Traffic Light Signal Parameters Optimization Using Particle Swarm Optimization

Case Study of Ooe Toroku Road Network Optimization

I Gede Pasek Suta Wijaya
Informatics Engineering Dept., Engineering Faculty
Mataram University
Mataram Lombok, Indonesia
Email:gpsutawijaya@te.ftunram.ac.id

Keiichi Uchimura, and Gou Koutaki
Graduate School of Science and Technology
Kumamoto University
Kumamoto Shi, Japan
Email:{uchimura, koutaki}@cs.kumamoto-u.ac.jp

***Abstract*—This paper proposes a traffic light signal parameters optimization using particle swarm optimization (PSO) for real road network called as Ooe Toroku road network. The main aim of this method is to find out the best traffic light signal parameters, which can solve the traffic congestion on the real road network. The traffic light signal parameters that are optimized are offset, cycles, and splits time of each node of the considered road networks. The considered real road network consists of four junctions/nodes having different time signaling models. In this research, the PSO is attached in Aimsun 6.1 simulator via application interface (API) that is provided by Aimsun 6.1 simulator. The PSO algorithm creates *n*-particles of traffic light signal parameters and sends them to the Aimsun 6.1 simulator to perform the simulation. The output of simulation will be used to perform the particles evaluation and updating. The experimental results show that the proposed method provides better performance than base-line method (multi-element Genetics Algorithms (ME-GA) based optimization method) which can increase the real and base-line percentage of vehicle flow by about 15.76% and 4.13% of that of real and MEGA, respectively. In addition, the PSO is faster to achieve convergence than base-line method for considered network.**

Keywords: traffic signal parameters, optimization, signaling model, GA, PSO, artificial intelligence

I. Introduction

The traffic jam becomes a hot issue not only in developing countries like big cities in Indonesia but also in modern countries like Japan. As well known, Japan has good transportation system which covers from train, bus, taxi, and high-speed railway (shinkansen), but it also has traffic jam in some road networks due to high growth of vehicles and pedestrians cross in the road. The effects of traffic jam are not only to road users physiological but also to economical and environmental problems. In terms of physiological problem, the traffic jam makes the pedestrians and drivers pay a lot of attention to drive safely the vehicles. It means the pedestrians and drivers get stress during in the road. In terms of economical problem, the traffic jam increases the fuel consumption, which implies to transportation cost. In addition, the traffic jam also makes the deliver time be longer than its usual that also implies to working productivities of human resources and transportation cost. In term of environmental problem, the traffic jam increases the pollution of vehicle disposal gas such as CO_2 raising the greenhouse effect on the environment.

Therefore, an efficient transportation system is needed not only by modern cities in developed countries, but also by many cities in developing countries. One strategy that can be applied to reduce the congestion problem is to optimize the parameters of the traffic light signals of the intersections that have a high congestion. This approach is short-term solution, which is one of the most popular methods because it does not require rebuilding road infrastructure, which is costly. The optimal solution is indicated by less vehicle stop, short delay time, and maximum throughput of road network.

In order to find optimal traffic light signal parameters, particle swarm optimization (PSO) based searching method is employed instead of Multi-Element Genetics Algorithms (ME-GA). The aim of the proposed method is not only to find the best traffic light signal parameters for considered road network but also to improve the ME-GA method[1] in terms of convergence time. In this research, the PSO is attached in the Aimsun 6.1 simulator through the API module to perform the simulations for finding the best traffic light signal parameters of Ooe Toroku road network. The Ooe Toroku road network located in Kumamoto city Japan has high congestion in the rush hours.

This paper is organized as follows: section 2 presents the previous methods and the base-line method (ME-GA based method); section 3 explains signaling models, the PSO algorithm, and how to integrate it in the Aimsun 6.1 simulator; section 4 presents the experimental setup, results and discussions; and the rest concludes the paper.

II. Previous Works

Artificial intelligence such as Neural Networks, Genetic Algorithm (GA), PSO, etc., plays important rule on the optimization. The implementation of artificial intelligence for traffic light signal parameters optimization can be divided into three groups. The first group is the GA based optimization methods[2], [3], [4], [5], [1], [6], the second group is fuzzy logic-based approaches which determine the best signal parameters using rule that relate to fuzzy logic as presented in Refs. [7], [8], and the third group is stochastic and dynamic based approaches which were proposed by Refs. [9], [10]. The GA-based approaches were mostly implemented to find the suitable cycle and offset parameters of traffic light. However, some of them were not implemented on real network model.

In addition, a variation of GA such as the multi element genetic algorithm (ME-GA) based approaches for optimization of traffic light signal parameters had been proposed in Refs. [4], [5], [1], [6]. However, they did not reach 100% network throughput (100% vehicle flow percentage). However, the ME-GA based method needed very large populations and generations to obtain the best solution. Consequently, they took very long simulation time.

The ME-GA performs the population recombination using fitness formulation which is derived by considering delay time, vehicles gone out (V_{go}), and vehicles inside the road network (V_{in}) and vehicles wait out (V_{wo})[1], [6]. By this fitness formulation, the optimum traffic signal parameters was obtained which was indicated by the highest percentage of vehicle flow. In this research, this fitness formulation will be implemented for PSO algorithm to improve the ME-GA based method (base-line)[1] and to solve traffic jam problem in the Oee Toroku road network.

III. Proposed Method

In this method, the main part is PSO that is employed to search the optimum offset, cycles, splits time of four nodes/junctions of the Ooe Toroku road network. It means this method consists of signaling model, signal parameters, Aimsun 6.1 simulator, PSO, an API.

A. Signaling Model

Given the Oee Toroku road network as shown in Fig. 1, it has 4 junctions named as Node 1, 2, 3, and 4. Node 2 and 4 have the same signaling model called pair-signaling model, as shown in Fig. 2. The signaling model represents vehicles and pedestrians movement rules on the junction. In the pair-signaling model, signal 1 is pair signal of Left-Right and Right-Left directions, which represent the vehicles movement rules from left to right side vice versa simultaneously. The signal 2 and 4 are pedestrian signals of top and bottom, and left and right of the Node 2 and 4, respectively. The same as signal 1, the signal 3 is pair signal of Top-Bottom and Bottom-Top directions.

The Node 1 and 3 have six signals, which are shown in Fig. 3. The same as previously, this signaling model represents the rule of vehicles and pedestrians movement in the junction. However, the signaling model of Node 2 and 4 differs from signaling model of Node 1 and 3 in terms of a reduction of collisions at junction. It seems that the vehicles movements run alternately in different pathways in the Node 1 and 3.

B. Signal Parameters

Each node/junction has the traffic light signal parameters called as offset, cycle, Yellow, all Red, and split[1], [6]. The offset parameter represents the time coordination between traffic light (node); the cycle parameter represents the total time of traffic light starting from Green then returning to Green; the Yellow and all Red (AR) represents the time for Yellow and all Red signal; and split which consists of main and sub split means the Green time percentage of main road and sub road,

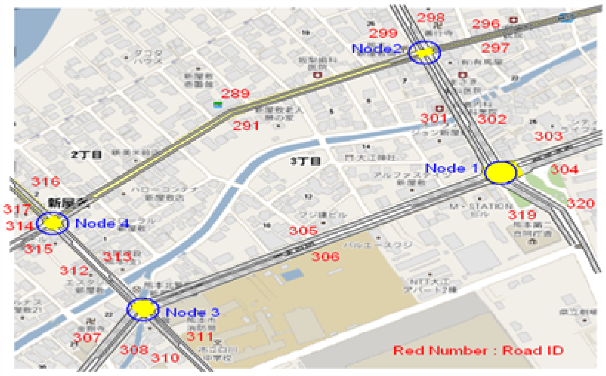

Fig. 1. The real Ooe Toroku road network of Kumamoto Shi, Japan[4], [5], [1], [6].

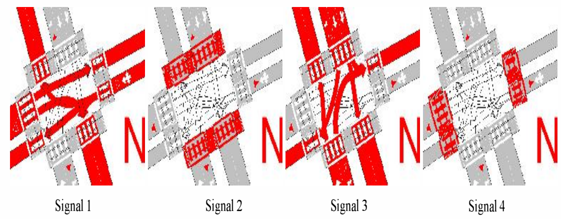

Fig. 2. Signaling model of Node 2 and 4 of Ooe Toroku road network.

respectively. Usually, the Yellow and AR is setup by a constant value. In this case, the Node 2 and 4 have four timing signals corresponding to the signaling models of these nodes (see Fig. 2), which is shown in Fig. 4. While the Node 1 and 3 have six timing signals corresponding to the signaling models of these nodes (see Fig. 3) which is shown in Fig. 5. All of these signals must be defined optimally to get less vehicle stop, short delay time, and maximum throughput of a road network.

The detail explanation of signal timing that are presented in Fig. 4 and 5 can be found in Refs. [6].

C. Aimsun 6.1 Simulator

Transport modeling software called as Aimsun 6.1 is used to perform the simulation in this research. This software is developed and marketed by TSS-Transport Simulation Systems

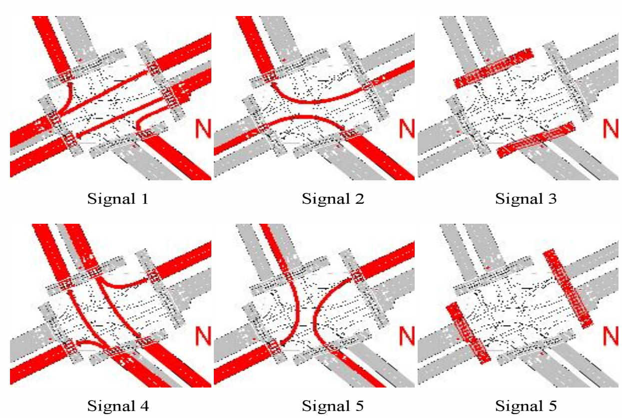

Fig. 3. Signaling model of Node 1 and 3 of Ooe Toroku road network.

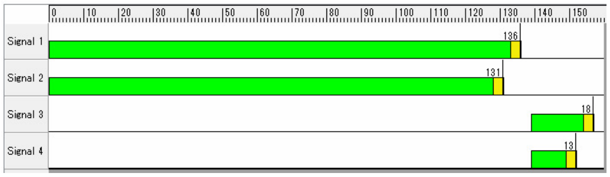

Fig. 4. Timing of signals of Node 2 and 4 of Ooe Toroku road network.

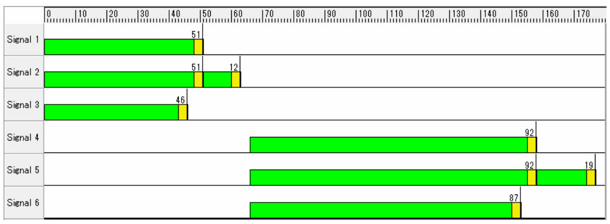

Fig. 5. Timing of signals of Node 1 and 3 of Ooe Toroku road network.

and is widely used by universities, consultants, and government agencies worldwide for transportation planning, traffic simulation, and emergency evacuation studies. It is employed to improve road infrastructure, reduce emissions, cut congestion and design urban environments for vehicles and pedestrians. In this research, the Aimsun 6.1 is integrated with PSO through API dynamic link library (DLL) modul to optimize traffic light signal parameters. It means the system consists of three main modules called as simulator, API and PSO. The simulator performs the simulation based on the signal parameters that are given by PSO through API. The API functions as the communication coordinator between the simulator and PSO, and taking the simulation data that are required by the PSO for fitness evaluation and updating the signal parameters.

D. API of Aimsun 6.1

The API is a DLL modul that is provided by Aimsun 6.1 written in C++. The structure of API modul consists of seven subroutines called as AAPILoad, AAPIInit, AAPIManage, AAPIPostManage, APIFinish, AAPIUnLoad, and AAPIPreRouteChoiceCalculation. In this research, just two subroutines (AAPIInit and APIFinish) are utilized for performing the simulation. The AAPIInit is utilized to put initialization process and data that are needed by Aimsun6.1 simulator and PSO, and the APIFinish is utilized to get simulation results and the particles evaluation. Based on the function references provided by Aimsun 6.1, the API can be used to collect the simulation outputs such as vehicle flow, total travel distance (tot^D_{Tr}), and delay time (t_D) of the passing vehicles in the network. The vehicle flow is determined from V_{go} which means the total vehicles that have gone out from the network, V_{in} which means the total vehicles that still exist in the road network, and vehicle wait out (V_{wo}) which means the total vehicles which are waiting to enter into the road network. The block diagram of simulation system using Aimsun 6.1, API, and PSO including their communication is shown in Fig. 6

E. PSO Algorithms

Similar to Genetic Algorithms (GA), PSO is a searching algorithm that finds the solution by following current optimum particle. The PSO algorithm for optimization is presented by flow chart in Fig. 7. This method was inspired by social behavior of bird flocking or fish schooling that was developed by Eberhart and Kennedy[9]. The similarities between the PSO and GA are the initialization using randomly the population and finding the optimal solution by updating the generation. However, the PSO does not have recombination such as crossover and mutation. The optimal solution, called particle, is obtained by updating process by following current optimum particles through fitness evaluation. The advantage of PSO compared to GA is easy to be implemented and few parameter to be adjusted such as particles velocity.

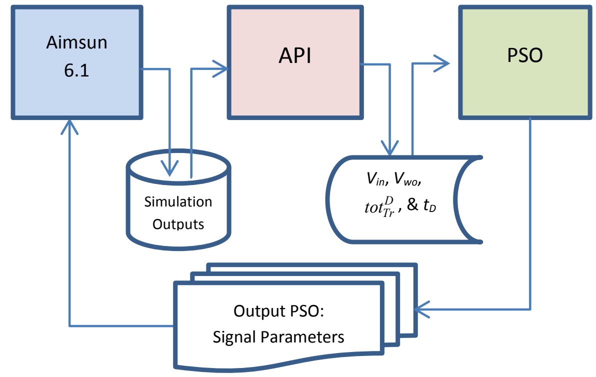

Fig. 6. Diagram block of simulation system using Aimsun 6.1, API, and PSO including their communication.

TABLE I. THE SIGNAL PARAMETERS OF NODES IN OOE TOROKU ROAD NETWORK.

	P[*i*], *i*=0, 1, 2, …, *N*-1			
Node	Offset(s)	Cycle(s)	mSplit (%)	sSplit(%)
01	0	170	65	45
02	35	90	40	30
03	20	120	55	35
04	55	70	45	20

In addition, each particles also consists of the velocity value which represents the fitness of particle itself. The particles are initialized randomly at the first stage of PSO algorithm. Based on these particles, the simulations are carried out by adjusting the nodes signal parameters using defined particles. Next, the fitness evaluation is performed using simulation outputs which consist of vehicle wait out (V_{wo}), vehicle in (V_{in}), travel distance (tot^D_{Tr}), and time delay (t_D). The main aim of the fitness evaluation is to find the potential particle that is indicated by smallest fitness. In this case the fitness is determined by the following equation[1], [6].

$$F_p = exp\left(\frac{V_{wo}}{C_{wo}}\right) + exp\left(\frac{V_{in}}{C_{in}}\right) + exp\left(\frac{t'_D}{C_{tD}}\right) \quad (1)$$

and

$$t'_D = \frac{t_D}{tot^D_{Tr}} \quad (2)$$

Where C_{wo}, C_{in}, and C_{tD} are constant values that are defined as follows: C_{wo} = 100, C_{in}=500, and C_{tD} =500. These constant values were chosen to minimize the effect of each variables to the fitness value. In addition, this fitness

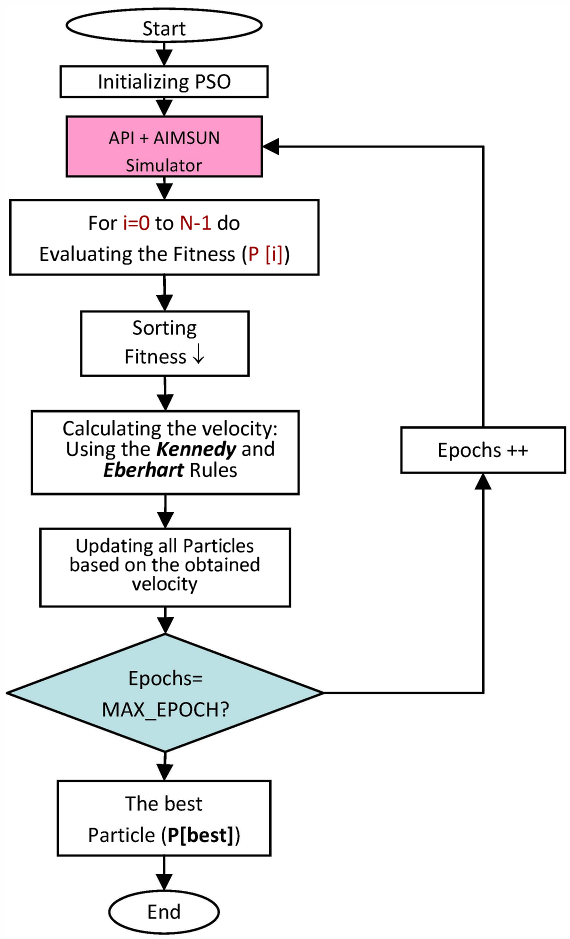

Fig. 7. Flow chart of PSO to find the best signals parameters.

```
Input   : Array of Particles (P), best fitnes pbestx, and
          global best fitness (gbestx)
Output  : Updated velocity of P.
function Calculate_Velocity(Particles  P, pbestx , gbest)
    nParticles ← size (P)
    for (i← 0; i<nParticles; i++)  do
        t1← pbestx – presentx;
        t2← gbestx – presentx;
        vValue ←P[i].VelocityCycle + 2 * rand() * t1 +
               2 * rand() * t2
        if(vValue > V_MAX_CYC)
            P[i]. VelocityCycle ←V_MAX_CYC;
        elseif(vValue < -V_MAX_CYC)
            P[i]. VelocityCycle ←-V_MAX_CYC;
        else
            P[i]. VelocityCycle ←vValue;
        endIf

        vValue ← P[i].VelocitySplit + 2 * rand() * t1 +
               2 * rand() * t2
        if(vValue > V_MAX_ SPL)
            P[i]. VelocitySplit ←V_MAX_ SPL;
        elseif(vValue < -V_MAX_ SPL)
            P[i]. VelocitySplit ←-V_MAX_ SPL;
        else
            P[i]. VelocitySplit ←vValue;
        endIf

        vValue ← P[i].mVelocityOffsett + 2 * rand() * t1 +
               2 * rand() * t2
        if(vValue > V_MAX_ OFF)
            P[i]. VelocityOffsett ←V_MAX_ OFF;
        elseif(vValue < -V_MAX_ OFF)
            P[i]. VelocityOffsett ←-V_MAX_ OFF;
        else
            P[i]. VelocityOffsett ←vValue;
        endIf
    endFor
endFunction
```

Algorithm 1: The process of updating velocity of particles.

formulation has successfully been implemented and shown that it could find the best solution of traffic light signal parameters using ME-GA[1], [6] and this formula was concluded as the best fitness formulation.

From this fitness, the particles are updated by following the smallest fitness using Eberhart and Kennedy[9] rule. Before updating the particles, the particles velocity also have to be updated using Eberhart and Kennedy[9] rule. The algorithm of updating particles velocity is presented in Algorithm 1.

The output of the updating particles is used for updating the particles data consisting of offset, cycle, main split (mSplit) and sub split (sSplit). The updated particles is saved to text files called as signal parameters that will be loaded by Aimsun 6.1 for setting up the nodes and performs the simulations. The algorithm of updating particles is presented in Algorithm 2.

According to PSO flowchart as given in Fig. 7, those mentioned processes are repeatedly performed until reaching maximum epoch given in the initialization stage.

IV. Experiments and Result Discussions

The experiments were setup as the same as conducted in Refs. [4], [5], [1], [6]. The data preparation consists of creating road network model, setting-up PSO, and setting up the Aimsun 6.1 parameters. In detail, some data setting-up of the experiments are described as follows:

1) Preparing Oee Toroku road network which is real traffic signal problem, as shown in Fig. 1.
2) Setting up the Aimsun 6.1 using data as given in Table II. The data setup were the same as the real conditions of Oee Toroku site
3) All traffic light signal parameters had to follow the following constraints:
    - Offset : Min =0, Max = 120 and it incremental (δ_{offset}) = 1,
    - Cycle : Min =60, Max = 180 and it incremental (δ_{Cycle}) = 5,
    - Split : Min =10, Max = 90 and it incremental (δ_{Split}) = 5,
    - All red and yellow time is setup equal to 3 second, and
    - Signal timing (t) is determined based-on green time (gT) only.
4) Experiments were done using 5 minutes warming up.

The real data as given in Table II were captured manually by coming to the Oee Toroku site, and counting the vehicles flow and vehicles turning at peaks sessions (8:00 AM to

```
Input   : Array of Particles (P) and index of
          best particle (idxPbest)
Output  : Updated  P.
function updateParticles(Particles  P, idxPbest)
    nParticles ← size (P)
    bestP←P[idxPbest].data;
    for (i←0; i<nParticles; i++)  do
        for (j←0; j<nNode;j++) do
            //Offset
            if (bestP [j].offset!=P[i].data[j]. offset)
                P[i].data[j]. offset ←P[i].data[j]. offset +
                        P[i].data[j]. VelocityOffset;
            endIf
            //Cylcle
            if (bestP [j].cycle!=P[i].data[j]. cycle)
                P[i].data[j]. cycle←P[i].data[j]. cycle+
                        P[i].data[j]. VelocityCycle;
            endIf
            //SplitMain
            if (bestP [j].mSplit!=P[i].data[j]. mSplit)
                P[i].data[j]. mSplit ←P[i].data[j]. mSplit +
                        P[i].data[j]. VelocitySplit;
            endIf
            //SplitSub
            if (bestP [j].sSplit!=P[i].data[j]. sSplit)
                P[i].data[j]. sSplit ←P[i].data[j]. sSplit +
                        P[i].data[j]. VelocitySplit;
            endIf
        endFor
    endFor
endFunction
```

Algorithm 2: The process of updating data of particles.

TABLE II. VEHICLES FLOW OF THE OOE TOROKU ROAD NETWORK[5], [1].

No	Road ID	Flow /hour		
		Car	*Bus*	*Truck*
1	297	486	8	24
2	298	586	18	28
3	304	1594	24	64
4	307	1122	30	64
5	310	318	0	12
6	314	164	0	6
7	316	432	2	30
8	319	456	12	30
Total		**5158**	**94**	**258**

9:00 AM). The total vehicles and pedestrians flow per hour were 5510 and 3708 respectively. The pedestrians flow were distributed into four junctions/nodes about 636, 1386, 415, and 860 people crossing on the junctions (Node 1, 2, 3 and 4) respectively. While, the vehicles flow per hour of each roads were summarized in the Table II.

In this experiment, the optimization algorithm based on PSO was evaluated to solve the Ooe Toroku road network traffic jam problem. The experiment was performed by 100 particles (similar to population in GA methods) and 40 epochs (similar to generation in GA). The experimental result shows that the PSO based optimization method tends to provide optimum traffic light signal parameters. It can be known by

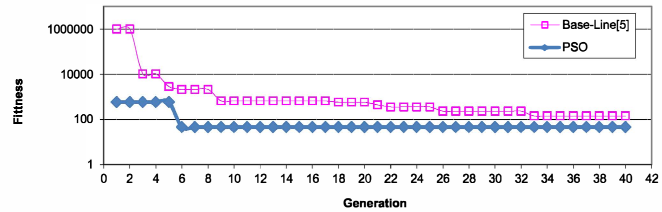

Fig. 8. The fitness of PSO compared to the base-line method[1].

TABLE III. THE BEST TRAFFIC LIGHT SIGNAL PARAMETERS OBTAINED BY PSO FOR OOE TOROKU ROAD NETWORK.

Junction	Offset (sec)	Cycle (sec)	Split (M1)	Split (S1)
Node 1	0	170	65	35
Node 2	7	95	50	15
Node 3	86	100	80	15
Node 4	53	95	50	35

fitness graph of PSO as shown in Fig. 8 that can achieve the convergence at 6-th generations. It means that the best traffic light signal parameters presented in Table III for all nodes in the considered road network is found in the 6-th generations and at 95-th particles. In addition, the Fig. 8 also shows that the PSO is more quickly convergence than base-line method, which means that the best solution can be achieved by PSO on the 6-th generations but by the base-line method on the 33-th generations.

By using the best traffic light signal parameters given by a method based on PSO, as shown in Table III, the Ooe Toroku road network gives higher V_{go}, and less V_{in} and V_{wo} than the real condition and base-line method[1], as shown in Table IV. In detail, the best traffic light signal parameters can improve the real and base-line percentage of vehicle flow (F_F) by about 15.76% and 4.13%, respectively (see Table IV). It means the PSO algorithm successfully finds the best traffic light signal parameters for solving the traffic jam on the considered road network.

These experimental results agree to theoretical concept of PSO that it can be implemented for optimization in the area/fields where the GA can be implemented. As mentioned early, that PSO works to follow the potential solution particles indicated by the smallest fitness and according to this potential particles solution, all particles are going to this destination by updating the particles.

V. CONCLUSION AND FUTURE WORK

The proposed traffic light signal parameters optimization using PSO has been successfully implemented to solve traffic congestion in the Oee Toroku, Kumamoto city, road network. The successfulness in resolving congestion is indicated by much higher vehicle gone out, less vehicles inside the network, and short enough vehicle delay time than those of base line method (ME-GA). In detail, the best traffic light signal parameters obtained by PSO can improve the real and base-line percentage of F_F by about 15.76% and 4.13%, respectively. It means the PSO is alternative solution of searching best traffic light signal parameters to decrease the traffic congestion on

TABLE IV. SIMULATION RESULT SUMMARY OF OOE TOROKU NETWORK ON THE BEST TRAFFIC LIGHT SIGNAL PARAMETERS.

Cases	Vehicle	VF	V_{go}	V_{in}	V_{wo}	Δ=VF-V_{go}	Delay Time	tot_{TR}^{D} (km)	$F_F(\%)$
Real	Bus	94	81	20	32	13	NA	**NA**	**71.0**
	Car	5158	3085	1132	1340	2073			
	Truck	258	159	55	65	99			
	Pedestrian	3708	3239	34	0	469			
	Total	**9218**	**6564**	**1241**	**1437**	**2654**	**NA**		
Base Line[5]	Bus	94	86	12	5	8	913.987	**5790.43**	**82.63**
	Car	5158	3784	894	381	**1374**			
	Truck	258	254	37	23	4			
	Pedestrian	3708	3453	162	79	255			
	Total	**9218**	**7577**	**1105**	**488**	**1641**	**0.222***		
PSO Based Method	**Bus**	**94**	**82**	**7**	**5**	**12**	**1682.416**	**6089.83**	**85.76**
	Car	**5158**	**4052**	**742**	**329**	**1106**			
	Truck	**258**	**273**	**50**	**17**	**-15**			
	Pedestrian	**3708**	**3502**	**150**	**13**	**206**			
	Total	**9218**	**7909**	**949**	**364**	**1309**	**0.212***		

* The delay time divided by V_{go} and $F_F = V_{go}/(V_{go} + V_{in} + V_{wo})*100$

road network. In addition, PSO also proves that it can achieve faster convergence than base-line method.

In future, we will try to find out the best particles updating algorithm to obtain more optimum traffic light signal parameters and find best combination of particles (population) and generations by carrying out more experiments on the real road networks.

ACKNOWLEDGMENT

I would like to send my great thank to Image Media Laboratory of Kumamoto University, for providing hardware and software to complete this research. In addition, our great thank is to Japan Students Services Organization (JASSO) for supporting to my research in GSST Kumamoto University.

REFERENCES

[1] I. G. P. S. Wijaya, K. Uchimura, G. Koutaki, S. Isigaki, and H. Sugitani, "Fitness evaluation of multi-element genetic algorithm for traffic signal parameters optimization," in *Proceeding of 3rd International Conference on Soft Computing, Intelligent System and Information Technology*, Bali, Indonesia, 2012, pp. 58–64.

[2] L. Singh, S. Tripathi, and H. Arora, "The optimization for traffic signal control using genetic algorithm," *International Journal of Recent Trends in Engineering*, vol. 2, no. 2, pp. 4–6, 2009.

[3] S. Takahashi, H. Kazama, T. Fujikura, and H. Nakamura, "Adaptive search of an optimal offset for the fluctuation of traffic flow using genetic algorithm," *IEEJ Trans. on Industry Applications*, vol. 123, no. 3, pp. 204–210, 2003.

[4] T. Nishihara, N. Matsumura, K. Kanamaru, I. G. P. S. Wijaya, G. Koutaki, K. Uchimura, H. Sugitani, , and S. Ishigaki, "The verification with real-world road network on optimization of traffic signal parameters using multi-element genetic algorithms," in *Proceeding of 19th ITS World Congress*, Vienna, Austria, 2012.

[5] I. G. P. S. Wijaya, K. Uchimura, G. Koutaki, T. Nishihara, S. Matsumoto, S. Ishigaki, and H. Sugitani, "The improvement me-ga based traffic signal control optimization using new fitness model," *GSTF Journal on Computing*, vol. 2, no. 2, pp. 64–69, 2012.

[6] I. G. P. S. Wijaya, K. Uchimura, G. Koutaki, and T. Nishihara, "Traffic signal control optimization using genetic algorithm and signaling model modification," in *Proceeding of 20th ITS World Congress*, Tokyo, Japan, 2013.

[7] C. H. Chou and J. C. Teng, "A fuzzy logic controller for traffic junction signals," *Information Sciences*, vol. 143, p. 7397, 2002.

[8] S. Rahman and N. Ratrout, "Review of the fuzzy logic based approach in traffic signal control prospects in saudi arabia," *Transpn Sys Eng and IT*, vol. 9, no. 5, pp. 58–70, 2009.

[9] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of IEEE International Conference on Neural Networks*, Piscataway, NJ, 1995, pp. 1942–1948.

[10] X. H. Yu and W. W. Reckert, "Stochastic adaptive control model for traffic signal systems," *Transportation Research Part C*, vol. 14, p. 263282, 2006.