Fu-Sheng Cheng, and Ming-Tong Tsay, "An Improved Tabu Search for Economic Dispatch With Multiple Minima", IEEE Transaction on Power Systems, vol. 17, no. 1, February 2002

[8] Adem Kalinli, Dervis Karaboga, "Training recurrent neural networks by using parallel tabu search algorithm based on crossover operation", Engineering Applications of Artificial Intelligence, 17 (2004) 529–542

[9] R.T. ZHENG, N.Q. NGO, P. SHUM, S.C. TJIN, L.N. BINH, "A Staged Continuous Tabu Search Algorithm for the Global Optimization and its Applications to the Design of Fiber Bragg Gratings", Computational Optimization and Applications, 30, 319–335, 2005.

[10] Marcin Molga, Czesław Smutnicki, "Test functions for optimization needs", 3 kwietnia 2005

[11] R.T. ZHENG, N.Q. NGO, L.N. BINH, S.C. TJIN, "Two-stage hybrid optimization of fiber Bragg gratings for design of linear phase filters", Optical Society of America, vol. 21, no. 12/December 2004