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1 **ABSTRACT**

2 Lane changes can lead to disturbances in traffic flow, whilst the uneven distribution of traffic
3 over different lanes as a result of lane changes can also lead to instabilities and congestion on
4 one specific lane. Therefore, giving advice on lane change can be beneficial for both individual
5 drivers and traffic state in the network. However, there are many variations in advice content and
6 objective, all of which may impact the performance of advice. This paper focuses on the
7 optimization of traffic flow through the performance of specific lane changes. We model traffic
8 flow on a two-lane stretch and consider lane-change time instants of a subset of vehicles as
9 decision variables. Optimizations with three objectives are constructed: reaching a collective
10 optimum, a group optimum and a user optimum. These optima are found by total travel delay
11 minimization of different vehicle groups. To solve the problems, a genetic algorithm as a
12 heuristic method is implemented. Each optimum leads to different lane changes. Specifically, by
13 the proposed algorithm, vehicles will be suggested to change lanes in bigger gaps to improve
14 collective or group efficiency; while they are supposed to overtake as many vehicles as they can
15 by changing lanes for their own benefit. The algorithm can be further extended to a more
16 effective in-car advice system, which can improve traffic efficiency for future situations through
17 communicating partly automated vehicles.

1. INTRODUCTION

Lane changes on high way are essential to traffic operations. Systematic lane changes can lead to a significant capacity drop (*1*), and are proved to be the primary reason of density oscillations and traffic instabilities (*2*, *3*). Besides, a considerable amount of collisions are also generated by lane changes (*4*). On the contrary, controlling lane changes of equipped vehicles can absorb congestions (*5*)and mitigate traffic oscillations (*6*).

Moreover, intelligent transport systems (ITSs) have been widely investigated and used to improve drivers' safety and comfort, as well as to improve the traffic efficiency and emission. In addition, ITSs in vehicles are constantly being developed and usually referred to as advanced driver assistance systems (ADASs). Benefitting from the development of accurate positioning (e.g., via point precise positioning (*7*)), as well as vehicle-to-vehicle and vehicle-to-infrastructure communication technologies (*8*), a more advanced in-car system is envisioned, which can give instructions to drivers down to the lane level.

As a first step towards in-car algorithms for lane-change advice, a fundamental approach on controlling lane changes is proposed in this paper. The proposed algorithm cannot be implemented in-car, but shows what the effect of lane changes could be on traffic flow, and how optimization of lane change can improve the traffic flow. In addition, three different objectives are targeted respectively, they are: collective optimum, group optimum, and user optimum. By comparing the optimization results produced by following these objectives, general rules on good lane-change moments are extracted.

The remainder of paper is organized as follows: section 2 presents a literature overview of lane-change impacts and vehicle controls on lane change. In section 3, a problem formulation is presented, in which those three control objectives are elaborated. The next section describes the optimization algorithm implemented in this paper; a design of optimization process for reaching the user optimum is also elaborated in this section. Next, the settings in simulation and the development of a case study is introduced in section 5. In section 6, optimization results of the developed case under three objectives are presented and analyzed. The final section summarizes the findings and conclusions of this paper, it furthermore discusses a potential implementation of the results, and further research directions.

2. LITERATURE OVERVIEW

This section consists of two parts: the first part gives an overview of how lane changes can influence traffic efficiency; while the second part of this section presents studies on lane-change control approaches.

So far the impacts of lane changes have been investigated both empirically and theoretically. For empirical analyses, Jin collected vehicle trajectories on a highway during 75 minutes, and found that lane changes can generate significant capacity drops (*1*). He also proposed a new interpretation of lane change intensity to capture this impact. Observations from Cassidy et al. also provide empirical evidences for this impact (*9*). In addition, Zheng et al. pointed out that lane changes are predominately responsible for oscillation propagations and stop-and-go waves (*3*). Moreover, by modelling energy propagation in traffic flow, this argument is theoretically supported by him.

The lane-change Impacfts are theoretically analyzed in other studies as well. For instance, by modelling the density of each lane, Gazis et al. found that the traffic state of each lane on

1 highways can be disturbed by lane changes; in addition, the oscillation is unstable and easily
2 amplified in time (*2*). Besides, Daganzo describes lane flows by constructing a model of slugs
3 and rabbits (*10*). In the model, the rabbits indicate aggressive drivers with higher speeds and the
4 slugs indicate less aggressive drivers with lower speeds. Hereby, uneven lane distribution and
5 congestion created by lane changes can be explained by their behavioral patterns.
6   The studies above show that mitigating the negative lane-change impacts on traffic
7 efficiency are crucial to highway traffic operations; moreover, finding a feasible control
8 approach on lane change is necessary. Below, we list studies which present vehicle control
9 approaches on lane change.
10   Some control approaches target to improve the overall traffic state. For example, Schakel
11 et al introduced a rule-based control strategy for in-car advice (*6*). This strategy gives advice on
12 speed, headway and lane use to equipped vehicles based on detected or predicted unstable traffic
13 situations, which is referred to as "triggers" in the paper. In addition, a heuristic rule is described
14 to mitigate and resolve the traffic pressure on these situations. Being evaluated by the case study
15 in simulation, this strategy showed substantial improvement on traffic state. However, the
16 objective of individual drivers are not considered in the approach, nor is there an indication that
17 the results are optimal.
18   Moreover, an integrated traffic optimal control algorithm is presented by Roncoli et al.
19 (*5*) This algorithm takes traditional control actions into account, including ramp-metering,
20 mainstream traffic flow control, and lane-change control. Additionally, macroscopic
21 characteristics are considered to form cost functions (objective functions) of each lane-segment,
22 which is formed by a first-order multi-lane model of highway (*11*). An optimal problem with
23 linear constraints is formulated hereby to alleviate congestions. The optimization results
24 achieved through simulations also showed that this algorithm can improve traffic efficiency
25 significantly with a reasonable computational time. However, the implementation of this
26 algorithm requires a large penetration rate of equipped vehicles, so real-world testing of the
27 algorithm remains unpractical. Besides, the algorithm is not able to give advices on lane-change
28 maneuvers to individual drivers. There are other studies also attempting to give macroscopic
29 suggestions on lane change, such as facilitating lane distribution by variable speed limit near on-
30 ramps of highways (*12*), and optimizing the lane assignment by dynamic linear program (*13*).
31   Apart from facilitating the overall traffic state, there are works focusing on increasing
32 benefits for the controlled vehicle group. Interestingly, a game theoretical approach on
33 controlling predictive lane changes is proposed by Wang et al. (*14*). In this paper, two controlled
34 vehicles are considered, and both non-cooperative and cooperative control systems are
35 formulated. Particularly, controlled vehicles in the non-cooperative system only optimize their
36 own cost, while they jointly consider the group benefit in the cooperative system. A differential
37 game is formulated under the assumption that the controlled vehicles make their decisions based
38 on their expectations of other vehicles' behaviors. The framework of this algorithm is referential
39 and can be further extended to cases with a higher penetration rate.
40   Additionally, approaches like improving vehicles' safety and smoothing lane-change
41 trajectories by the game theoretical method (*15*, *16*, *17*), generating a feasible and safe lane-
42 change trajectory by controlling longitudinal and latitudinal accelerations in a dynamic model
43 (*18*), and accomplishing a smooth lane change by an integrated lane-change optimization
44 algorithm (*19*) present how users' benefit can be increased by controlling lane changes.
45

1

FL [2] →
Slow down

SL → →
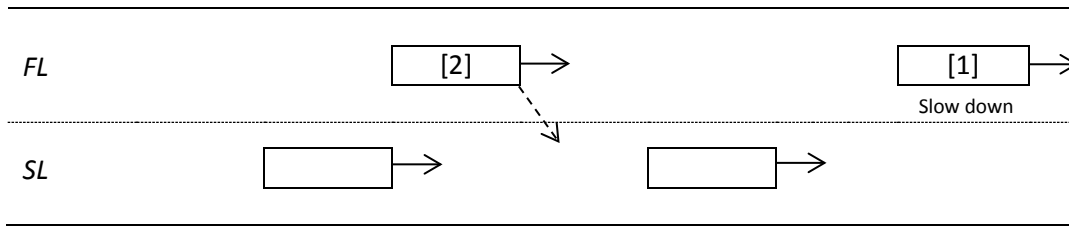
2 **FIGURE 1. Situation layout**
3   As the overview shows, the problem of controlling lane changes optimally, while
4 considering both cooperative and non-cooperative objectives, needs to be investigated further.
5 This paper aims to fill this gap by formulating an optimal control approach on lane change under
6 different objectives. Finally, this paper gives a general rule of selecting proper lane-change
7 moments by comparing optimization results.

8   **3. PROBLEM FORMULATION**

9 A two-lane straight road stretch is focused in this paper, FIGURE 1 depicts the scheme of the
10 research situation. In FIGURE 1, the solid arrows are driving directions, while the dashed arrow
11 is the changing direction. In this stretch, a fast lane (*FL*) and a slow lane (*SL*) are presented. This
12 paper considers the situation that the leader on the fast lane (vehicle [1]) has to reduce his speed
13 for a while, and thus forms a moving bottleneck. Consequently, vehicles downstream of vehicle
14 [1], such as vehicle [2] may want to change his lane to avoid delay. After overtaking vehicle [1],
15 they can go back to the fast lane. In this paper, the lane-change time instants are controlled
16 variables. Therefore, the actions of a controlled vehicle are defined to be a subset of moments
17 that he changes to the adjacent lane and back again . Newell's car-following model is assumed
18 for all the longitudinal movements in this paper. In addition, vehicles will not change their lane,
19 unless they are under control, and are suggested to do so.
20   In this section, controlled variables are optimized by forming various objectives, and they
21 are all formulized as the minimization of the total travel delay. Three objectives are formed, the
22 first two objectives are under the assumption that cooperation will exist in the control process,
23 while in the third objective, vehicles will not cooperate. These objectives are:
24   • Cooperative objective:
25   (1) Collective optimum
26   (2) Group optimum
27   • Non-cooperative objective:
28   (1) User optimum

29 The cooperative objectives are found by the collective and the group optimization, while the user
30 optimum is found within the framework of game theory. TABLE 1 provides an overview of the
31 symbols used in this paper.

32   **3.1.Cooperation objective**

33 For the cooperative objective, we assume that controlled vehicles will cooperate and compromise
34 in order to increase the collective or the group benefit. Accordingly, we form two objectives: one
35 is the collective optimum and the other is the group optimum.

1   **TABLE 1. Symbols and Description**

Symbol	Description
i	The index of vehicles
a_i	The set of actions taken by vehicle i, including two elements: the lane-change time instant from the fast lane to the slow lane, and the lane-change time instant from the slow lane to the fast lane of vehicle i
ar_i	The lane-change time instant of vehicle i from the fast lane to the slow lane
al_i	The lane-change time instant of vehicle i from the slow lane to the fast lane
A_I	The set of actions taken by all the vehicles within set I, which includes all the lane-change time instants
NC	The vehicle set including all the controlled vehicles
NT	The vehicle set including all the vehicles on road stretch
TTD_i	The total travel delay of vehicle i
$TTDist_i$	The total travel distance of vehicle i
T_{sim}	The total simulated time
Ve_i	The free flow speed of vehicle i

2

3   *3.1.1. Collective optimum*

4   For the first objective, the overall traffic state is supposed to be facilitated by lane changes of
5   controlled vehicles. The total travel delay of all vehicles is used to evaluate the traffic state in
6   this paper. Therefore, the optimized lane-change time instants of all the controlled vehicles are
7   formulated as:
8
9
$$A_{NC} = \operatorname*{argmin}_{A_{NC}} \left(\sum_{i \in NT} TTD_i(A_{NC}) \right) \qquad (1)$$

10   To be clarified, A_{NC} is the action set of controlled vehicles, which contains their lane-change

11   time instants, namely $a_i \in A_{NC}, \forall i \in NC$. Note that in this definition, the action of each vehicle

12   consists of two elements, which are the moment of changing lane and the moment of changing

13   back, for instance: $a_1 = \{ar_1, al_2\}$.

14   By equation (1), all vehicles driving on the road stretch will benefit from their lane
15   changes, and the controlled vehicles will cooperate to each other to achieve the objective.

16   *3.1.2. Group optimum*

17   For the group optimum, the controlled vehicles will cooperate in order to optimize the total travel
18   delay among this controlled group. Analogously, the optimized lane-change time instants of
19   controlled vehicles are formulated as:
20
$$A_{NC} = \operatorname*{argmin}_{A_{NC}} \left(\sum_{i \in NC} TTD_i(A_{NC}) \right) \qquad (2)$$

1 3.2.Non-cooperative objective

2 Alternatively, we can assume that drivers will not cooperate, but compete to each other for the
3 best travel time. It is conceivable that the optimal solution for these competitions will be an
4 action equilibrium among controlled vehicles, in which "nobody can benefit from changing his
5 action individually", similar to a Nash equilibrium (*20*). As the controlled vehicles are supposed
6 to anticipate in each other's lane changes, we formulate the optimization under the framework of
7 game theory.

8 *3.2.1. Game definition*

9 In this case, the process of finding the optimal lane changes is considered as a game.
10 Accordingly, a multi-player, completed information and static game is formed, meaning that all
11 the players are aware of the complete information set and make their decision simultaneously.
12 Hereby, the game between controlled vehicles is defined as: (*20*)

$$\text{G}=\langle NC, A, \text{u} \rangle \tag{3}$$

14 Symbols will also be rephrased in game theoretical framework:

15 • NC denotes the players, which are controlled vehicles in this case, it is a finite set of *n*
16 and indexed by *i*, $NC = \{1, 2, ..., n\}$.

17 • A is an action profile, $a = \{a_1, ..., a_n\} \in A = A_1 \times ... \times A_n$. Where a_i denotes the action of
18 player *i*, which is the lane-change time instant pair of vehicle *i* (ar_1 and al_2).

19 • u is a profile of pay off functions, $u_i = \{u_1, ..., u_n\}$, and u_i denotes the utility function of
20 player *i*. Analogously, the utility functions are represented by the total travel delay of
21 each vehicle (TTD_i).

22 *3.2.2. Optimization formulation*

23 A game in the normal form is described in this objective, based on the nature of game that we
24 designed previously, all players will decide their actions simultaneously and optimize their
25 individual total travel delays. The action profile of this multi-player game is formulated as:

$$
26 \quad
\begin{cases}
a_1 = \underset{a_1}{\text{argmin}}(TTD_1(a_1 | A_{NC/\{a_1\}})) \\
... \\
a_n = \underset{a_n}{\text{argmin}}(TTD_n(a_n | A_{NC/\{a_n\}}))
\end{cases}
\tag{4}
$$

27 This optimization process will find an action set a_i^*, and lead to an equilibrium, in which:

$$\forall a_i \in A_i, TTD_i(a_i^*, a_{-i}) \le TTD_i(a_i, a_{-i}) \tag{5}$$

1 Where a_{-i} denotes the action sets taken by other players. The inequality (5) indicates that in the
2 equilibrium, "nobody can profitably deviate from their actions" (*20*), so that their actions depend
3 on each other. Therefore, one of the approximate pure Nash equilibrium is reached in this
4 situation, and it is considered as the individual optimum in this paper.

5 **4. OPTIMIZATION**

6 This section describes the optimization algorithm. First, section 4.1 describes the genetic
7 algorithm used for optimizing the group and collective optimum, and section 4.2 describes how
8 the optimum is found for the individual optimum. Readers interested in the result, can move on
9 to section 5.

10 **4.1. Heuristic algorithm**

11 Three non-linear integer optimization problems are formed in section 3, we choose a genetic
12 algorithm (GA) to solve them due to the complexity of problems. In the algorithm, individuals
13 are evolved towards a better performance of one certain optimization, and iterations of the
14 evolution are denoted as generations. The evolution follows the process of encoding,
15 initialization, crossover, selection and mutation; hereby, the last three steps are iterated until
16 reaching the stop criteria. These steps are elaborated as follows:
17 (1) Encoding: In this algorithm, each action set (A_{NC}) is considered as one individual. Note
18 that one individual contains actions of all controlled vehicles. Each lane-change moment
19 is coded in a string of 11 binary numbers. This string is called a chromosome. We choose
20 11 as the fixed length of chromosome to cover sufficient time instants, and the property
21 of fixed size makes those chromosome pairs are easily aligned (*21*).
22 (2) Initialization: 30 individuals are generated initially, elements within individuals are
23 restricted by constraints:

$$24 \quad \begin{cases} a_i = \{ar_i, al_i\} \\ LB < a_i < RB \\ ar_i \leq al_i \end{cases} \quad (6)$$

25 Where *LB* and *RB* indicate the pre-defined lowest and highest boundaries. By the
26 constraints, the controlled vehicles will change back to the fast lane only after changing
27 to the slow lane.
28 (3) Crossover: Two chromosomes in an individual are randomly chosen as parental
29 chromosomes, then a crossover point is randomly selected. These two chromosomes will
30 break from the crossover point into four sub-chromosomes, two children chromosomes
31 will generate eventually by exchanging and recombining those four sub-chromosomes.
32 This procedure is depicted by FIGURE 2(a)
33 (4) Selection: The probability of selecting one individual for the next generation is based on
34 the value of its fitness function. Objective values of all the individuals in g^{th} generation
35

(a) Crossover

Individual before
mutation

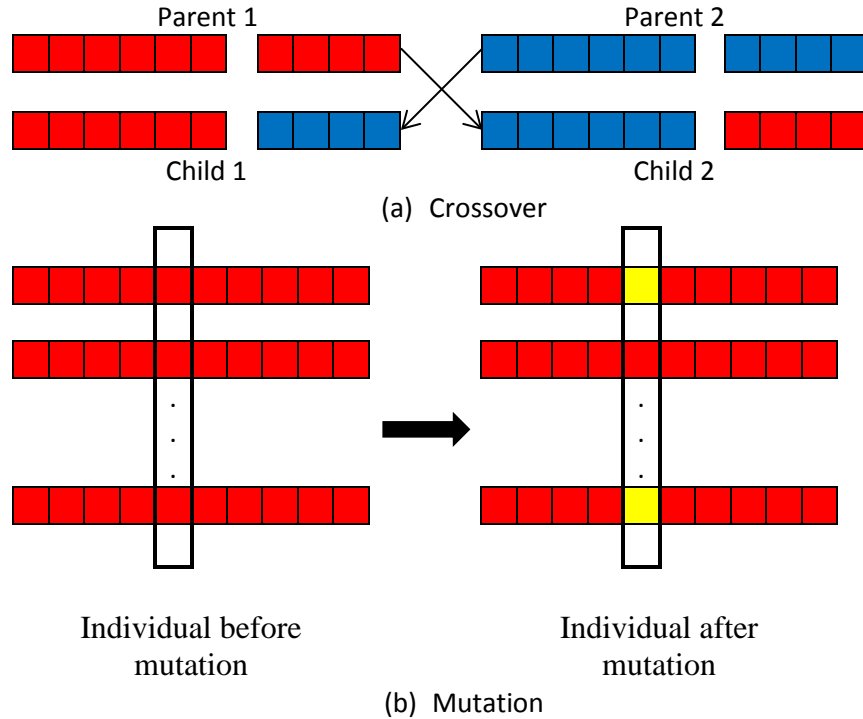Individual after
mutation

(b) Mutation

FIGURE 2. Crossover and mutation in GA

are calculated initially ($TTD(g)$), and the fitness function of individual $indi$ is calculated by:

$$fit(indi) = \max TTD(g) + 1 - TTD(indi, g) \tag{7}$$

Where $TTD(indi, g)$ indicates the total travel delay derived from individual $indi$ in generation g, and $\max TTD(g)$ indicates the maximum value of all total travel delays derived from individuals in generation g. From equation (7), the individual which can derive a shorter total travel delay will have a higher value of fitness function; in addition, the lowest value of fitness function is 1. Hence, the selected probability of individual $indi$ is formulated as:

$$p(indi) = \frac{fit(indi)}{\sum_{indi \in Pop} fit(indi)} \tag{8}$$

Where Pop indicates the population that includes all the individuals in a generation. By equation (8), the selection probability of each individual is proportional to its fitness function. By implementing this method, the child with a better fitness value has a higher probability to be selected, meanwhile the child with a lower fitness value will not be eliminated completely.

(5) Mutation: firstly, a mutation position will be randomly chosen. After this position for a possible mutation has been selected, it is chosen whether the values at this position will change (probability 0.1) or not (probability 0.9). A demonstration of mutation is shown in FIGURE 2(b).

1   (6) Stop criteria: the iteration will stop if: (1) the maximum iteration threshold is reached, or
2   (2) both the average objective value and the best objective value stop improving.
3   The first criterion guarantees this optimization algorithm will operate within a
4   reasonable computational time; while the second criterion indicates a relatively optimal
5   individual is selected and this optimal individual is within an optimal generation.

6   **4.2. Optimization process for individual optimum**

7 Except for the optimization algorithm, an optimization process is designed to find the
8 approximate Nash equilibrium in the individual optimum, by the equation:

9
$$a_i^k = \arg\min_{a_i^k}(TTD_i^k(a_i^k \mid a_1^k,...,a_{i-1}^k, a_{i+1}^{k-1},...,a_n^{k-1})) \tag{9}$$

10 Where a_i^k denotes the action set of vehicle i in iteration k and TTD_i^k denotes the total travel
11 delay of vehicle i in iteration k. In the process, k is iterated from 1 to the final iteration K, in
12 which all the optimized action sets stop changing significantly; while in each iteration, i is
13 iterated from 1 to the total number of controlled vehicles n. As an initialized value, a_i^0 is
14 generated randomly in section 4.1. The equation means that in the kth iteration, we find the
15 optimum for vehicle i by assuming the actions from kth iteration for vehicle 1 to vehicle i-1, and
16 the actions from the k-1th iteration for vehicles with an index higher than i.
17   By the process, the actions of all the controlled vehicles will converge to a preferred
18 profile, from which nobody will profit by deviating; as a result, the optimized results can be
19 considered as a pure Nash equilibrium.

20   **5. SIMULATION SETTINGS**

21 In this paper, lane change is considered at a conceptual level, namely they are simplified in
22 several aspects:
23   • Vehicles are point particles, so they cannot collide when changing lanes.
24   • Vehicles do not change lanes, unless they are instructed to do so by the algorithm in
25   section 3.
26   • Lane-change actions are considered as an instantaneous movement.

27 The optimization algorithm is tested in a microsimulation. In the simulation, the two-lane
28 straight road stretch, without any on-ramp and off-ramp, is developed, which has a pre-defined
29 critical density of 25veh/km/lane. 120 vehicles are generated and evenly distributed on each
30 lane, the free flow speed of each vehicle is assigned randomly under the restriction of speed limit
31 in each lane (80-100 km/h in the slow lane and 100-130 km/h in the fast lane). The headways are
32 manually initialized, several platoons are formed by introducing some large gaps. Vehicles
33 behave according to Newell's simplified car following model, in which the longitudinal
34 movement is limited by leaders' trajectories transposed in time (0.1 second in this paper) and in
35 space (inverse of jam density, varying per vehicle) (22). The simulation is sliced in time steps of
36 0.1 second, and the simulated time (T_{sim}) will be 120 seconds. Additionally, these two lanes are
37 coupled in the simulation, which means when a vehicle changes his lane, he will appear on his
38 target lane one time step after disappearing on his current lane.

1   Subsequently, a case study is formed in the simulation, which describes a typical traffic
2   situation of triggering lane changes. In this case, vehicles are driving on the two-lane road stretch
3   by lane specific speed restrictions, while one vehicle on the fast lane is disturbed by some
4   external factors and reduces his speed for a time period. Consequently, this vehicle forms a
5   moving bottleneck that can influence the traffic state downstream of him. Note that that the
6   leading vehicle's deceleration on the fast lane is the only disruption considered in this paper.
7   Besides, the drivers' preferences will not be considered. Examples of simulated trajectories
8   without lane change is presented in FIGURE 3, in which trajectories are depicted for each fifth
9   vehicles:
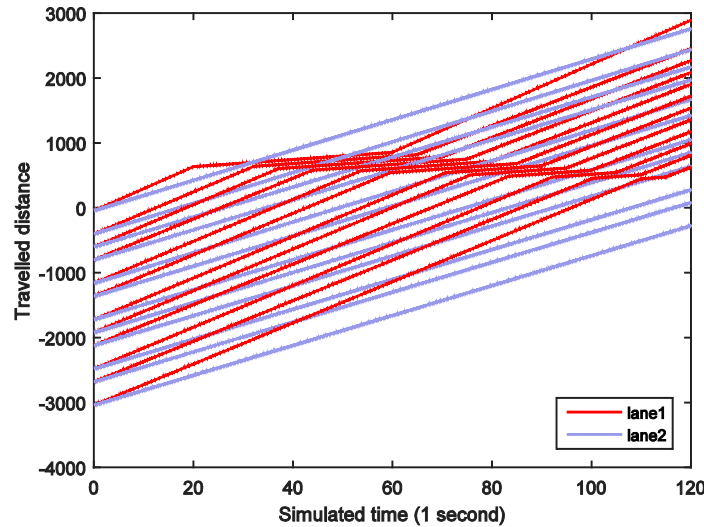
10
11   **FIGURE 3. Simulated trajectories without lane change**
12   In the case study, the controlled vehicles can change their lane, overtake the bottleneck and
13   change back to the fast lane to avoid travel delay. All the controlled vehicles must change to the
14   slow lane first, and change back to the fast lane afterwards. The time instances at which they do
15   are determined by the controller.
16   Both objectives of the collective optimum, the group optimum and the user optimum are
17   found in the case study. In this paper, a group of five vehicles (with vehicle indices of *12, 17, 22,*
18   *32* and *37*) are controlled vehicles, belonging to different platoons. Optimizations are deduced
19   from minimizing the total travel delay of different vehicle groups, where the *TTD* of vehicle
20   group *I* can be formulated by:

21 $$\sum_{i \in I} TTD_i = \sum_{i \in I} T_{sim} - TTDist_i(A_{NC}) \Big/ Ve_i \qquad (10)$$

22   Mentioned by Papageorgiou et al., the total delay can be derived from the travel times (*23*).
23   Since the end time of the simulation is fixed, while the end location of each vehicle is influenced
24   by the controller, we will work with the distance covered. In this case, the total delay and the
25   travel times can convert to each other, since the speed is constant. From the equation, the total
26   travel delay of vehicle group *I* can be considered as the difference between their expected travel
27   time (travelled by their free flow speed) and their actual travel time (identical to simulated time,
28   1200 second). Specifically, in the collective optimum, $I = NT$ and in the group optimum,
29   $I = NC$; while in the individual optimum, *I* indicates each single controlled vehicle.

1   In this paper, simulations and optimizations are operated in MATLAB. A single
2 optimization costs 660 seconds on average (single-core performance on an Intel Core i7-5600U
3 2.60GHz CPU). The optimization results are elaborated in the next section.

4 **6. RESULTS**

5 In this section, we will analyze the effects of lane changes, especially the effects on traffic
6 operations. To this end, we use the following quantitative criteria:

7   • The average delay of vehicles which originally drive on the slow lane. It shows to what
8   extent lane changes disturb the slow lane.
9   • The average travel duration on the slow lane of controlled vehicles. It shows to what
10   extent the controlled vehicles are comfortable with adapting to a slower speed.
11   • The average accepted merging gaps for controlled vehicles. It shows how much the
12   controlled vehicles are willing to disturb the traffic state.
13   • The average number of vehicles that have been overtaken by controlled vehicles. It shows
14   how much users' benefit the controlled vehicles are able to achieve.

15 Optimization results of three objectives are presented in FIGURE 5. Besides, TABLE 2 lists the
16 values of the criteria and objective functions (*TTD*) under the three different objectives. In
17 addition, FIGURE 5 shows the convergence of action set in the process of solving the individual
18 optimum.
19   In FIGURE 5, red lines indicate trajectories on the fast lane, blue lines indicate
20 trajectories on the slow lane, they are depicted for each fifth vehicles. The vehicles are numbered
21 from downstream to upstream, i.e., from top to bottom. Thicker lines represent controlled
22 vehicles and thinner line are trajectories of other vehicles. The lane-change time instants of all
23 the controlled vehicles are marked by yellow dots.
24   In the collective optimum, the total travel delay of all vehicles is optimized and the
25 trajectories are shown in FIGURE 5(a). It can be observed that vehicle 12, 17 and 37 change to
26 the slow lane before the bottleneck, and change back to the fast lane after the bottleneck;
27 additionally, vehicle 12 overtakes the moving bottleneck and becomes the new leader on the fast
28 lane. Vehicle 22 performs his all actions after the bottleneck and vehicle 32 performs two lane
29 changes before the bottleneck.
30   By this optimum, all the controlled vehicles were trying to perform their actions in a
31 proper gap, for the purpose of minimizing the negative effects on the overall traffic state. This
32 argument is strengthened by some action characteristics of controlled vehicles. For instance,
33 vehicle 12 and 17 did not change back to the fast lane immediately after passing the slow-
34 moving section, they travelled on the slow lane until there was a bigger gap to merge. In
35 addition, vehicle 22 and 32 did not avoid delay by their lane-change actions, they travelled
36 through the congested section instead.
37   Additionally, the collective optimum has the longest average travel duration on the slow
38 lane (33 seconds) and the largest average merging gap (114 meters). Hence, compared to the
39 other two optima, the controlled vehicles by this optimum can overtake the least number of
40 vehicles (3.8 in average) and the vehicles on the slow lane have the lowest average delay (148
41 seconds).

For the group optimum, the trajectories are shown in FIGURE 5(b). Analogously, it can be observed that when the controlled vehicles perform their lane changes, finding proper gaps is also prior to overtaking the bottleneck by this optimum.

However, compared to the collective optimum, more controlled vehicles are able to overtake the congested section by changing lanes in the group optimum. Moreover, the average travel duration on the slow lane is shorter (21 seconds) and the average merging gap is smaller (110 meters) in this optimum. These results can be predicted from the different considerations on proper gaps in the collective and the group optimum: in the group optimum, the controlled vehicles compromise to each other rather than compromising to uncontrolled vehicles to maximize their group benefit; however, other vehicles may suffer from their actions. In addition, this argument is strengthened by a lager average delay of vehicles on the slow lane (151 seconds) and a bigger number of overtaken vehicles (7.4 in average) in this optimum.

The trajectories in the user optimum is depicted in FIGURE 5(c), in which the controlled vehicles fight for their own benefits, by knowing the actions of other controlled vehicles. It can be observed from FIGURE 5(c) that the trajectories of controlled vehicles are smoother than their trajectories in the collective optimum and the group optimum.

Compared to the other two optima, the user optimum has the lowest average travel duration on the slow lane (16 seconds) and the smallest average merging gap (54 meters). By this optimum, more vehicles will be overtaken by controlled vehicles (11 in average) and vehicles on the slow lane have the largest average delay (165 seconds). The results reveal that all the controlled vehicles try to overtake the bottleneck, rather than finding a proper gap in this optimum. In addition, they try to shorten their travel durations on the slow lane. This optimum could describe the most common situation in reality, in which drivers try to increase their own benefit based on their expectations, regardless of the fact that the traffic state could deteriorate by their actions.

Generally speaking, the more the controlled vehicles consider only their own benefit, the less they will cooperate with others. Hence, they will merge in a smaller gap and drive on the slow lane for a shorter duration. Consequently, the traffic state of the slow lane will be disturbed more and controlled vehicles will be able to overtake more vehicles.

In short, values of objective functions in the collective optimum, the group optimum and the user optimum are included in TABLE 2. Compared to the collective optimum, the collective travel delay is less in the group optimum, while the controlled vehicle group benefit from it and the user's *TTD* of all controlled vehicles is reduced. In the user optimum, it is observed that the values of collective *TTD* and group *TTD* are between the corresponding values in the collective optimum and the group optimum, the users' *TTD* also deviates from the values in the other two optima. However, as the Nash equilibrium is reached by this optimum, each controlled vehicle is supposed to have a higher *TTD* if he changes his action, given the action profile of other four controlled vehicles.

In general, both the overall traffic state, the controlled group and each controlled vehicle can benefit from optimized lane changes compare to the original situation (no lane change).
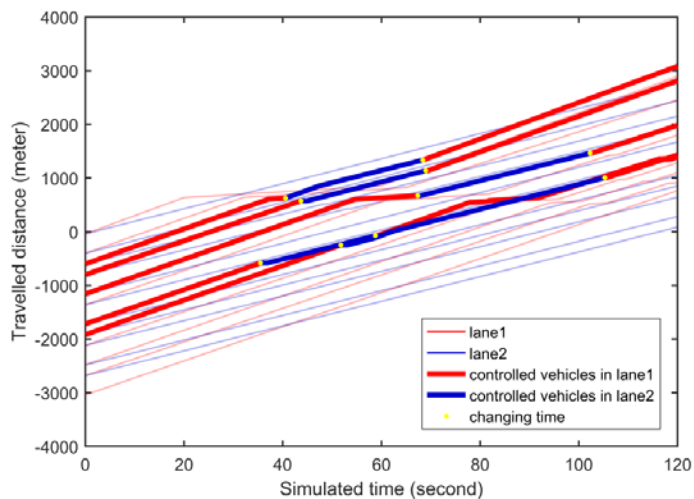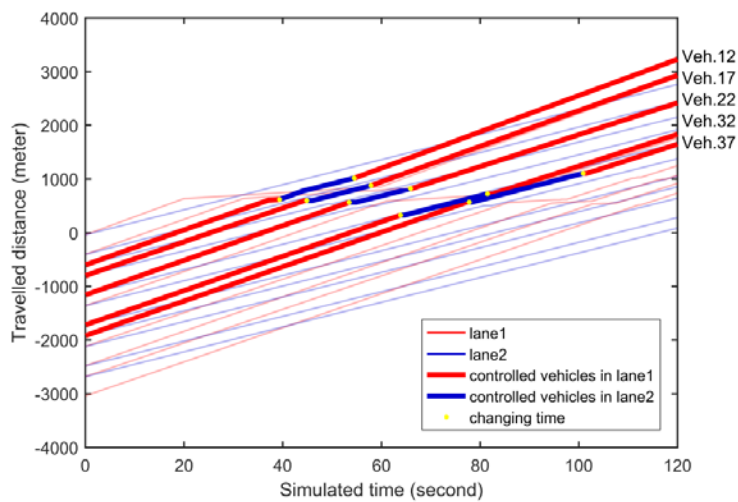
(a) Collective optimum
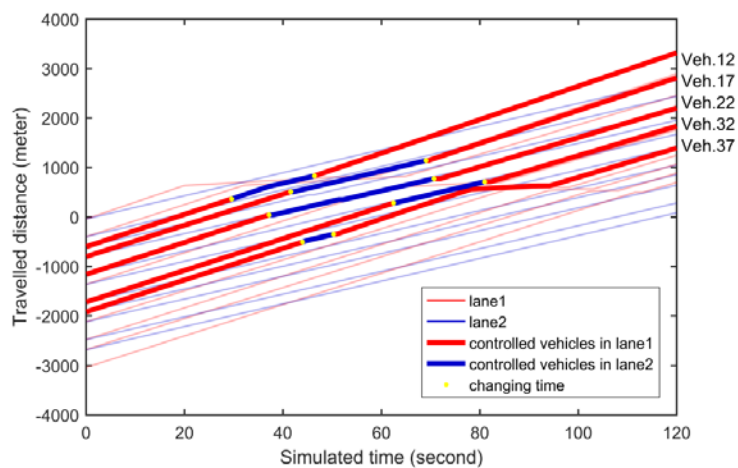
(b) Group optimum

(c) User optimum

FIGURE 5. Simulated trajectories in three optima

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<div align="center">TABLE 2. Lane Change Criteria</div>

Objectives	Collective optimum	Group optimum	User optimum	No lane change
Average delay on lane 2 (second)	148	151	165	-
Average duration on lane 2 (second)	33	21	16	-
Average merging gap (meter)	114	110	54	-
Average overtake vehicles	3.8	7.4	11	-
Collective TTD (second)	1616	1654	1642	1777
Group TTD (second)	100	59	75	146
TTD of vehicle 12 (second)	11	7	4	35
TTD of vehicle 17 (second)	11	7	11	33
TTD of vehicle 22 (second)	31	18	25	33
TTD of vehicle 32 (second)	25	13	13	22
TTD of vehicle 37 (second)	22	14	22	23

2 **7. DISCUSSION AND CONCLUSION**

3 This paper investigates the influence of objectives on lane-change optimization. Three
4 optimization problems are formulated based on three objectives, which are: the collective
5 optimum, the group optimum and the individual optimum. These optimizations are solved by
6 employing a genetic algorithm (using game theory for the individual optimum).
7 The different results indicate that the controlled lane-change actions can differ for
8 objectives of different groups. In addition, optima with less cooperation will introduce more
9 disturbance in the traffic state, have a lower requirement in merging gaps, travel a shorter
10 distance on the slow lane and have more overtaken vehicles.
11 Generally speaking, equipped vehicles controlled by the objective of collective and group
12 optima will be suggested to launch the lane change when a larger gap is available, as well as to
13 drive on the slow lane for a longer time. On the contrary, by the individual optimum, vehicles
14 will be suggested to change to the slow lane when the congestion is encountered, and to change
15 back when it has overtaken the bottleneck.
16 One limiting factor in this work is the simple simulated network, with a simplified car
17 following model; additionally, the global optimum cannot be guaranteed by employing genetic
18 algorithm (GA). Furthermore, in the user optimum, the action equilibrium can only be
19 approximately found by implementing the optimization process, and the optimization sequence
20 in the process can influence the final results. Besides, the benefits of the overall traffic state and
21 each controlled vehicle could be influenced by the initial location of the controlled vehicles. In
22 addition, the sequence of controlled vehicles could also influence their individual benefits in
23 each optimum. These relationships should be further investigated.
24 Nonetheless, a structure of formulating lane-change control problems is developed, and
25 this structure can be consistently implemented in a more effective control system. Without
26 calculations in optimization algorithm, this system will instruct vehicles to change lane during a
27 bigger gap and drive on the slow lane as long as possible to improve the collective or the group
28 traffic efficiency. On the contrary, controlled vehicles will be instructed to overtake as many
29 vehicles as they can to maximize their own benefit.
30 As a theoretical overview of the lane-change optimal control is given, the proposed
31 algorithm can be further extended and implemented in intelligent driving systems, such as in-car

advice system, more precise and advanced navigation systems and traffic control systems. The next step is to convert the results found by the full optimization in this paper into simple algorithms implementable in vehicles, by which the computational consumption will be drastically reduced, and the algorithm will have a wide prospect in the development of real time advice or intelligent driving systems.

For researches in the future, the estimation on lane specific traffic state will be embedded into the optimization, and effort will be put on reducing computational consumption. Moreover, to be more practical, predictive models on lane-change behavior and lane specific traffic state will also be embedded.

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