Traffic Urban Control Using an Intelligent PSO Algorithm Based on Integrated Approach

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Abstract: In this paper, we intend to contribute to the improvement of urban traffic mobility using a learning method of traffic lights controllers. We proposed a Particle Swarm Optimization (PSO) method in which the intelligent swarm acts as the cycle time of the traffic signal. The best swarm (solution found) meets the evaluation criteria selected to describe desired objectives. The main measures of traffic lights efficiency are to maximize flow-rate at which vehicles can cross a road junction and minimize the additional travel time of the driver called vehicle delay. Particle Swarm Optimizer was coupled with the traffic flow model based on Continuous Petri nets (PN). One potential advantage of CPN model is to provide insights regarding a behavior of the platoon of vehicles on the target road network. The result obtained from this study has tested with various scenarios related to intersections in different situations. The developed self-scheduling of the optimal signal timing ensures safety and continuous traffic flow, thus increasing the mobility and reducing fuel consumption and pollutant emissions.

Keywords: PSO, large scale-optimization, prediction, traffic flow modelling, traffic lights, Petri nets

1. INTRODUCTION

In the vehicular traffic flow field, the vehicle dynamics is enough complex. This complexity is due to the nonlinear interaction between travel decision behaviour, routing of vehicles and traffic congestion in networks [4]. In practice it is hard to take into account all interacting elements when processing a given engineering transportation problem. The traditional approach of transportation engineering is to isolate the elements most relevant for separate handling and to bring these elements and the relationships between them together into a unified modular system. From viewpoint of traffic flow modeling, the behaviour of vehicles in road is often seen as in two main levels: macro-mobility and micro-mobility. Micro-mobility level focuses on the individual vehicle behaviours in road. Vehicles are individually represented by considering the interactions between them taking into account (headway, speed, acceleration). Although, the macro-mobility level has been inspired from the kinematic wave model of Lighthill and Whitham and Richards (LWR) [16][19]. In this case, the traffic flow is described by global variables as the flow-rate, the flow density and the flow average speed. Traffic congestion occurs frequently within traffic networks. Indeed, in order to absorb the streams induced by the growing of socio-economic activities (transportation of humans, goods and products), traffic networks have been extended more and more so that they represent almost half of surface area of urban cities. However this development of traffic networks is not enough to eliminate traffic congestion phenomena. Under some circumstances (rush hours, road accident) traffic flow exceeds the road and crossroads capacity causing large queuing of vehicles. Traffic management systems are intended to reduce congestion and the resulting negative effects: vehicle delay, fuel consumption, pollution, etc. The significant increase in computing power allowed implementing online optimization algorithms that improve the efficiency of controllers in real time.

The main purpose of this paper is to present a new methodology for traffic lights control using Particle Swarm Optimization (PSO) and an integrated approach based on Rakha model [10] and a Macroscopic Traffic Flow (MTF) model commonly known Lighthill, Witham and Richards (LWR) model [16][19]. This latter is used for estimating the arrival profiles of vehicles. PSO algorithm performed the cycle time optimization of traffic lights using the cumulative platoon arrival profile provided by MTF model. The prediction of the platoon movement and arrivals in intersections are reproduced both using the VCPN (Continuous timed Petri Net with Variable speeds) and Rakha vehicle dynamics model. The meta-heuristic algorithm (PSO) is used to compute the optimal traffic signals with aim to minimizing the traffic jam.

The traffic flow macroscopic parameters such as: density, flow-rate and speed are determined by LWR-VCPN model. The deterministic parameters of LWR-VCPN model namely the free speed of each road segment is obtained from the Rakha model. Thus, the advent cumulative platoon at each intersection is provides by LWR-VCPN model. The estimated cumulative platoon arrival is used as an input data of PSO algorithm [11] for minimizing the traffic jam by finding the optimal signal time plan.

A continuous timed Petri net with variable speeds (VCPN) traffic model [5][6] is used to describe in macroscopic manner of platoon evolutions in time and space [15].

This paper is arranged as follow: In section 2 review of related work is presented. Section 3 exhibits the architecture of the proposed traffic light control system. The modeling system approach is described in section 4. Section 5 is devoted to the optimization part which is coupled with the modeling part. The main contribution known an integrated approach and its application is detailed in section 6. Finally, conclusions and future work are given in the last section.

2. RELATED WORK

Various researches on modeling of traffic flow progression use different approaches to solve problems of traffic light scheduling, and optimization methods to reach the optimal traffic lights sequence utilize specified criteria such as the minimization of waiting times, delays, etc., the maximization of the number of vehicles outflow, etc. In this regard different works use Petri Net (PN) tool to modeling the urban traffic network, and several studies employ the Particle Swarm Optimization Algorithm (PSO) combined with other techniques or algorithms in order to find the optimal traffic light timings. For the sake of simplicity, the unfamiliar reader with PN can refer to [21].

Reference [17] offer a macroscopic model for urban traffic network based on First Order Hybrid PN (FOHPN) formalism, where the traffic flows is represented as a fluid approximation, and the traffic signal is considered as a discrete part and modeled by timed Petri nets. The dynamic of FOHPN model is governed by time-driven and event-driven dynamics. Obtained model is validated and compared with a microscopic model based on colored timed PN (CTPN). Jùlvez and Boel [9] use a several features of continuous PN with infinite server semantics (Time is discretized in steps, empty places in finite time). Each time step can be seen as the travelling time (delay) of vehicles between two places and in order to avoid a negative marking (vehicles) of place, its input flow during each time step is bounded. Moreover, in order to determine urban road traffic behaviors, the continuous PN are combined with discrete part that represents traffic lights. Consequently, the resulting model is characterized by hybrid dynamic. The management of road traffic by hybrid formalism have been developed based on minimizing the total delay of cars.

Reference [1] use the Hybrid Petri Nets (HPNs) model who is modeling the flow of vehicles as a fluid, to present an urban traffic network of signalized intersections, and to solve the problem of synchronizing many traffic signals, in the goal of developing the performance of some special vehicles such as public and emergency vehicles. The proposed model is validated employed real traffic data of Italian. A microscopic model is proposed by [2] based on deterministic timed PN (DTPN) for representing the traffic and signalized intersections, to proceed the aim of traffic management, this proposed model is tested on real traffic data. The model of urban traffic system considered by [3] and its representation with stochastic timed PN for optimizing the duration of green signal in each stage in order to augment the performance of the system by minimizing the queue delay. The work elaborate by [18] used the deterministic and stochastic Petri net model [DSPN] to represent the urban traffic system in intersection, this model permits easy modification of vehicle flow which has been validated with real traffic data, the aim of this work is to augment the performance of vehicle flows. Authors in research papers [5][6] proposed a new approach to model macroscopic traffic flow and representing its variables through sections of road using Continuous PN with Variable speed (VCPN) in which the VCPN parameters are described by road traffic ones. The research work in [23] proposed a new signal control method based on the Petri net model. When the urban signalized intersection is modeled by a hybrid colored Petri net to optimize the traffic signal control of isolated intersections, which divided on two parts the traffic signal control module and a traffic flow module.

Reference [12] Propose an optimization strategy based in particle swarm optimization method to find optimum signal timings and then the results obtained are evaluated with a microscopic simulator in the context of two areas, in the aim to maximize the number of vehicles that reach arrive in their destination. A new method to optimize the traffic-jam probability is introduced by [7] where the probabilistic distribution of the ready vehicles is predicted from The Bayesian Network (BN) model and the Cellular Automaton traffic model (CA) is used to update this probabilities, and then used the Particle Swarm Optimization Algorithm (PSO) to obtain the optimal traffic signal scheduling, and determine the efficiency of the offered method by a micro-simulator. a system was also proposed by [22], (IOCA-PSO) which is a method applied to attain an urban traffic signalization schedule dynamic and optimum, combined two approaches the inner and outer cellular automaton model (ICM –OCM) with particle swarm optimization algorithm (PSO) who calculate the fitness value. In [13] Particle Swarm Optimization Algorithm (PSO) is used like a method of optimization to find an optimal traffic light programs, and a microscopic traffic simulator evaluate the solution obtained, in this work two areas American, and European city are tested, in which objectives to maximize the number of vehicles that reach the downstream line and to minimize the total delay. Reference [14] designed a real time traffic signal control approach at isolated junctions and bridges based on Fuzzy Artificial Neural Network (FANN), the aim of this work is to minimize delays and maximize the number of vehicles outflow, the authors used two optimization algorithms to compute the performance of (FANN) such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). A new method using Particle Swarm Optimization Algorithm (PSO) proposed by [20], aims to optimize traffic signal time, cycle length, and phase splitting in intersections by minimizing the total delay, to improve the performance of road network.

According to the synthesis of the different works concerning the Petri nets and the PSO algorithm, we note that there is no work integrating these two approaches to determine the optimal cycle time of traffic lights, which is our proposed work.

3. INTEGRATED ROAD TRAFFIC MANAGEMENT ARCHITECTURE

The main objective of all contributions in this area is the search for more fluid and efficient circulation levels. A new method of controlling traffic lights is proposed, the Rakha model of vehicle dynamics integrated with the LWR-VCPN model. Then, the estimated cumulative platoon arrival is used as an input data of PSO algorithm for minimizing the traffic jam by finding the optimal signal time plan.

Our contribution focus on the bringing together three component sub-systems into one system: modeling, optimization and performance metrics assessment. The topology of the proposed system is illustrated in the following fig. 1.

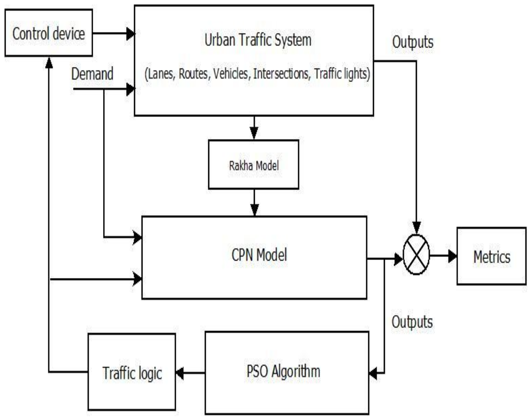


Fig.1 System architecture.

4. SYSTEM MODELISATION

A. VCPN Model of Urban traffic network

In this section we present a continuous timed Petri net with variable speeds (VCPN) traffic model [5][6] used for macroscopic modeling of urban traffic flow. One of the major features of macroscopic traffic flow approach is the fundamental diagram (FD) that gives the relation between the three traffic flow average parameters: density (vehicles/km), speed (km/hour) and flow-rate (vehicles/hour).

Definition 1 VCPN is a marked graph depicted by quintuplet G = (P, T, Pre, Post, θmax) where P and T are respectively the finite-set of places and the finite-set of transitions, Pre and Post are two incidence functions where $Pre(P_i, T_j)$ is the weight of the input arc directed from place Pi ($P_i \in P$) to transition T_j ($T_j \in T$) and $Post(P_i, T_j)$ is the weight of the output arc directed from place T_j to transition Pi. θ_{max} is the real positive vector of transitions maximal firing speeds, $\theta_{max} \in$

$(IR^+)^q$. where the real positive firing speeds vector at time t, $Q(t) \in (IR^+)^q$ and the real positive marking vector $M(t) \in (IR^+)^n$. The marking evolution of the VCPN is given by the following differential system:

$$\begin{aligned} dM(t)/dt &= \Gamma . Q(t) \\ M(t_0) &= M_0 \end{aligned} \quad (1)$$

Where M_0 is the initial marking vector of places at time t_0 and Γ is the incidence matrix of VCPN defined as $\Gamma = Post - Pre$. The components of the firing speeds vector Q(t) depend continuously on the marking of the VCPN according to the following equation:

$$q_j(t) = \theta_{max\,j} \mu_j(M(t)) \quad (2)$$

$$\mu_j(M(t)) = \min(m_k(t)/Pre(P_k, T_j)) \quad (3)$$

For all $P_k \in {}^{\circ}T_j$, $\theta_{max\,j} \in \theta_{max}$ and $m_k(t) \in M(t)$

B.LWR Model

VCPN is used for modeling the LWR macroscopic model to estimate the cumulative platoon arrival profile, this model is based on hydrodynamical theory and consider the flow as a compressible fluid[16][19], where vehicles are not represented individually but as a continuous flow, and on the theory of waiting line [8]. The LWR approach is based on three principle laws such as (4), (5), and then (6).

- The conservation law

$$\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial q(x,t)}{\partial t} = 0 \quad (4)$$

- The continuous temporal traffic variables

$$q(x,t) = \rho(x,t).S(x,t) \quad (5)$$

- The fundamental diagram

$$q(x,t) = f(\rho(x,t)) \quad (6)$$

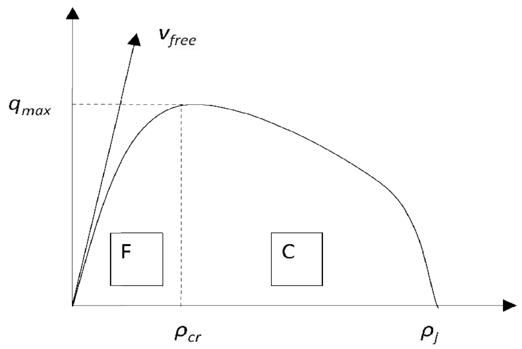


Fig. 2 fundamental diagram

The parameters are defined as:
v_{free}: free flow speed.
q_{max}: maximum flow allowed.
ρ_j: jam density.
ρ_{cr}: critical density (the density that characterizes the appearance of congestion).
In the case when the number of vehicles in a segment is bigger than what is required, a congestion is defined. If a segment i is congested (C), the density ρ_i in this last is greater than the critical density ρ_{cr}. And if a segment i is not congested (or free (F)), the density ρ_i is less than or equal the critical density ρ_{cr}.
So,The two modes are defined as follows: free mode ($0 \leq \rho_i \leq \rho_{cr}$) and congested mode ($\rho_i > \rho_{cr}$).

The model requires spatial and temporal discretization, the spatial discretization consists of decomposing the road into a set of segments of length Δ_i (i = 1, ..., N). Each segment of road is modeled by the average traffic parameters such as density $\rho(t)$, flow-rate $q(t)$ and speed $S(t)$.

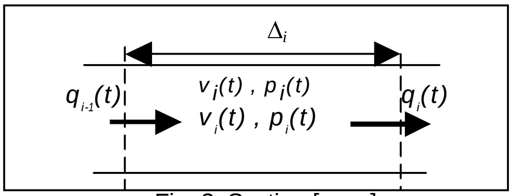


Fig. 3. Section $[x_{i-1}, x_i]$

References [5][6] presented the possibility to describe the LWR model based a VCPN formalism that used for macroscopic modeling of urban traffic flow. One of the principal laws of macroscopic traffic flow approach is the fundamental diagram (FD) that gives the relation between the three traffic flow average parameters such as: density, speed and flow-rate.

In VCPN the place P_i represent a segment road i, and the transition T_i correspond to the junction between two segments i and $i+1$. Each segment i has the marking $m_i(t)$ which is the available number of vehicles in place P_i. The flow-rate $q_i(t)$ is formulated according the firing speed $v_i(t)$ associated to the transition T_i. As consequent, the relationship between the average density $\rho_i(t)$ and the average velocity $S_i(t)$ for each segment i is given by (7) and (8).

$$\rho_i(t) = \frac{m_i(t)}{\Delta_i} \quad (7)$$

$$S_i = \frac{v_i(t).\Delta_i}{m_i(t)} \quad (8)$$

Figure 4 illustrates the VCPN traffic model [5][6] in which the road segment i is described by the place Pi and the two transitions T_{j-1} and T_j.

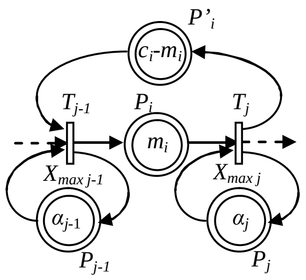


Fig. 4 VCPN traffic model of segment *i*

The marking m'_i (t) of the place P'_i stands for the available vehicles emplacement segment $[x_i, x_{i+1}]$. In addition, the place P_j associated to the transition T_j represents its maximum vehicles number that passes simultaneously. The flow rate $q_j(t)$ of the segment *i* is defined as follow:

$$q_j(t) = X_{\max j}.\min(m_i(t), m`_i(t), \alpha_j) \quad (9)$$

v_{free} is the free speed in segment i and $X_{\max j}$ represents the maximal firing speed of transition T_j.

C. Rakha Model

Based on the free speed found by the Rakha model which allows the segmentation of the road, the authors in [10] have proposed the vehicle dynamic model with constant power. The maximum acceleration of vehicle is expressed by the different forces acting on vehicle divided by the vehicle total mass M (11).

$$a = (F - R)/M \quad (11)$$

The instantaneous acceleration $a(t_i)$ can be deduced according to the net force $F(t_i)$ at time *t* and the total resistance $R(t_i)$ at time *t*. Thus, the relationship in (12) allows calculating the dynamic equations system constituted by (14) and (15).

$$a(t_i) = \frac{[F(t_i) - R(t_i)]}{M} \quad (12)$$

$$(dv(t_i)/dt, dx(t_i)/dt) = (a(t_i), v(t_i)) \quad (13)$$

$$x(t_i) = x(t_{i-1}) + v(t_{i-1})\Delta t \quad (14)$$

$$x(t_i) = x(t_{i-1}) + v(t_{i-1})\Delta t \quad (15)$$

Where:

a: acceleration [m/s];
v: velocity [m/s];
x: distance travelled [m] during Δt;

Algorithm: The procedure of PSO

```
initializeSwarm();
ComputeGlobalBestParticle (b);
while  g < MaxNumbIterations   do
  for ( i=1 to size of swarm) do
    Calculation of new velocity by (16)
    Calculation of new position by (16)
  end for
  updateComputeGlobalBestParticle (bg)
end while
```

$t_i = t_0 + i\Delta t$ for $i = 1,2,\ldots,N$.

5. SYSTEM OPTIMIZATION

A. The PSO algorithm for the optimization of traffic signals

Based on the arrival profiles of vehicles found bya LWR model, The PSO algorithm using to find optimal traffic signal cycle program. These programs coordinate traffic signals at adjacent intersections to maximize the number of vehicles leaving the junction and minimize the traffic jam.

The computational population based meta-heuristic PSO was introduced by the pioneers Kennedy and Eberhart [11]. PSO is based on the exploring the search-space of any problem in order to find the set of particles that maximizes/minimizes a defined objective function and each potential solution to the problem is called particle position. PSO algorithm is presented as follow:
To apply the PSO algorithm in the traffic signal control, it is enough to consider each particle as a cycle of the traffic signal. Each traffic light dimension is determined by the number of phases allowed at the considered intersection

In this algorithm at each iteration, the particle i will move between the iterations i and i+1 in terms of its velocity and its two known best positions (its own and that of the swarm) according to two equations (16).

$$\begin{cases} x_{g+1}^i = x_g^i + v_{g+1}^i \\ v_{g+1}^i = w.v_g^i + \varphi \\ \varphi = c_1.rnd1.(p_g^i - x_g^i) + c_2.rnd2.(b_g - x_g^i) \end{cases} \quad (16)$$

where:

p_g^i: the best personal solution of the particle i;
b_g: the best global solution of all particles;
w: the mass of inertia of the particle;
c_1 and c_2 are respectively the personal and global learning coefficient that accelerate and control the relative components;
rnd_k is a random value [0.1 , 1] où $k \in 1,2$.

As mentioned above, each particle describes a cycle of traffic lights and its dimension is determined by the number of phases allowed at the intersection. So, each phase is known by duration and its state which is a sequence of possible traffic lights (green, yellow, red). In order to estimate the quality of the particle *i*, it is necessary to calculate its fitness function.

This last is calculated using a special function for the problem addressed. In order to update the values of x_i, *pbest* and *gbest*, their fitness which is defined by the following equation are computed at each iteration of the algorithm. Thereby the initial values of the fitness function are extracted from the Rakha-LWR model.

$$F(x) = \frac{\sum_{h=1}^{h=H}(z1 + z2)}{\sum_{h=1}^{h=H}(\rho_{EW_{end}} + \rho_{NS_{end}})} \qquad (17)$$

Where:
$z1 = \rho_{EW} - \Delta h * q_{EW}$
$z2 = \rho_{NS} - \Delta h * q_{NS}$
ρ_{EW} : Density in east and west direction.
ρ_{NS} : Density in north and south direction.
q_{EW}: Flow rate in east and west direction.
q_{NS} : Flow rate in north and south direction.
ρ_{EWend} : Output Density in east and west direction.
ρ_{NSend} : Output Density in north and south direction.
Δh =1: The time step.
Fitness function algorithm is presented as follow:

Algorithm: The procedure of Fitness Function

```
Simulation_parameters();
IntializeSauvegaredVariables();
ComputeFlowRateInitialTime_EW();
ComputeFlowRateInitialTime_NS();
while h < CycleTime do
    ComputeDensitySegments_EW();
    ComputeDensitySegments_NS();
    UpdateFlowRateSegments_EW();
    UpdateFlowRateSegments_NS();
    Compute(z1);
    Compute(z2);
    updateComputeGlobalBestParticle (bg)
end while
Compute(F(x));
```

6. APPLICATION AND INTEGRATED APPROACH

The studied system is composed of two parts as follows:

- Part 1: use the Rakha-LWR model to determine the traffic data values;
- Part 2: use the optimization algorithm PSO to determine the optimal traffic signal cycle program.

A. Integration of the LWR-VCPN and the Rakha models

The notion of integration of the two approaches is founded on the next points:

- The behavior of the leading vehicle as the speed and the acceleration is simulated by the Rakha model.
- The inputs in the different LWR model segments are the optimum speed and vehicle head time characteristics.
- To determine the maximum speed that a vehicle can reach in each segment. The Rakha model generates the vehicle speed / time curve.
- Before the leading vehicle reaches the free flow speed, the segments are 100 meters each, as the vehicles move at free speed the length of the segment is residual distance of road to the stop point.

B. Simulation and Implementation Model

The considered system is a motorway section (Fig. 5), which has a length of 700m, with one intersection contained four traffic lights (east-weast and north-south). If we consider that the length of the vehicle is 6.6 m, then this motorway can contain of 106 vehicles.

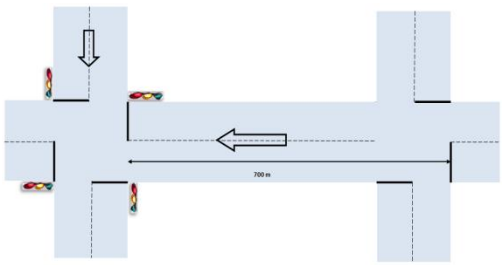


Fig.5 Test Road

1. Vehicle Arrival Model Using Poisson Distribution Model

In this proposed work the inputs of the system follow Poisson distribution model which is defined as follows:

When the number of vehicles arriving in a given period of time is random, The Poisson Distribution is proposed as early as the 1930s is commonly used to describe such a random process. For this distribution, the probability that a number x of vehicles will arrive during a period of time Δt is given as:

$$p(x) = \frac{\mu^x e^{-\mu}}{x!} \qquad (18)$$

μ the average number of vehicles arriving during a period *Δt*.
The probability that some number of vehicles (*n*) arriving in a period can be calculated as:

$$p(x \leq n) = \sum_{i=1}^{n} p(i), \quad i \in I \qquad (19)$$

*2.*Simulation of Rakha and LWR-VCPN models

To find speed and time characteristics we implement the Rakha model in which the input parameter is based on the Snare database [13], using Δt =0.1s, the speed and distance travelled by the vehicle are obtained by the equations from (11) to (15) implemented via MATLAB.
Speed simulation of the leading vehicle according to the distance is showing in fig. 6.

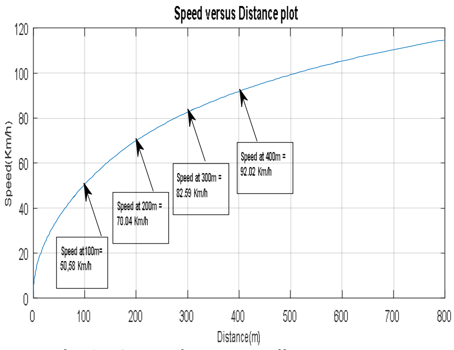


Fig.6. Speed versus distance curve

According to Fig. 6, it is observed that a vehicle attained speed of 50.58 km/h after it travels 100 m from the upstream stop line; speeds of 70.04 km/h, 82.59 km/h and 90.02 km/h are attained at 200 m, 300 m and 400 m respectively.
It is observed that the leading vehicle arrives at the free flow-rate $v_{free\ i}$ which is equal to 82 km/h at 300 m. From this moment the vehicle is supposed to keep on going to pass over 300 m at the same speed.
So, the road of the motorway studied can be segmented into four segments as shown in figure 8. By using the speed profile, the first three segments are 100m and the fourth one is 400m.

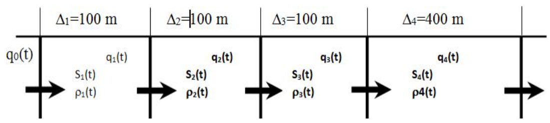


Fig. 7 Road segments

The VCPN model of the road is presented as follow:

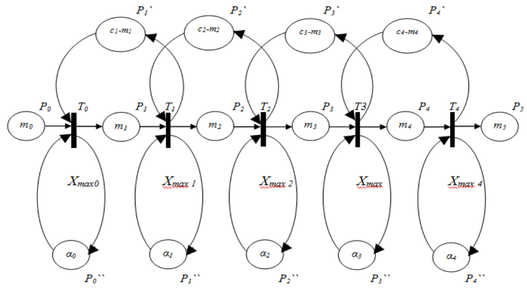


Fig.8. VCPN model of road

In fig. 8, Marking m0 represents the number of vehicles ready to depart; and the number of vehicles vehicles in segment 1, 2, 3 and 4 respectively are represented by: m1, m2, m3, and m4, the number of vehicles that reached the downstream is represented by m5, markings (c_i-m_i) represent the number of available site in each segment.
The incidence matrix of VCPN Γ(P,T) is defined as follow:

$$\Gamma(P,T) = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ -1 & 1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & 1 \end{bmatrix}$$

where:
P: places (P1, P2, P3, P4, P1`, P2`, P3`, P4`)
T: Transitions (T0, T1, T2, T3, T4)

The following table 1 present the VCPN parameters.

Table 1 VCPN parameters

Segment	01	02	03	04
Δ_i	100	100	100	400
$V_{free\ i}$ *(m/s)*	14.05	19.45	22.94	25.00
C_i-m_i (veh)	15.15	15.15	15.15	60.61
α_i (veh)	3.55	2.57	2.17	8

Δ_i: the segments length.
$V_{free\ i}$: the free flow-rate obtained with the implementation of Rakha model.
C_i-m_i: the number of available sites in each segment, calculated based on the segment

length (Δ) and the maximum occupancy length of 6.6 m per vehicle.
α_i: the average number of vehicles that can cross the junction simultaneously, is calculated based on the maximal flow rate ($v_{\text{free i}}$), segment length (Δ_i) and the segment limited maximal firing speed ($q_{max\,i}$) according to equation (21)

$$\alpha_i = \frac{q_{\max i} \cdot \Delta_i}{v_{free\ i}} \qquad (20)$$

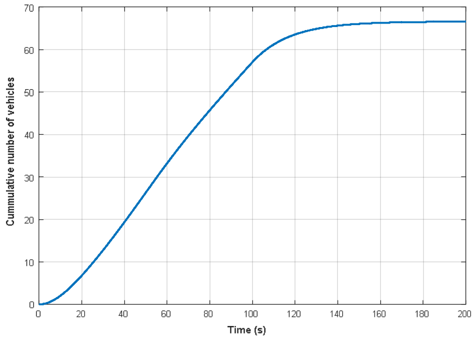


Fig. 9 cumulative number of vehicles versus time curve.

Considering saturation flow rate of 1800 veh/h/lane, which is 0.5 veh/s/lane.
Thus, the VCPN model is ready to be implemented to estimate the arrival profile at the road:

3. Simulation of PSO algorithm

Particle Swarm Optimization Algorithm adopted to find the optimal cycle programs of traffic lights, it works as follow:
- The initial swarm initialized with a set of a random values representing the phase durations, this values are within the Lower Bound VarMin = [30 5 30 5] , and the Upper Bound VarMax = [40 10 40 10], constitute the range of possible time spans (Green Red, Yellow Red, Red Green, Red Yellow).
- The values of velocity is specified according to the following defined limits:
VelocityMax=0.1*(Vmax-Vmin),
VelocityMin= -VelMax;
where Vmin = -4 and Vmax = 4;
Other parameters of simulation are defined in the following table:

Table 2 PSO algorithm parameters

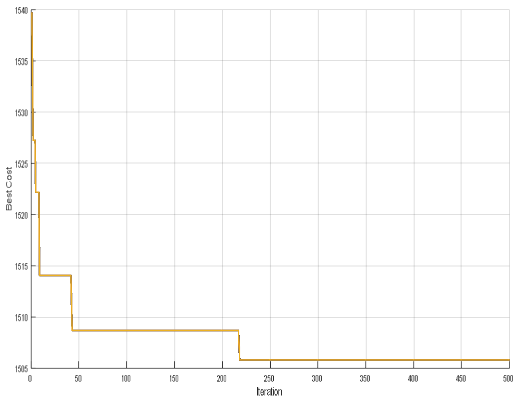
Parameter	Value
- Swarm Size	20, 50, 100, 150, 200
- Acceleration coefficients ($c_1 = c_2$)	2.05
- The inertia weight (*w*)	0.5
- Inertia Weight : damping Ratio (*wdamp*)	0.99

We show a representation view of the behavior of PSO algorithm under different conditions of swarm size, maximum number of iterations. In the following table present the best cost values and the traffic logics (positions) correspond to different configurations of swarm size with: 50, 100, and 200 particles, and maximum number of iteration 100, 300,500.

Table 3 Best cost values of PSO

Swarm Size	Max Iteration	Cost	Position	Cycle time
50	100	2000	[30 6 32 6]	74 s
	300	**1915**	[30 5 31 5]	71s
	500	1926	[30 6 31 5]	72s
100	100	1904	[30 5 30 6]	71s
	300	1902	[30 7 30 6]	73s
	500	**1865**	[31 5 31 5]	72s
200	100	1889	[30 5 30 7]	72s
	300	1889	[30 7 30 6]	73s
	500	**1865**	[30 6 30 5]	71s

From viewpoint, Fig 10 plots the trace progress of the best cost values Vs Iterations, we can observe that our algorithm



practically converged after the first 200 iteration.

Fig.10 Evolution of the best cost of PSO.

- Our optimization solver is able to report successful cycle programs for the different instances.
- As shown in previous figure.10 for almost all the combinations (of Swram Size and MaxIt) our PSO is able to converge on the interval of 300 and 500 iterations.

7. CONCLUSION & FUTURE WORKS

In this paper, a new methodology for traffic signal control using a Particle Swarm Optimization (PSO) based on integrated approach is presented. PSO is used to compute the optimal sequence of traffic signal using the arrival profile of vehicles. This latter is provided by the Macroscopic Traffic Flow model. The parameters of MTF model are determined according the speeds profile obtained by Rakha model. The combination between these models highlighted the integrated approach. As a future works this contribution may be large scale optimization with enhancement for adjacent intersections.

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