A Computational Experiment Method in ACP Framework for Complex Urban Traffic Networks

Yaran Chen, Shu Lin, GangXiong, Qingjie Kong, Fenghua Zhu

Abstract—**Urban traffic congestion has already become an urgent problem. Artificial societies, Computational experiments, and Parallel execution (ACP) method is applied to urban traffic problems. In ACP framework, optimization for urban road networks achieves remarkable effect. Optimization for urban road networks is a problem of nonlinear and non-convex programming with typical large-scale continual and integer variables. Due to the complicated urban traffic system, this paper focuses on the ACP-based Computational experiments modeling. It hopes to find an optimization model that is further accord with the practical situation. To this end, we use a mixed integer nonlinear programming problem (MINLP) and an genetic algorithm (GA) for urban road networks optimization. The systemic simulation experiments show that the approach is more effective in improving traffic status and increasing traffic safety.**

I. INTRODUCTION

With the increase of vehicles, urban road network getting more crowded, so it is necessary to develop scientific methods to alleviate traffic congestion. Traffic signal control is a cheap, effective and practical method for optimizing the road network and solving the general traffic congestion problems [1].

Considering the complexity of urban traffic system, it is becoming an important development trend to apply the research results of complex systems to the traffic problem. Among these researches, the Artificial societies, Computational experiments, and Parallel execution (ACP) approach is efficient for complex traffic problems and considers problems in a higher level than tradition method [2]. Many factors of engineering, society, human, environments and so on have been considered and an artificial system which equal to the real system is established in ACP approach [3]. The approach can solve problems that are difficult to model by traditional methods and has two essential characteristics: inseparability and unpredictability, which are consistent with the real traffic situation. Under the principle of continuous research and improvement, Wang establishes a new mechanism for traffic control and management in the paper [4]-[5]. This paper presents the concepts, architectures, and applications of the ACP approach in traffic control and management, implementing the computational theory and methods of complex systems for studying complex traffic problems. Wang's research results have opened up a new field of traffic control and management. Many new ideas have been proposed for urban traffic control and achieve remarkable effect.

Computational experiment is a method of artificial traffic system, solving problems with experiments by modeling based on ACP framework. It is able to simulate anything "impossible" and consists of plan design, experiment tool and result analysis experiment. There are some researches on computational experiment of rush hours, bad weather and traffic accident. In this paper, a further study of the Computational experiments is carried out for urban traffic network congestion.

Road congestion is influenced by many factors, such as network programming, traffic signal control and so on. The traffic signal control mainly involves cycle times, phases and green times. In [6], S Lin uses sequential quadratic programming involving continual variable (green times), to optimize traffic signal. The programming method reduces online computational complexity and alleviates traffic congestion more effective. In this paper, we take more influence factors into consideration with an optimization (MINLP) method that involves integer invariable (cycle times and phases) and continual invariable (green times), to solve this problem. As a result, it is further accord with the practical situation. Moreover, an enhanced genetic algorithm is applied to solve the MINLP problem. The result of optimization via MINLP method is effective and remarkable for alleviate traffic congestion and outperforms than the previous.

II. MIXED INTEGER NONLINEAR OPTIMIZATION

A. *Concept of Mixed Integer Nonlinear Programming (MINLP)*

The urban traffic problem is a complex system optimization problem which involves continuous and integer variables and is an NP hard problem. This paper proposes a effective method to solve this kind of Mixed Integer Nonlinear Programming problem (MINLP).

Non-convex programming problems often appear in engineering and operations research such as the production equipment plans for using, portfolio optimization and so on[7]. Because MINLP is a mathematical programming problem involving continuous and integer variables and

Yaran Chen. Beijing Engineering Research Center of Intelligent Systems and Technology

Institute of Automation, Chinese Academy of Sciences, Beijing 100190,China, (e-mail: chenyaran2013@ia.ac.cn).

Shu Lin. University of Chinese Academy of Sciences, Beijing, China (email: slin@ucas.ac.cn).

Gang Xiong. Cloud Computing Center, Chinese Academy of Sciences, Songshan Lake, Dongguan, 523808, China (Fhone: 0769-22893027; Fax: 0769-22892662; e-mail: gang.xiong@ia.ac.cn).

Qingjie Kong. Cloud Computing Center, Chinese Academy of Sciences, Songshan Lake, Dongguan, 523808, China (e-mail: kongqingjie@casc.ac.cn)

Fenghua Zhu. Cloud Computing Center, Chinese Academy of Sciences, Songshan Lake, Dongguan, 523808, China (e-mail: zhufh@casc.ac.cn)

the programming is often used to solve real problems. MINLP has a very wide application in many fields of modern science, including the process industry and the engineering, financial and operations research sectors [8].

The form of MINLP is [8]

$$\begin{aligned} &\min z = f(\mathrm{x}, \mathrm{y}) \\ &\text{s.t.} \quad g(\mathrm{x}, \mathrm{y}) \le 0, \\ &\qquad x \in X \subset R^n, \\ &\qquad y \in Y \subset R_+^m, \end{aligned} \tag{1}$$

where $f(\mathrm{x}, \mathrm{y})$ is a nonlinear objection function : $R^n \to R$, $g(\mathrm{x}, \mathrm{y})$ is a nonlinear constraint, x is the continuous variable ($x \in R^n$) and y is the integer variable ($y \in R_+{}^m$).

B. *the solution of MINLP*

The MINLP (1) is very difficult problems to solve, because it is a combination of mixed integer program (MIP) and nonlinear program (NLP). MIP and NLP are among the class of theoretically difficult problems. At present the MINLP is a Non-deterministic Polynomial (NP) problem [8].

A large amount of global optimization algorithms have been put forward to solve the MINLP problems. Branch-and-Bound [9] and Outer Approximation (OA) methods [10] are two of the most common methods.

In detail, OA algorithm leads to a decomposition of the constraint set. So MINLP problem (1) is decomposed into two sub-problems. One is NLP sub-problem(2) $s(\mathrm{y})$ with the fixed integer variables and another is a linear MIP (3) $s(\mathrm{x})$ problem with the fixed continual variables. Frist, solve $s(\mathrm{y})$ and obtain the best solution y^* ; Then solve $s(\mathrm{x})$ based on fixed the integer variable y^*. Problem (1) is solved by alternately solving problem (2) and problem (3). So the MINLP problem is solved in this method.

$$\begin{aligned} &\min s(y) = \min f^{s(\mathrm{x})}(x) + \mathrm{f}^{s(\mathrm{y})}(y) \\ &\text{s.t.} \quad g(x^*, y) \le 0, \\ &\qquad y \in Y \subset R_+^m, \end{aligned} \tag{2}$$

$$\begin{aligned} &\min s(x) = f^{s(\mathrm{x})}(x) + \min \mathrm{f}^{s(\mathrm{y})}(y) \\ &\text{s.t.} \quad g(x \;\, , y^*) \le 0, \\ &\qquad x \in X \subset R, \end{aligned} \tag{3}$$

III. MACROSCOPIC URBAN TRAFFIC MODEL (S MODEL)

The macroscopic urban traffic model has developed recently, boosting the velocity of transportation research over all. In this section we present the original urban traffic model (S model) proposed by Lin et al. [6].

From the S model, the number of the vehicles in two adjacent intersections *u* and *d*, called *link (u, d)*, is updated as following formula (2).

$$n_{u,d}(k_d + 1) = n_{u,d}(k_d) + (\alpha_{u,d}^{enter}(k_d) - \alpha_{u,d}^{leave}(k_d)) \cdot c_d \tag{2}$$

where k_d is the simulation step for intersections *d*, c_d is the cycle time for intersection d , $\alpha_{u,d}^{enter}(k_d)$ and $\alpha_{u,d}^{leave}(k_d)$ respect the entering average flow rate and leaving average flow rate over c_d , which can be calculated by the following formula(3)and(4).

$$\alpha_{u,d}^{enter}(k_d) = \frac{1}{c_d} \int_{k_d \cdot c_d + \Delta c_{u,d}}^{(k_d+1)\cdot c_d + \Delta c_{u,d}} \alpha_{i,u,d}^{leave,cont}(\mathrm{t})\, dt \tag{3}$$

$$\begin{aligned} \alpha_{u,d,o}^{leave}(k_d) = \min(&\beta_{u,d,o}(k_d) \cdot \mu_{u,d} \cdot g_{u,d,o}(k_d) / c_d \\ &\frac{q_{u,d,o}(k_d)}{c_d} + \alpha_{u,d,o}^{arriv}(k_d) \\ &\frac{\beta_{u,d,o}(k_d)}{\sum_u \beta_{u,d,o}(k_d)} \cdot \frac{C_{d,o} - n_{d.o}(k_d)}{c_d}) \end{aligned} \tag{4}$$

$\alpha_{u,d}^{enter}(k_d)$ is determined by continuous-time flow rates leaving upstream links $\alpha_{i,u,d}^{leave,cont}$ which can be obtained by formula (4). In the second item, $q_{u,d,o}$ is the number of waiting vehicles in $link(\mathrm{u}, \mathrm{d})$ which tends to turn to the intersection *o* shown in formula (5).

$$q_{u,d,o}(\mathrm{k}_d + 1) = q_{u,d,o}(\mathrm{k}_d) + (\alpha_{u,d,o}^{arriv}(\mathrm{k}_d) - \alpha_{u,d,o}^{leave}(\mathrm{k}_d)) \cdot \mathrm{c}_d \tag{5}$$

The arriving flow rate $\alpha_{u,d,o}^{arriv}$ is related to the enter flow rate $\alpha_{u,d}^{enter}(k_d)$ and the leaving flow rate $\alpha_{u,d,o}^{leave}$ shown in formula (6).

$$\begin{aligned} \alpha_{u,d,o}^{arriv}(\mathrm{k}_d) = &\frac{c_d - \gamma(\mathrm{k}_d)}{c_d} \alpha_{u,d,o}^{enter}(\mathrm{k}_d - \tau(\mathrm{k}_d)) + \\ &\frac{\gamma(\mathrm{k}_d)}{c_d} \alpha_{u,d,o}^{enter}(\mathrm{k}_d - \tau(\mathrm{k}_d) - 1) \end{aligned} \tag{6}$$

In formula (6), (*T*) is the time of vehicle spending on $link(\mathrm{u}, \mathrm{d})$. T / c_d is divided into two parts. τ is the integer part of and γ is the remainder part.

IV. MINLP FORMULA FOR URBAN TRAFFIC NETWORKS

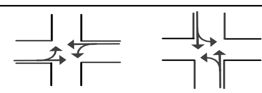
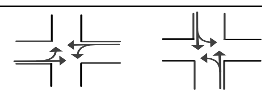
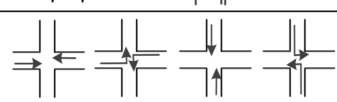
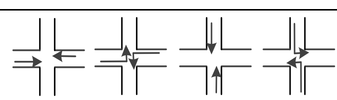
Based on the S model provided in section III, the paper which S Lin published [6] proposed a solution on the traffic optimization problem. It involved a type of variable – integer variable (green times), turned the MILP traffic optimization problem into the sequential quadratic programming (SQP) which was solved by Sequential Quadratic Programming solver. And the method reduces online computational complexity and alleviates traffic congestion more effective. Because the traffic signal control involves cycle times, phases and green times, the paper continues to study the intelligent traffic control system based on the research result [6], and uses MINLP programming to optimize traffic signal control.

A. *Optimization problem.*

The nonlinear mathematical programming problem of traffic signal control involves both integer variable (cycles and phases of traffic signal) and continuous variable (green times). This paper proposes a transportation optimization model that involves integer variables (cycle times and phases) and continuous variables (green times).

In order to increase the flexibility of traffic signal control, phase and its configuration at an intersection have a variety of options. These phases, order phases and cycle times can make up a set of strategy library A . In this paper, we define a set of strategy library $A=\{a(1),a(2),a(3),a(4)\}$ consisted of cycle time and phase, such as (60, 2), (90, 2), (120, 4), (150, 4) and so on, shown as table I. In the library, the first element represents the cycle whose units are seconds, and the second element represents the number of phases in a cycle time of intersections. For example, a_d = (60, 2) represents the cycle time is 60 seconds and each cycle time has two phases in intersection *d*. Different cycle time has a unique phase to correspond with it. Then we can reduce the number of optimal variables by using the strategy library. In the following paper, we use $a_d \in A$ to replace the different available combinations of cycle times and phases.

TABLE I. STRATEGY LIBRARY OF CYCLE TIMES AND PHASES

***Strategy* (a)**	***Cycle time***	***Phase***
$a(1)$	60s	
$a(2)$	90s	
$a(3)$	120s	
$a(4)$	180s	

To describe the optimization problem, we define several sets : I as the set of intersections of the road network and L as the set of $links$(roads) in the road network..

According to the model built in the third part, every intersection has its own cycle time. In order to all intersections can communicate with each other and be synchronous, this paper introduces a control time interval $T_{ctrl} = N \cdot T_{lcm}$, in which N is an integer and $T_{lcm} = N_d \cdot c_d$ is the least common multiple of all the cycle times in the intersections[].

In a given time interval T_{ctrl} and prediction horizon N_p , the number of vehicles entering the road network can be calculated by multiplying $\alpha_{u,d}^{enter}(k_d)$ by T_{ctrl} . The output of the S model presented in Section III. It can be generally described as formula (7)

$$n_{u,d}(k_d+1) = f(n_{u,d}(k_d),\mathbf{g}(k_{ctrl}),\mathbf{a}(k_{ctrl}),\mathbf{d}(k_d)) \tag{7}$$

where $\mathbf{n}_{u,d}(k_d)$ is the traffic model output and $\mathbf{d}$ (k_d) is the demand of the road network at step k_d , $\mathbf{g}(k_{ctrl})$ is the continual control input and $\mathbf{a}(k_{ctrl})$ is the control action represent the disperse control input for control step k_{ctrl} .

$$\begin{aligned}\mathbf{g}\ (k_{ctrl}) = [\mathrm{g}^T(k_{ctrl} \mid k_{ctrl}), \mathrm{g}^T(k_{ctrl}+1 \mid k_{ctrl})\cdots \\ \mathrm{g}^T(k_{ctrl}+N_p-1 \mid k_{ctrl})]^T\end{aligned} \tag{9}$$

$$\begin{aligned}\mathbf{a}(k_{ctrl}) = [a^T(k_{ctrl} \mid k_{ctrl}), a^T(k_{ctrl}+1 \mid k_{ctrl})\cdots \\ a^T(k_{ctrl}+N_p-1 \mid k_{ctrl})]^T\end{aligned} \tag{10}$$

$$\begin{aligned}\mathbf{d}(k_d) = [d^T(k_d \mid k_d), d^T(k_d+1 \mid k_d)\cdots \\ d^T(k_d+\mathrm{M}_d\mathrm{N}_p-1 \mid k_d)]^T\end{aligned} \tag{11}$$

where $g(k_{ctrl}+j/k_{ctrl})$ and $a(k_{ctrl}+j/k_{ctrl})$ are the control inputs in the j_{th} control step in the future from the current control time step k_{ctrl} . $d(k_d+j/k_d)$ is the future demand of the road network in the j_{th} control step.

The total time spent (TTS) is a function of two control inputs--green times and control actions.

$$\begin{aligned}J_{TTS} &= \sum_{(u,d)\in \mathrm{L}} \sum_{k_d=NN_d+1}^{(k_c+1)\cdot NN_d} c_d \cdot n_{u,d}(k_d) \\ &= G(n_0(k_d),\mathbf{a}(k_{ctrl}),\mathbf{g}(k_{ctrl}),\mathbf{d}(k_d))\end{aligned} \tag{12}$$

where $n_{u,d}(k_d)$ is the number of vehicles in in $link(u,d)$ at simulation step k_d , $n_0(k_d)$ is the initial number of vehicles of network and $\mathbf{d}(k_d)$ is the demand of network at simulation step k_d , $n_0(k_d)$ and $\mathbf{d}(k_d)$ are known, $\mathbf{g}(k_{ctrl})$ is the continual control input and $\mathbf{a}(k_{ctrl})$ is the control action represent the disperse control input of the network at control time step k_{ctrl} .

It hopes that, in a control cycle, the total time spent on all the vehicles is as short as possible. The optimization problem can be expressed as

$$\begin{aligned}J &= \min_{g(\mathrm{k}_{ctrl}),a(\mathrm{k}_{ctrl})} J_{TTS} \\ &= \min_{g(\mathrm{k}_{ctrl}),a(\mathrm{k}_{ctrl})} G(n_0(k_d),\mathbf{a}(k_{ctrl}),\mathbf{g}(k_{ctrl}),\mathbf{d}(k_d))\end{aligned} \tag{13}$$

$$\begin{aligned}s.t.\ \ &\Phi(g)=0 \text{ (cycletimes constraints)} \\ &\mathbf{n}_{u,d}(k_d) = f(n_{u,d}(k_d),\mathbf{g}(k_{ctrl}),\mathbf{a}(k_{ctrl}),\mathbf{d}(k_d)) \\ &g_{\min} < g_{u,d}(k_d) < g_{\max} \\ &0 \le n_{u,d}(k_d) \le C_{u,d} \\ &d \in I,(u,d) \in L, a_d \in A\end{aligned}$$

where the first constraint represents that in one cycle time, the sum of all the green times is the cycle time. The second is the

S model constraint. The third constraint gives the upper and lower bounds values for the green time. The forth one represents the number of vehicles in $link(u,d)$ is no more than the capacity of $link(u,d)$ expressed in number of vehicles. The last one shows that intersection d belongs to the intersection set (I), (u,d) belongs to the link set (L) the cycle times of each intersection are chosen from the strategy library (A).

The optimization problem in (13) contains a nonlinear, non-convex objective function and nonlinear, non-convex constraints. It is a typical non convex mixed integer non-linear programming problem which means that there may be multiple local minima. In order solve this problem, this paper apply a global optimization method.

B. the solution of optimization problem

The paper use Genetic Algorithm [12]-[15] to optimize the (transportation MINLP) problem. The idea of algorithm is based on Outer Approximation (OA), decomposing the optimization master problem (8) into two sub-problems shown in formula (14) and (15). It can be solved by iterative optimization of these two sub-problems. Specifically, the first step is initialization which gives variables initial values- a_0 and g_0 . Then solve the optimization problem (14) based on the initial values and obtain the best value a^* . In the third step, the sub-problem (15) parameter is given the origin values (a^* and g_0), solving by genetic algorithm and obtaining the optimal value g^* . Then repeat the first step based on the initial values (a_0 and g^*). It continues until the solution meets condition for the recursion. The master problem can be solved iteratively to approach the optimal solution.

$$J = \min_{a(k_{ctrl})} G(n_0(k_d), \mathbf{a}(k_{ctrl}), \mathbf{g}^*(k_{ctrl}), \mathbf{d}(k_d)) \qquad (14)$$

$$\begin{aligned} s.t. \quad & \mathbf{n}_{u,d}(k_d) = f(n_{u,d}(k_d), \mathbf{g}^*(k_{ctrl}), \mathbf{a}(k_{ctrl}), \mathbf{d}(k_d)) \\ & \Phi(g) = 0 \text{ (cycletimes constraints)} \\ & 0 \le n_{u,d}(k_d) \le C_{u,d} \\ & d \in I, (u,d) \in L, a \in A \end{aligned}$$

where the control option a is belongs to the strategy library A of combinations of cycle times and phases, shown in table I. The input of S model is a strategy of A, and $\mathbf{g}^*(k_{ctrl})$ is constant. So the sub-problem (14) is the optimization that only considers cycle times and phases. It is a nonlinear, non-convex programming.

$$J = \min_{g(k_{ctrl})} G(n_0(k_d), \mathbf{a}^*(k_{ctrl}), \mathbf{g}(k_{ctrl}), \mathbf{d}(k_d)) \qquad (15)$$

$$\begin{aligned} s.t. \quad & \mathbf{n}_{u,d}(k_d) = f(n_{u,d}(k_d), \mathbf{g}^*(k_{ctrl}), \mathbf{a}(k_{ctrl}), \mathbf{d}(k_d)) \\ & \Phi(g) = 0 \text{ (cycletimes constraints)} \\ & g_{\min} < g_{u,d}(k_d) < g_{\max} \\ & 0 \le n_{u,d}(k_d) \le C_{u,d}\ ; \\ & d \in I, (u,d) \in L \end{aligned}$$

where $g_{\min}, g_{\max}$ respectively represent the upper and lower bounds of green times. The input of S model is green times $\mathbf{g}(k_{ctrl})$, and $\mathbf{a}^*(k_{ctrl})$ is constant. So the sub-problem (15) is the optimization that only considers discrete control variable (green times) based on fixed cycle times and phases. It is a nonlinear, non-convex programming.

Genetic algorithm (GA) is a stochastic search method for optimization problems based on the mechanics of natural selection and natural genetics. It can solve the global optimization [1-5]. Non convex mixed integer non-linear programming problem (MINLP) is the most common form of global optimization problems. The paper solve MINLP problem by genetic algorithmic.

The process of using GA to solve MINLP programming shows as Fig 1: First, decompose the optimization master problem into two sub-problems. Then solve the sub-problem (12) via GA and obtain the best cycle times. Third, solve the other sub-problem (13) based on fixed cycle times which obtained in the second step. The best green times can be got. Last, repeat the second step based on the best green times and repeat the second step. It continues until it reaches the stop condition for the recursion. That is, the difference of objective function ΔJ between successive generations is less than infinitesimal ε then the algorithm will stop[18]-[19].

V. SIMULATION

The whole system realized in MATLAB platform, the calculation of objective function and Enhance Genetic Algorithm are developed with MATLAB programming language (in .m files).

The number of vehicles of next cycle is forecast by formula (2)-(4) and the system allocates to each intersection

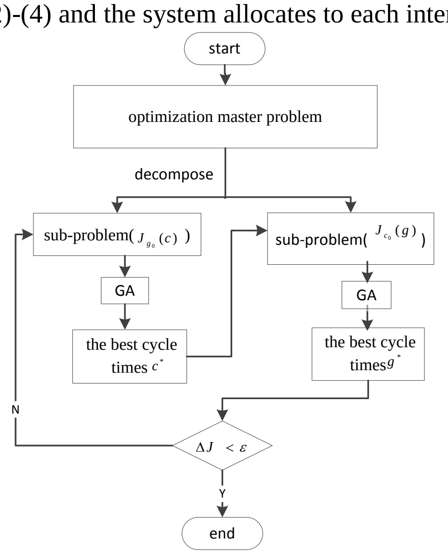


Figure1. The flow chart of the optimization MINLP

the best real-time green time and cycle time. The objective function is formula (13), noted $J(g(k_d), c(k_d))$ which is optimization evaluation index.

In the experiment, the urban traffic network is a grid network which contains four intersections shown in figure 2. The strategy library (A) of cycle times and phases is (60, 2), (90, 2), (120, 4), (180, 4). Control time interval (T_{ctrl}) is 360seconds.The simulation experiments run for a time period (T) of 7200 seconds. It assumes that the length of each link is 1300meters which has three lanes. Each lane has an average of the flow. The initial values of the Enhance Genetic Algorithm are Strategy I (90, 2) and 50% green time.

The flow rate entering into intersections is constant, such as 500veh/h. The solver for traffic optimization problem that was proposed in S Lin's paper [6] only involved a variety (the green time) noted 'SQP'. While the optimization this paper proposed is noted 'MINLP'. Based on three different saturations-unsaturated, saturated, and over saturated, the simulation is done to compare 'SQP' and 'MILNP'.

When a_d is low (cycle times are short and phases are few) and the entering flowing rate is large, signal lights switch so frequently that road network is inefficiency. When a_d is high (cycle times are longer and phases become a little more) and the demand of network is small, the network saturation is low. As a result, the road network is also inefficiency [16]-[17].

From figure 3, we can see the performance of the 'MINLP' is better than that of 'SQP'. The reason can be found in the model built in the third part. When the entering flow rate is always 500veh/h, the network is the unsaturated scenario. From the formula (4), leaving average flow rate is determined by the waiting and arriving flow rates at the intersection. The number of vehicles leaving the intersection to enter the next intersection, only depends on the number of waiting vehicles in the queues, and the number of waiting vehicles will be affected by the vehicles arriving from upstream after a certain time delay in the link. The role of 'MINLP' optimization is to reduce cycle times, the waiting time that vehicles spend when vehicles wait for the traffic light to cross the road. So reducing cycle times can let vehicles enter the next link more quickly in comparison with 'SQP' optimization. From formula (5), we also can see that the number of vehicles in the 'MINLP' network nearly as many as those in the 'SQP' network, while the cycle times of 'MINLP' are no longer than that of 'SQP', because the network is the unsaturated scenario.

Figure 4 is executed in the 2000veh/h entering flow rate. From it we can see that the TTL of 'MINLP' is also shorter than that of 'SQP'. Figure 5 is also executed in the 5000veh/h entering flow rate. It shows that the TTL of 'MINLP' is shorter than that of 'SQP'. The paper also supplies a variable flow rate for the urban road network, shown in figure 6. The TTL of 'MINLP' is shown in figure7. In a variable flow rate supplied for the urban road network, the performance of 'MINLP' is a little worse than that in for 500veh/h. So to some extent, the 'MINLP' has automatic regulation.

The optimization performance and the relative improvements are listed in Table 2 for 'SQP' and 'MINLP'. Table2 TTS of 'MINLP' and 'SQP'

TABLE II. COMPARION TTS OF 'MINLP' AND 'SQP' IN DIFFERENT

	500veh/h	**2000veh/h**	**3000veh/h**
MINLP	3468.8(-23.78%)	5864.4(-19.17%)	6899.9(-12.17%)
SQP	4550.7	7254.8	7910.4

Table II gives the values of TTS in different flow rates supplied for network. From the table, we can see that in 500veh/h, TTL of the 'MINLP' is 3468 h and TTL of 'SQP' is 4550.7. TTL of 'MINLP' reduces by 23.78%. The performance of 'MINLP' is better than 'SQP'. In 2000veh/h and 3000veh/h, we can obtain the same conclusion.

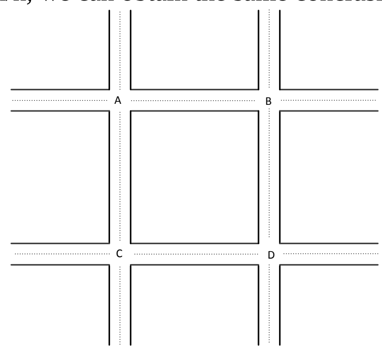


Figure 2. The model of an urban road network.

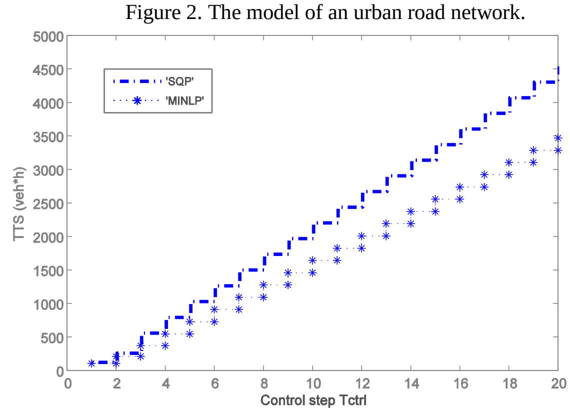


Figure 3. TTS comparison of the 'MINLP' and 'SQP' for 500veh/h

VI. CONCLUSION

Road congestion is directly influenced by cycle times, pulses and green times of traffic signal lights. Giving full consideration to these influence factors, this paper uses an optimization (MINLP) method, involves integer invariable (cycle times and pulse) and continual invariable (green times) to accord with the practical situation. And the paper uses genetic algorithm to solve the problem.

From the simulation result, it is obvious that the 'MINLP' solver is better performance than 'SQP'. The optimization method can significantly improve effect of relieving traffic congestion and increase traffic safety.

In the future, we hope to further promote the effectiveness of the method in ACP framework for solving the difficulty of real-world complex systems.

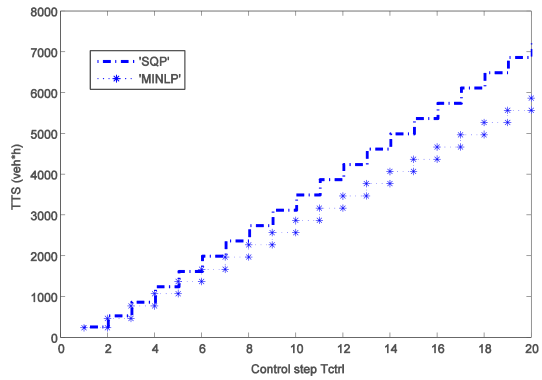


Figure 4. TTS comparison of the 'MINLP' and 'SQP' for 2000veh/h

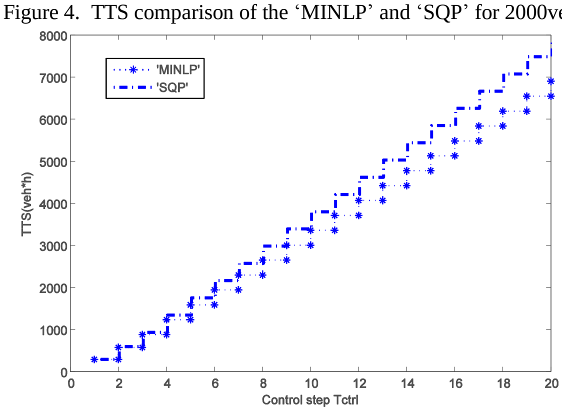


Figure 5. TTS comparison of the 'MINLP' and 'SQP' for 3000veh/h

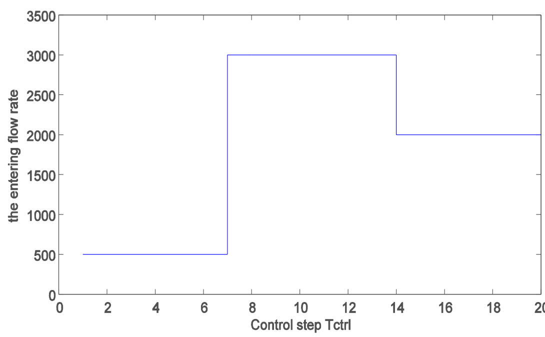


Figure 6. The variable flow rate supplied for the urban road network

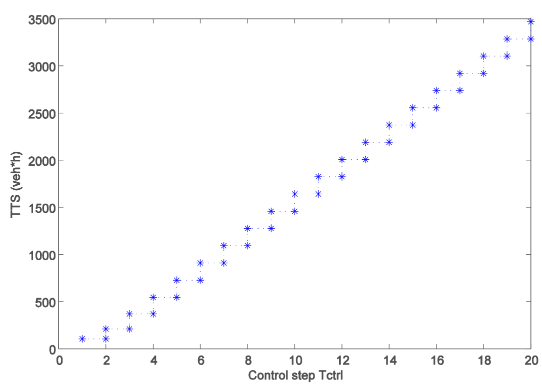


Figure 7. TTS comparison of the 'MINLP' for variable flow rates

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