Journal of Computers and Applied Science Education
Volume 5, Number 3, 2018

ISSN 2409-7284 (Online)

A New Optimization Based on Flower and Sine Cosine for Saving Fuel Consumption Problem

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Received February 2018; Revised July 2018

ABSTRACT. *One of the recent trends of developing optimizations is to hybridize two algorithms or several numbers of variants to find out the better quality of practical optimal applications. This paper proposes a new optimal algorithm based on hybrid Flower pollination algorithm (FPA) and Sine-cosine algorithm (SCA) to solve the numerical optimization problems and the vehicle fuel consumption. We introduce a new parallel computation in a combination of the pollens and agents for exploring and exploiting the diversity of the algorithm. In experimental section, we use a set of six testing functions and the real vehicle fuel consumption problem to evaluate a new proposed algorithm. The experimental result compared with the other algorithms in the literature shows that the proposed method increases the accuracy of optimizations and the vehicle traveling in the logistics.*
Keywords: *Hybrid flower and sine-cosine optimization, Sine cosine algorithm, Flower pollination algorithm*

1. Introduction

The vehicle traffic congestion and rough driving pattern can cause increased fuel consumption, loaded emissions, longer traveling time and accidents directly or indirectly(Choudhary &Gokhale,

2016). There are many proposed solutions to this hard problem (Li, Wen, &Yao, 2014). Building new high-capacity streets and highways is as a solution to alleviate the vehicle congestion problem. However, it is seemly very costly, time-consuming, and in some cases are impossible execution because of space limitations. On the contrary, the optimization applying for existed roads and capacity streets can lessen the congestion problem in cities at the lower cost. Indeed, the implementable optimization needs accurate information about current status of roads and streets. This optimization is a challenge due to the complex and change environments(Xu, Yue, &Li, 2013). Fortunately, the advancement in technology of electronics and Internet had made rapid the proliferation of wireless sensor networks (WSN) (García-hernández, Ibargüengoytia-gonzález, García-hernández, &Pérez-díaz, 2007). Applying WSN can be envisioned a promising answer to the above-mentioned problem. Sensor-enabled products and their networks become a commonplace, e.g., traffic control and navigation, object tracking, and monitoring. Alternative paths based on offering accurate information about current status of roads, streets and shortest path distances can be helpful to reduce fuel consumption and lessen traffic congestion if the traffic navigation mounted the WNS. A large number of inexpensive sensors, small size and integrated with a sensing unit and wireless communication capabilities in WSNs can support the traffic control system. The sensor nodes are deployed in a wide terrain to execute the intended tasks efficiently(Pan, Dao, Nguyen, &Chu, 2015).

Furthermore, the optimization process is one of the highly effective techniques to try searching the best possible results in a benchmark and real-life functions with scatting seeds randomly(Jin &Branke, 2005). Traditional optimization approaches have some deficiencies in finding the optimal global solutions of classical optimization problems(Boussaïd, Lepagnot, &Siarry, 2013). These shortcomings are primarily interdependent in their natural search systems. These ranking algorithms are strongly under effects of choosing proper types of variables, objectives and constraints functions(Dao, Pan, Nguyen, & Chu, 2015). They also do not grant a universal solution method that can be applied to find an optimal global solution of the duties by several types of constrained functions, variables, and the objective(Nguyen, Pan, Chu, Roddick, &Dao,

2016). For covering these deficiencies, a new technique with the name of metaheuristic as artificial intelligence research was originated based on original inspirations such as evolution, swarm, and physical laws (Baghel, Agrawal, &Silakari, 2012). Nature inspired techniques developed for solving the several types of hard global optimization functions without having to the full accommodate to each function.

However, the optimal metaheuristic cannot always be plainly archived best results (drop in trap local) due to physical constraints of real problems in the different search space(Boussaïd et al., 2013)(Shi &Eberhart, 1998). Hybridizing between two algorithms is to take advance high points of the algorithms. The good point of the algorithms is considered motivation to merge them in parallel to overcome the issue of trapping optimal local. The parallel processing also plays a vital role in the efficient and effective computations of function optimizations. The idea for this paper is based on the communication strategies in parallel processing for intelligent swarm algorithms. The communications among agents while parallel processing would enhance the cooperating individuals, share the computation load, and increase the diversity optimizations. The algorithms can exchange information between the populations whenever the communication strategy is triggered.

This paper considers the advantages of the metaheuristics such as Flower pollination algorithm (FPA)(Yang, 2012), and Sine Cosine Algorithm (SCA) (Mirjalili, 2016). These algorithms have applied to solve successfully many problems in the fields of engineering and finance (Kotthoff, 2016). However, these algorithms also have the disadvantages such as a dropping into local optimal for complex problems or earlier convergence in the later searching period. So that accuracy of the optimal results could not meet the demands in some cases. Enhancing diversity agents is one of the effective ways that can deal with the above-mentioned issue. The processing parallel can be applied to develop a diversity solution. This study introduces newly a hybridization meta-heuristic optimization technique based on FPA and SCA (named FSO) for the vehicle fuel consumption and global optimization problems.

The remaining paper is organized as follows. A brief review of FPA and SCA is stated in

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

Session 2. The description detail for the proposed method is presented in Session 3. Experimental results and the comparison with the other algorithms in the literature are discussed in Session 4. Apply the new proposed algorithm to the vehicle fuel consumption problem presented in Section 5. Conclusion is summarized in Session 5.

2. Related Work

2.1. Flower Pollination Algorithm

Please write down your subsection.

Flower Pollination Algorithm (FPA) obtained the inspiration from the flowering plant for the biological flower pollination (Yang, 2012). FPA was developed by emulating the character of the organic flower pollination of the flowering plant. By applying the flow pollination process rules, FPA had the states as follows. The first is global pollination process as cross-pollination that pollinators obey Lévy flights. The second is local pollination explored as self-pollination. The third is reproduction probability considered as flower constancy which is proportional to the resemblance of the two flowers in concerned. FPA used a switching probability p ∈ [0, 1] to control between the local and global pollination. FPA assumed that each plant has a single flower and each flower emit only a single pollen gamete. FPA considered as global and local pollination. FPA modeled the local pollination as following.

$$\vec{x}_{ij}^{t+1} = \vec{x}_{ij}^{t} + u(\vec{x}_{ih}^{t} - \vec{x}_{ik}^{t}) \tag{1}$$

where $\vec{x}_{ih}^{t}$, $\vec{x}_{ik}^{t}$ are pollen from different flowers of the same plant species, and a variable u is generated from the uniform distribution in the range [0, 1]. A random walk for local process if x_{ih}^{t} and x_{ik}^{t} come from the same species or selected from the same population of plants. In the global pollination, the pollens of the flowers are moved by pollinators e.g. insects, and pollens can be moved for a long distance since the insects typically fly for a long range of distances. This process guarantees pollination and reproduction of the fittest solution represented as. The flower constancy is expressed mathematically as:

$$\vec{x}_{ij}^{t+1} = \vec{x}_{ij}^{t} + \gamma \times L(\lambda) \times (\vec{x}_{ij}^{t} - g^{*}) \tag{2}$$

ISSN 2409-7284 (Online)

where x_i is solution vector at iteration *t*, γ is a scaling factor to control the step size. Lévy flight can be used to mimic the characteristic transporting of insects over a long distance with various length steps, thus, $L > 0$ from a Lévy distribution.

$$L = \frac{\lambda\Gamma(\lambda)\times\sin\left(\frac{\pi\lambda}{2}\right)}{\pi\times s^{i+\lambda}},\ (s \gg s_0) \tag{3}$$

where Γ(λ) is the standard gamma function, and this distribution is valid for large steps s > 0. A variable p is switching probability or the proximity probability that can be used to change the global pollination to intensive local pollination and reverse. Two reasons of active PFA include the first, insect pollinators can travel long distances which enable the FPA to avoid local landscape to search for a considerable space (explorations), and the second, the FPA ensures that similar species of the flowers chosen which guarantee fast convergence to the optimal solution (exploitation).

2.1 Sine Cosine Algorithm

Sine Cosine Algorithm (SCA) is a newly proposed metaheuristic developed based on Sine and Cosine function apply for exploitation and exploration phases in global optimization (Mirjalili, 2016). SCA creates different initial random agent solutions and requires them to fluctuate outwards or towards the best possible solution using a mathematical model based on sine and cosine functions. The update formulas of SCA represented as below.

$$\vec{s}_{ij}^{t+1} = \vec{s}_{ij}^{t} + rand_1 \times \sin(rand_2) \times \left|rand_3 \times l_{ij}^{t} - \vec{s}_{ij}^{t}\right|, \tag{4}$$

$$\vec{s}_{ij}^{t+1} = \vec{s}_{ij}^{t} + rand_1 \times \cos(rand_2) \times \left|rand_3 \times l_{ij}^{t} - \vec{s}_{ij}^{t}\right|, \tag{5}$$

where $\vec{s}_{ij}^{t}$ current position at t^{th} iteration in ij^{th} dimension, $rand_1, rand_2, rand_3 \in [0,1]$ are random numbers and l_{ij} is targeted global optimal solution.

$$\vec{s}_{ij}^{t+1} = \begin{cases} \vec{s}_{ij}^{t} + rand_1 \times \sin(rand_2) \times \left|rand_3 \times l_{ij}^{t} - \vec{s}_{ij}^{t}\right|,\ rand_4 \\ \vec{s}_{ij}^{t} + rand_1 \times \cos(rand_2) \times \left|rand_3 \times l_{ij}^{t} - \vec{s}_{ij}^{t}\right|,\ rand_4 \end{cases} \tag{6}$$

The above equation uses 0.5 <=$rand_4$ <0.5 conditions for exploitation and exploration.

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

3. Flower Sine Cosine Optimizer

In this section, we present the design of Flower Sine Cosine Optimizer (named FSO). We construct FSO based on hybrid FPA and SCA algorithms. Both of the FPA and SCA algorithms have been applied to solve several problems successfully in engineering, and financial fields because of their advantages of flexibility and robustness. However, the limited algorithms are diversity solutions that can cause dropping into local optimal in some cases of complex problems. The optimal results may cause the less accuracy as the requirements in sometimes.

To overcome this issue, we could apply the enhanced optimizations. We use the hybridized application for improving optimization by constructing the communication both of algorithms. The exchange information among populations figure out the enhancing optimizations whenever the communication strategy is triggered. A parallel structure is also made up of several groups by dividing the population into subpopulations. The diversity agents for the optimal method are built based on constructing of the parallel processing.

We describe the communication strategy for sharing information between agents and pollen as follows. The best agents in SCA could be copied to the FPA subpopulations. The poorer pollens of the FPA subpopulations are replaced with the best agents. The positions of all subpopulations are updated in every period of exchanging time. The flow information of communicating the actors and pollens employ with the communication strategy. In contrast, the finest artificial pollens among all the flowers of FPA's population would migrate to the weaker agents in SCA, replace them and update all positions for each community during every period exchanging time. The subpopulations are evolved into regular iterations independently.

The advantages of each side of algorithms take into account by replacing the poorer individuals of them with the finest ones. It is the benefit of cooperation between them. Let's R be an exchanging period of communication between FPA and SCA and N be the population size of FSO. Let the numbers of the population sizes of SCA and FPA are N1 and N2 be set to N/2 respectively. The top fitness k agents of in group with N1 will be copied to the place of worst actors in the group with N2 for replacing the same number of the agents, where t is the current

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

iteration, during running. Description of the proposed method can be summarized the basic steps as follows.

Step 1. **Initialization:** Generating FSO population randomly for initializing solutions. *R* is defined executing period of communication strategies. The N_1 and N_2 are the numbers of agents and pollens in solutions X_{ij}^t and S_{ij}^t for populations of SCA and FPA respectively, $i = 0, 1,.., N_{1,2} - 1$, $j = 0, 1,..D$. where *D* is dimension of solutions and *t* is current iteration with setting initializing to 1.

Step 2. **Evaluation:** Evaluating the objective function by $f_2(X_{ij}^t)$, $f_1(S_{ij}^t)$ for both SCA and FPA in each iteration according to the fitness values. Executing evolvement of the populations by both FPA and SCA.

Step 3. **Update:** Updating the global pollination and local pollination of FPA are by Eqs. (1-3) and the positions of SCA Eq. (6). Store the best value and their positions in memory.

Step 4. **Communication Strategy**: Copy the best pollens among all the flowers of FPA's population with *k* the top fitness pollens in N_1, migrate to the other place of the group in SCA population then replace the weaker bees in N_2, and update for each population in every *R*. In contrast, do the same with bees among all the agents of SCA's population.

Step 5. **Termination:** Go to Step 2 if the predefined value of the function is not achieved or the maximum number of iterations has not been reached, otherwise, ending with minimum of the best value of the functions: Minimize (f(S^t), $f(X^t)$), and the best bee position among all the bees S^t or the best pollen among all the agents X^t are recorded.

FIGURE 1. Execution steps of the proposed FSO

4. Experimental Results

To evaluate the proposed algorithm, in this section, we use a set of the benchmark functions to test the accuracy and the speed of FSO. Table 1 lists the initialization for a set of the trial functions [10]. Maxgen column in Table 1 is a maximum number of iterations (manager can be set to 500, 1000, 1500,.. 10000). In the experiments, we average the outcome values for each test function over 25 runs with different random seeds. All the optimizations for the trial functions are to minimize the result. We tested each benchmark function with 1500 iterations per a run. We

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

also compare the simulation results of the proposed method with those obtained results of the previous algorithms such as the SCA, FPA, and PSO (Shi &Eberhart, 1998) as shown in Table 2 and 3.

TABLE 1. Initializing dimensions, max generations, and boundaries for the testing functions

Testing functions	Bounds	Dims	Maxgen
$F_1(x)=\sum_{i=1}^{n}\sin(x_i).(\sin(\frac{ix_i^2}{\pi}))^{2m},\ m=10$	$0,\pi$	30	1000
$F_2(x)=\sum_{i=1}^{n}-x_i\sin(\sqrt{\lvert x_i\rvert})$	± 500	30	1000
$F_3(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	± 5.12	30	1000
$F_4(x)=[e^{-\sum_{i=1}^{n}(x_i/\beta)^{2m}}-2e^{-\sum_{i=1}^{n}x_i^2}]\prod_{i=1}^{n}\cos^2 x_i,\ m=5$	± 20	30	1000
$F_5(x)=-\sum_{i=1}^{4}c_i\exp(-\sum_{j=1}^{6}a_{ij}(x_j-p_{ij})^2)$	0,10	4	1000
$F_6(x)=-\sum_{i=1}^{5}[(X-a_i)(X-a_i)^T+c_i]^{-1}$	0,10	4	1000

Let $S=\{s_{i1}, s_{i2}, ..., s_{im}\}$, $X=\{x_{i1}, x_{i2}, ..., x_{im}\}$, and $P=\{p_{i1}, p_{i2}, ..., p_{im}\}$ be the real value vectors of m-dimensional for SCA, FPA and PSO respectively. The optimization goal is to minimize the outcome for all benchmarks. The results of the performed optimal for the test parameter function is a minimizing problem. We set the population size for the algorithms of FSO, SCA, FPA, and PSO to 40 for all runs in the experiments. The initial range, the dimension and total iterations for all test functions for SCA, FPA, and PSO in Table 1. For further parameters setting could be found in [6-8].

The total population size setting for FSO and SCA are N_1, and N_2 that set to $N/2$ respectively (e.g. it is equal to 20), and d denotes the dimension of solution space that set to 30. Each benchmark function is tested with Maxgen (Maxgen is set to1000 iterations) per a run. We evaluate the proposed method performance in the average of the results from all runs, then compare with alternatives. Comparing percentage is set to the absolute value of the results i.e. abs (FSO-original algorithm)*100/ (FSO) that shows in Table 2.

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

TABLE 2. Comparison of the SCA, and FPA, with the proposed FSO for solving the testing problems in term of the quality performance evaluation

Testing Functions	**Obtained results**			**Comparison**	
	SCA	FPA	**FSO**	with SCA	with FPA
1	1.35E+00	1.38E+00	1.05E+00	29%	31%
2	-3.87E+03	-3.10E+03	-5.09E+03	24%	39%
3	1.65E+02	1.73E+02	1.29E+02	28%	34%
4	1.50E-03	1.51E-03	1.10E-03	36%	37%
5	-2.91E+00	-3.02E+00	-3.30E+00	12%	8%
6	-7.25E+00	-8.25E+00	-9.92E+00	27%	17%
Avge	**-618.97**	**-489.48**	**-828.86**	**26%**	**28%**

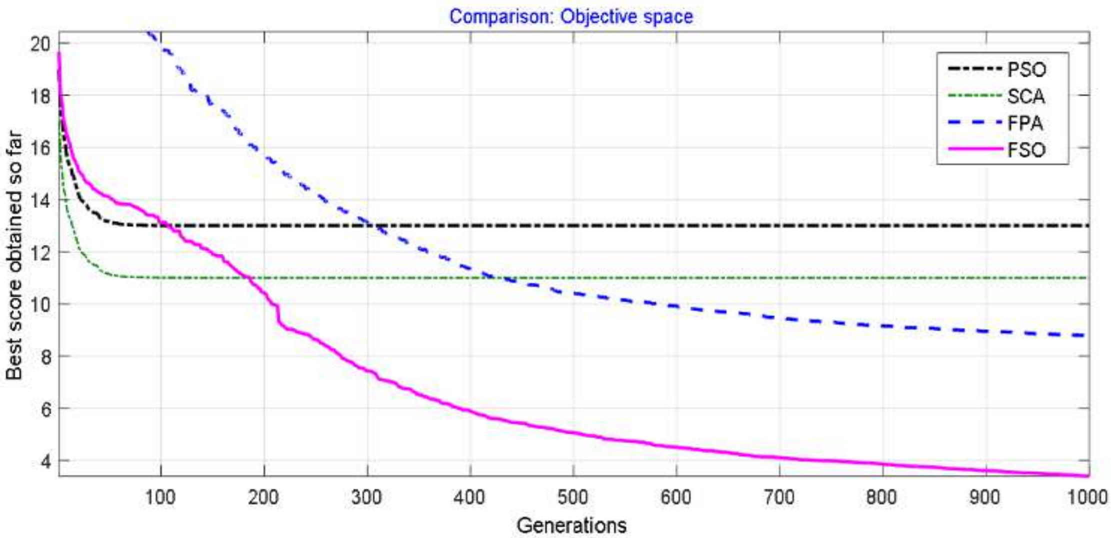

FIGURE 2. Comparison the experimental result curves of the proposed algorithm with PSO, FPA, and SCA for function $F_1(x)$

Tables 2 displays the performance of the proposed FSO and the algorithms of SCA, FPA in comparison for the testing functions. The result of the proposed algorithm on all of these cases of testing shows that the proposed algorithm provides 36% and 39% higher than those obtained from primary methods of SCA and FPA respectively. However, the figure for the minimum cases is only the increase 12% and 08% than the SCA and FPA respectively for a set of testing functions. In general, the proposed FSO increases the average values of the cases 26% and 28% than obtained from the SCA and FPA methods are respectively for testing problems in term of the

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

convergence rates. Figures 2, 3 and 4 showed the experimental results for the first three multimodal benchmark functions over 25 times output obtained from PSO, SCA, FPA and proposed FSO methods with the same iteration of 1000. Appearly, these figures show all of the cases of testing functions in the FSO have performance quality higher the other algorithm regarding the accuracy and convergence rate.

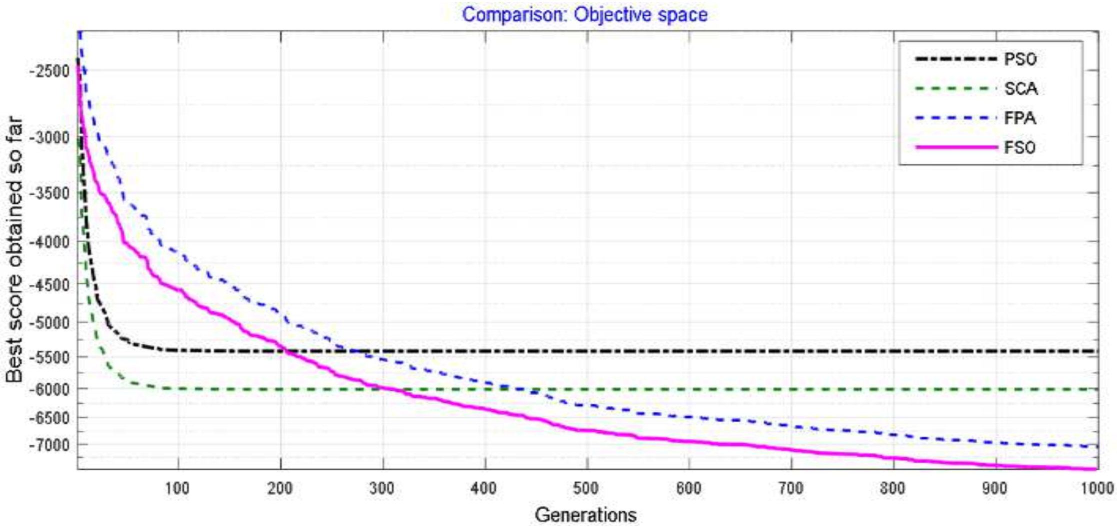

FIGURE 3. Comparison the experimental result curves of the proposed algorithm with PSO, FPA, and SCA for function $F_2(x)$

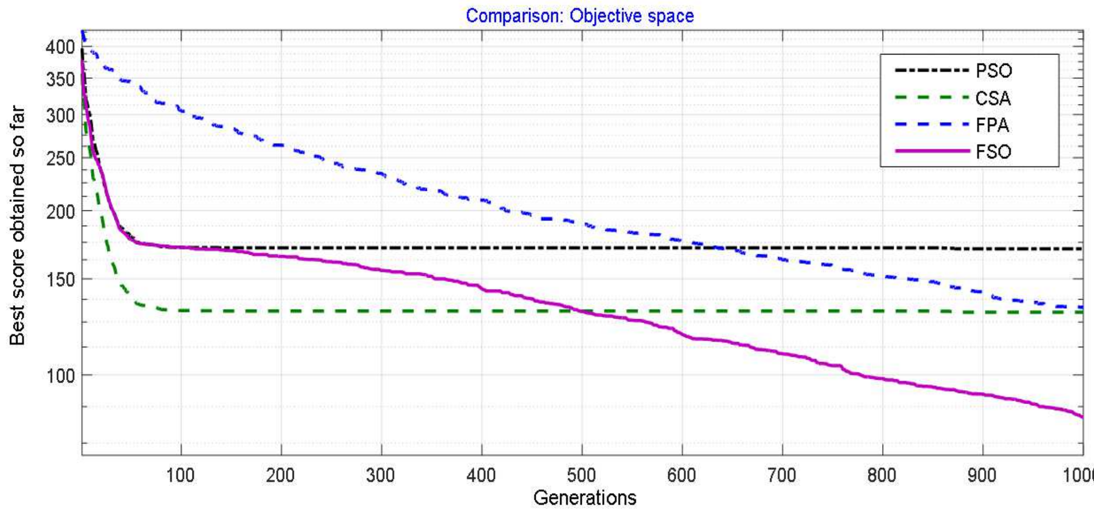

FIGURE 4. Comparison the experimental result curves of the proposed algorithm with PSO, FPA, and SCA for function $F_3(x)$

Table 3 shows the comparison of the FSO performance quality with PSO for the testing optimization problems. Apparently, the result of the proposed FSO on the cases of testing problems shows that FSO offers 19% higher accuracy than PSO. However, the execution time both FSO and PSO are pretty equal.

TABLE 3. Comparison of the proposed algorithm quality performance with PSO for testing problems

Test functions	Execution Time		Comp. times	Performances		Comp. qualities
	PSO	FSO		PSO	FSO	
1	1.4793	1.4371	2%	1.51E+00	1.22E+00	24%
2	1.8672	1.8686	3%	-4.17E+03	-5.09E+03	18%
3	1.9871	1.9503	4%	1.69E+02	1.37E+02	23%
4	0.7776	0.7834	1%	2.70E-03	2.50E-03	8%
5	1.8918	1.9072	2%	-2.34E+00	-3.09E+00	24%
6	1.9891	1.9792	1%	-8.15E+00	-9.82E+00	17%
Avg	**1.1703**	**1.1543**	**2%**	**-6.68E+02**	**-8.27E+02**	19%

5. Vehicle Fuel Consumption Optimization

The grid sensors of WSNs with the aided traffic surveillance system and global positioning systems can record and collect information of the roads or streets in real-time, e.g., length, lanes, vehicle density, direction, velocity restrictions for vehicle identification and navigation (Choudhary &Gokhale, 2016). The actual need for vehicle routing is to search the optimal way from a source to a destination that satisfies the driver. Application WSN for traffic navigation is an effective way in the applications of the city traffic surveillance system. We use a number of sensor nodes to monitoring a local area and getting the traffic information for small infrastructure (Guo, Fang, Wang, &Zheng, 2010).

We use the grid networks to simulate the traffic model in this work. The traffic information collected from the WSNs of the urban area is analyzed and navigated to optimize least fuel and congestion. The routing of vehicles can be modeled as a directed graph $G = (V, E)$ which V is a set of the intersections nodes and E is a set of the roads as edge in the grid network. Each navigation path candidate is composed of the node-edge sequence. All the intersection nodes of

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

the local area are labeled for the navigation and different permutation sequence of these nodes that contain a candidate path of a navigation is a potential solution. The objectives of the least gasoline consumption and the shortest paths are considered to formulate for a fitness function.

The length of the path for a vehicle can be approximated as given Eq. (7) with supposing that p_0 and p_{n+1} are the start state and the target state:

$$L(p) = \sum_{i=0}^{n} d(p_i, p_{i+1}) \tag{7}$$

where $L(p)$ is the length of path and $d(p_i, p_{i+1})$ represents the distance between p_i and p_{i+1}. In the coordinates $Start_{x_0, y_0,}$, since the path Start –Target is divided into $n + 1$ equal segments, the value of $d(p_i, p_{i+1})$ can be calculated as follow:

$$d(p_i, p_{i+1}) = \sqrt{\left(x'_{p_i} - x'_{p_{i+1}}\right)^2 + \left(y'_{p_i} + y'_{p_{i+1}}\right)^2}$$

$$= \sqrt{\left(\frac{d(p_0, p_{n+1})}{n+1}\right)^2 + \left(y'_{p_i} + y'_{p_{i+1}}\right)^2} \tag{8}$$

The shortness path that is defined as the Euclidean distance between the agent and the goal point in each iteration:

$$F_1(p) = \sum_{i=0}^{n-1} d_i \tag{9}$$

Moreover, the edge-travel gasoline cost and congestion weight are the other impact factor for the objective function. The congestion weight can be determined by the traffic condition at the regular time obtained from the traffic surveillance system. Edge-travel gasoline cost in the navigation path can be calculated with the congestion weight constructed according to the current traffic condition.

$$F_2(p) = \sum_{i=0}^{n-1} g(d_i) \times E(d_i) \tag{10}$$

where $g(d_i)$ is the congestion as weight of the segment d_i, and $E(d_i)$ is the gasoline consumption of the vehicle in the segment d_i. A congestion weight is set to 1 or 0 that depends on the current tra c condition. The optimal solution can obtain from the objective function in minimization two mentioned factors.

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

$$Minimize\ F(\boldsymbol{x}) = w \times F_1 + (1 - w) \times F_2 \tag{11}$$

where F(x) is the objective function of optimization fuel consumption for urban area vehicle navigation, and *w* is the balance weight.

6. Experimental Results

The environment map of the simulation is set to grid network of a specified area. We conduct some tests with different grid network setting based on the objective function based on the path length and path-travel fuel consumption. The number of coordinator nodes, grid network set or reset as GUI scheme shown in Figure 5. Setting parameters for algorithms is referencing to the section 4 but applying with the objective function as Eq. (11).

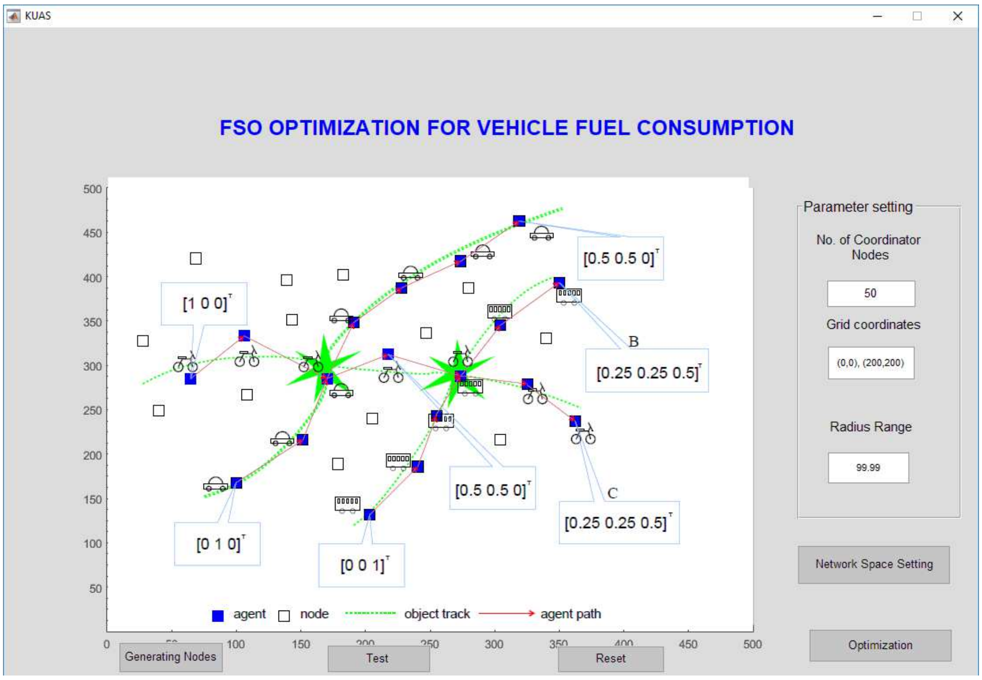

FIGURE 5. A mapping to optimization process for setting environments of an area vehicle navigation

Figure 6 shows the generating random network space for a grid of the environment of the path distances and current traffic condition. The experiment is to verify the effectiveness of the paths generated by grid setting scheme based on the proposed method and the performance is analyzed by comparison with another methods, e.g. Dijkstra and A∗ algorithm.

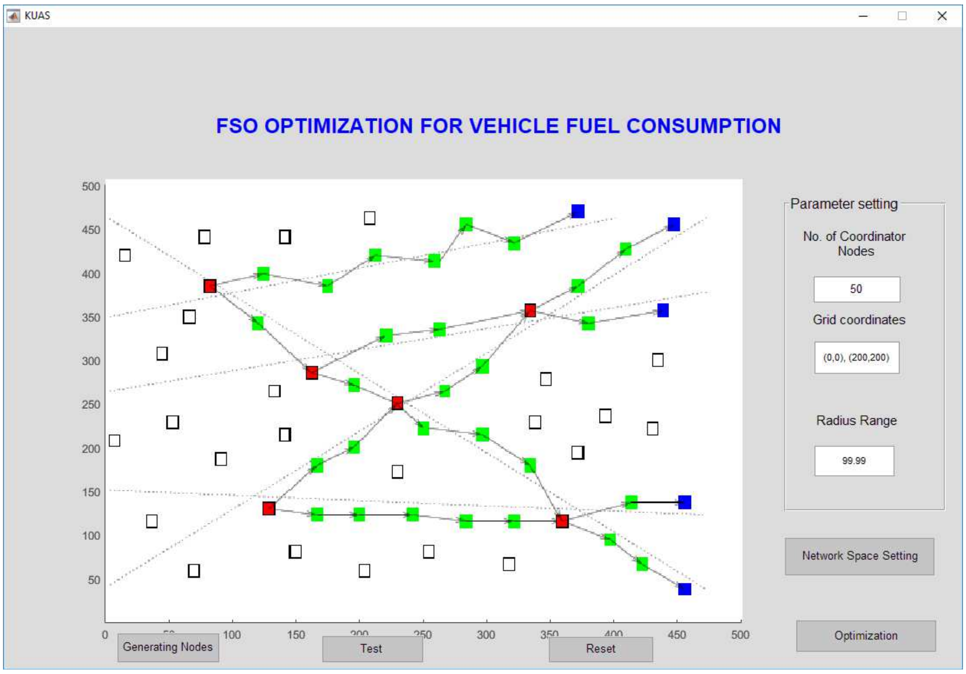

FIGURE 6. The GUI setting scheme experiment to verify the effectiveness of the paths generated

TABLE 4. The comparison the proposed method, with the Dijkstra, and the A+ algorithm methods in terms of quality performance evaluation for time and fuel costs in single objective of consumption

Methods	Ave time cost(h)	Ave fuel cost
Dijkstra [11]	1.29	$1.3\text{x}10^{-2}$L
A∗ algorithm [12]	1.26	$1.3\text{x}10^{-2}$ L
The proposed FSO	1.20	$1.2\text{x}10^{-2}$ L

Tables 4 shows the results of the average obtained least fuel consumption paths of the proposed method are compared with the obtained from Dijkstra (Chen, Shen, Chen, &Yang, 2014) and A∗ algorithm (Lamiraux &Laumond, 2001) methods. Fortunately, the proposed FSO's outperforms on the objective function for the gasoline consumption is better than the two methods of Dijkstra and A∗ algorithm. Figure 7 shows the comparison of a mean of best so far values of the proposed FSO with the Dijkstra and A∗ algorithm for fuel consumption. Apparently, the proposed method also provides the better performance than those obtained by Dijkstra and A∗ algorithm methods in terms of convergence speed.

Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

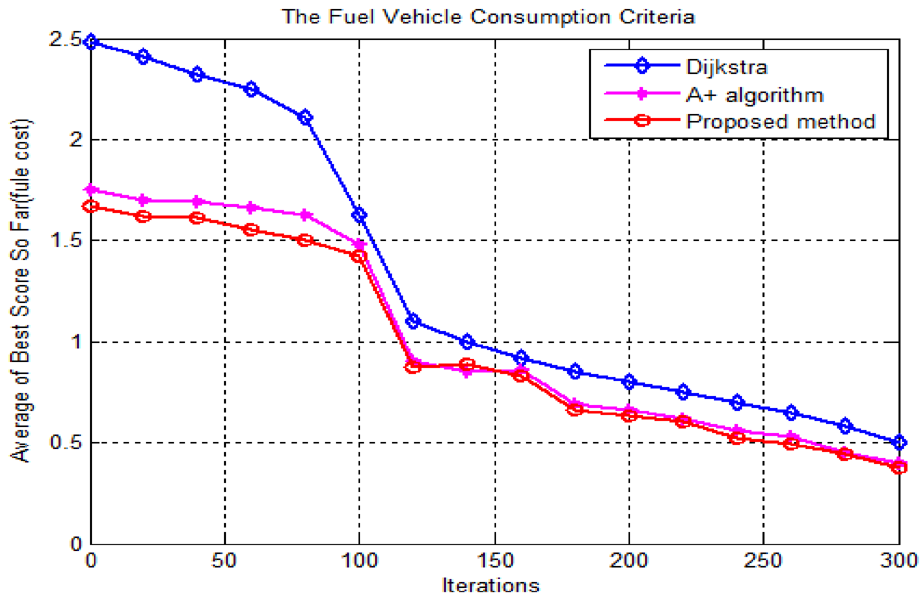

FIGURE 7. Graphical results of running the proposed FSO the optimal vehicle traveling by the average convergence of the proposed method in comparre with Dijkstra and A* algorithm methods

7. Conclusion

In this paper, we presented a new optimization algorithm namely FSO for the global optimization problems and the vehicle fuel consumption problem. Applied communication strategy based on the hybrid algorithms of Flower Pollination Algorithm (FPA) and Sine Cosine Algorithm (SCA) for incorporation optimization algorithms is considered in this proposed method. The proposed FSO has provided the diversity agents and parallel computation in optimization. It played a major significance in the solutions for the issue of losing the global optimum in the optimal algorithms for optimization problems. The poorer solutions in FPA are replaced with the best solutions in SCA and reverse the worst solutions in SCA are substituted with new finest solutions FPA.

In the simulation section, the environment of current traffic condition, the path distances, and the vehicle locations was modeled to the objective functions and search agents are mapped to a parsing solution in each iteration of a vehicle traveling during optimization. As the technology for traffic navigation advances and moves from simply improved traffic signs and message boards to automated online traffic information systems and vehicle specific route guidance advisories. A

 Volume 5, Number 3, 2018
ISSN 2409-7284 (Online)

traffic navigation system equipped with Wireless sensor networks (WSN) and the vehicle equipped with the Global positioning system (GPS) can make up a grid network of vehicle transportation.

The simulation result compared with the other algorithms in the literature e.g. FPA, SCA and particle swarm optimizer (PSO) shows that the proposed FSO increases the accuracy.

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