Collaborative Fault Tolerant Control of Non-Signalized Intersections for Connected and Autonomous Vehicles

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***Abstract*—With the potential of increased penetration of connected and autonomous vehicles (CAVs), intersectional signal control faces new challenges in terms of its operation and implementation. One possibility is to fully make use of the communication capabilities of CAVs so that intersectional signal control can be realized by CAVs alone – this leads to non-signalized intersectional operation for traffic networks in urban areas. In this paper, the state-of-the-art on collaborative fault tolerant control schemes for complex systems will be briefly described. This is then followed by the formulation of operational fault tolerant control that realizes the collaborative fault tolerance functionality at CAVs operational level in response to possible individual vehicle faults, where detailed modelling using vehicle movement dynamics will be described together with the construction of fast fault diagnosis and a collaborative fault tolerant control algorithm. A simple example will be given as well to demonstrate the proposed algorithm together with the discussions on other issues such as randomness of the system, communication errors and full energy consideration. These leads to several future directions of the research for the traffic flow control of non-signalized intersections with 100% penetration of CAVs.**

Keywords—Intersectional signal control, Connected and Autonomous Vehicles (CAVs), Fault diagnosis, Fault tolerant control, Simulation.

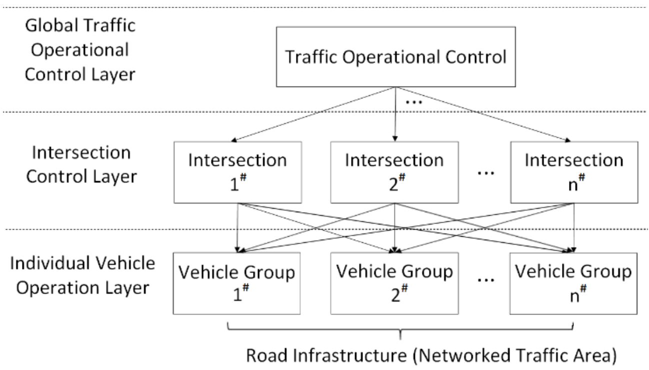
I. INTRODUCTION

Operation of complex systems such as traffic network and industrial processes involves multiple layers of control systems that work collaboratively to fulfill the required operation. For example, in transportation systems there is a generic three-layered operational structure as shown in the Figure 1, where the top layer performs traffic monitoring and management whilst the intersection layer looks after the distributed traffic signal-timing control for each intersection so as to ensure a smooth traffic flow with minimized congestion over a concerned urban area characterized by some networked intersections. In this context, intersection control plays a key role that ensures effective and safe passage of vehicles. Indeed, fixed timing traffic light control and adaptive signal control have been developed ([1] - [2]) over the past decades. In these signal control methods, the signal timing (i.e., the duration of green, red and yellow color of the traffic lights at intersections) is regarded as the control input and the traffic flow density or queueing length distribution is taken as the output ([14]).

The ultimate purpose of traffic signal control is to control the signal lights timing so that a smooth traffic flow can be realized at intersections with minimum energy consumption.

a) Signalized intersection

b)Non-signalized intersection



c) Three-layered operational control for traffic flow networks

Fig. 1. Signalized vs non-signal intersections control (picture source: www.google.com).

With the potential of increased penetration of connected and autonomous vehicles (CAVs) on the road in the near future, vehicles near intersections can now ‘talk’ to each other via their communication capabilities. This achieves the exchange of vehicle state information in terms of speed and position among them. For example, each vehicle would have the information on speeds and positions of other surrounding vehicles near their approaching intersections, and such extra information can effectively be used to manage the movement of the concerned vehicle when passing through the intersection. Indeed, using the speeds and positions information of other surrounding vehicles, the control systems of the concerned vehicle can pro-actively control its own speed and position in order to realize a smooth and effective intersectional passage with minimal energy consumption. This means that a possible solution would be to allow these CAVs to manage and optimize their intersectional passage by themselves rather than passively relying on the traffic signals. An eminent advantage would be that there is no need to install costly signalized traffic infrastructure at intersections, which would greatly simplify the intersection control.

In this context, intersectional signal control faces the following new challenges in terms of its operation and implementation,

1) How the communication capabilities of CAVs can be leveraged to develop control strategies that allow these CAVs to manage and control themselves when passing through non-signalized intersections;

2) If a CAV has a fault how other CAVs can autonomously control themselves in a fault tolerant way so that they can still pass through the intersections safely with a good speed profile.

This leads to non-signalized intersection operation for traffic networks and one of the key requirements is safety and smooth passage. This requires the development of fault diagnosis and collaborative fault tolerant control for the CAVs approaching and departing from the concerned intersections in terms of safety, smooth passage and minimum energy consumption.

Indeed, during the operation of these non-signalized intersections, smooth and safe movement of vehicles is an important issue that ensures the achievement for smooth traffic flow without accidents. Although some work has been carried out to analyze non-signalized intersection systems, these are largely performed for human-driven vehicles ([3] – [4], [8] – [9]), where passive analysis has been made together with system modeling on the characteristics of human-drivers' behaviors at these intersections. On the other hand, much research has been carried out on the collision avoidance among vehicles ([10] – [11]). This can be regarded as a prototype collaborative control between two or three vehicles when they are at risk of collision. However, the communications between the concerned vehicles have not been fully used and the number of vehicles under consideration is small. In this regard, collision avoidance is only a safety precautionary measure and is an added functionality for individual vehicles rather than their grouped collaborative controls. As a result, when a fault occurs in a vehicle it is important to establish novel fault tolerant control strategies that can be used by CAVs to collaboratively control themselves when passing through non-signalized intersections by making use of their communication capabilities among themselves so as to pass through the intersection safely at their maximum allowable speed with minimized energy consumption.

This forms the main topic of this paper, where modelling considering CAVs communication capabilities, fault diagnosis and collaborative fault tolerant control for CAVs near non-signalized intersections will be described – leading to a novel control strategy that ensures how healthy CAVs can pass through the non-signalized intersection safely, smoothly and also at maximum allowable speed. For this purpose, in the next section a brief review of fault detection, diagnosis and tolerant control will be given.

II. FAULT DIAGNOSIS AND FAULT TOLERANT CONTROL

A. Fault Detection and Diagnosis.

Given a dynamic system with available input and output, fault detection aims at using available inputs and outputs to detect the fault in the system. On the other hand, fault diagnosis (FD) and fault tolerant control (FTC) have been well developed over the past decades for control systems, where the purpose of FD is to estimate the fault in the system using available information such as inputs and outputs of the concerned system ([13]), and the purpose of fault tolerant control is to use the fault diagnosis result to reconfigure the controller so that the whole system may continue to operate safely until an economic repair is made ([15]). Indeed, depending upon the system representation, fault diagnosis can be performed using either the observer-based approach or system identification-based approach, whilst fault tolerant control can be realized in either passive or pro-active ways. As for the types of the fault, it can be either the actuator fault, or system fault or even sensor faults as shown in Figure 2, where *F* stands for the possible faults in different parts in a closed loop system. Of course, sometimes there are also faults in the controller itself, for example to represent the malfunctioning of the control software and hardware.

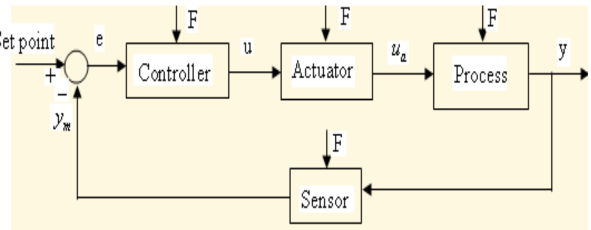


Fig. 2. Possible faults in a closed loop system.

In terms of the algorithm structure, Fig. 3 shows how a fault diagnosis can be implemented in a software perspective. Once a fault is detected and further diagnosed, its estimate will be considered in the construction of fault tolerant control where both structure and control parameters can be tuned in real-time for a continued safe operation of the system.

B. Collaborative Fault Tolerant Control.

In 2005, a novel concept has been reported in ([11], [17]) on the collaborative fault tolerant control. The key idea is to consider complex systems composed of a number of sub-systems, where if a fault takes place in a sub-system then other healthy system can pro-actively tune the control systems in a fault tolerant way so that the whole complex system can still function safely. This novel concept has also been applied recently to serially connected stochastic distribution systems ([5]). In this case, two sub-systems have been considered, where the output of the first sub-system provides a boundary condition to the second sub-system. It has been demonstrated that the effect of the fault onto the operation of the closed loop system can be significantly reduced – leading to a safer operation of the concerned system.

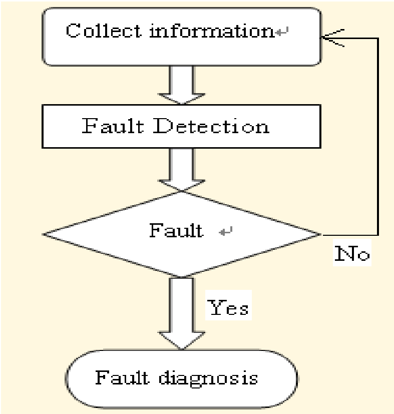


Fig. 3. Software structure of FD.

In this paper, the formulation of operational fault tolerant control will be made that realizes the collaborative fault tolerance functionality at CAVs operational level in response to possible individual vehicle faults. The detailed modelling using vehicle movement dynamics will be described together with the construction of fast fault diagnosis and tolerant control algorithms. An example will be given in order to demonstrate the effectiveness of the proposed algorithm together with discussions on future directions. In this context, the modelling for the dynamics for CAVs approaching an intersection will be firstly described in the next section.

III. DYNAMICS FOR CAVS APPROACHING AN INTERSECTION.

Taking each CAV approaching an intersection as a subsystem (i.e., an autonomous agent), then these subsystems should work together in a collaborative fault tolerant way to maximize the throughput of traffic flow when a fault occurs in a vehicle. This belongs to a collaborative fault tolerant control for multi-agent systems ([5], [11]) subjected to various constraints, where modelling, fault diagnosis and collaborative fault tolerant control should be carried out.

We consider an *N* number of CAVs approaching an intersection as shown in Figure 4, and assume that for *i = 1, 2, …, N*, the dynamics of the ith CAV is a self-closed loop system whose position and speed are denoted in a 2D plane shown in Figure 4 as

$$x_i = \begin{bmatrix} p_i \\ q_i \end{bmatrix}; \ \frac{dx_i}{dt} = \dot{x}_i = \begin{bmatrix} \frac{dp_i}{dt} \\ \frac{dq_i}{dt} \end{bmatrix}; (i = 1, 2, \dots, N)$$

where p_i stands for the longitude movement and q_i represents the latitude movement (i.e., lane changes) of the ith CAV in Figure 4. In this case the longitude movement is for the direction of the vehicle moving forward and the latitude movement is for lane changes.

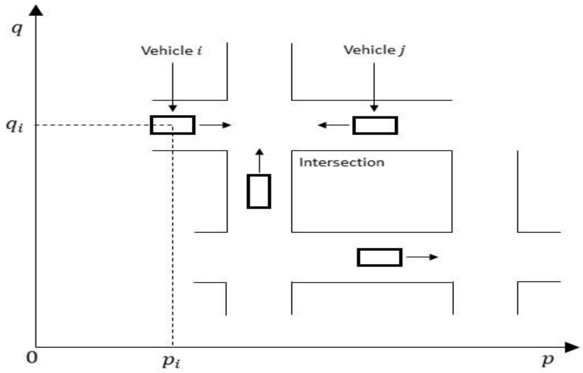


Fig. 4. A simple intersection with CAVs.

The position and speed are the two group of state variables defined as follows,

$$X_i = \begin{bmatrix} x_i \\ \dot{x}_i \end{bmatrix} \in R^4; \quad (i = 1, 2, \dots, N) \tag{1}$$

In this regard, the dynamics of the ith CAV (the ith agent or sub-system) can be expressed in the following form

$$\dot{X}_i = A_i X_i + B_i r_i + \sum_{i \neq j}^{N} C_{ij} X_j + E_i f_i \tag{2}$$

where $\{A_i, B_i\}$ are the assumed known parameter matrices that represent the own dynamics of the concerned CAV of appropriate dimensions, C_{ij} are the communication coefficient matrices that represent the communication capabilities between the ith and the jth CAVs, indicating the availability of vehicle-to-vehicle (V2V) information exchanges. If there is no communication between the ith and the jth CAVs, then $C_{ij} = 0$. In equation (2), r_i is the set-point of the position trajectory of the ith CAV.

It can be seen that, rather than using double integrals model ([9] – [10]) to represent the dynamics of each CAV, here we assume that each CAV has a fully automated system which only accepts the position set-point trajectory as the closed loop input. This allows us to simply model the dynamics of each CAV as a local closed loop system where the input to the vehicle is in fact the set-point of the position trajectory and the output is its actual position trajectory. This is a simplified local closed loop model as the speed (either actual or its set-point) can be obtained by the first order derivative operation of the position. In this way, we can model each CAV as a linear system albeit the dynamics inside a local open loop system at vehicle level can be nonlinear.

In equation (2), f_i is the fault for the ith CAV and if $f_i = 0$ then the ith CAV is considered healthy (no fault), otherwise it is considered as having a fault occurring in its system. This is a generic representation of the fault in a CAV and can stand for sensor faults, actuator faults and faults in the powertrain, etc. Also, E_i in equation (2) is the parameter matrix that shows how the fault is to affect the system dynamics.

It can be seen that the state vector (1) is always measurable and its V2V information is also available for other CAVs in the concerned vehicle group near the intersection. If we define the whole state vector as

$$x^T = [X_1^T \quad X_2^T \cdots X_{N-1}^T \quad X_N^T] \in R^{1\times 4N} \tag{3}$$

Then the whole connected system can be expressed using the following compact multi-variable state space model format

$$\dot{x} = Ax + Br + Ef \tag{4}$$

with the following output equation only for the position trajectory of each CAV.

$$y = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = Fx; \quad F = diag(\aleph, \dots, \aleph);$$

$$\aleph = [1 \quad 0] \tag{5}$$

In equation (4), it has been denoted that

$$A = \begin{bmatrix} A_1 & C_{12} & \cdots & C_{1N} \\ C_{21} & A_2 & \cdots & C_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ C_{N1} & C_{N2} & \cdots & A_N \end{bmatrix} \in R^{4N\times 4N};$$

$$B = diag(B_1, \dots, B_N) \in R^{4N\times 2N}$$

$$E = diag(E_1, E_2, \dots, E_N) \in R^{4N\times N};$$

$$f = \begin{bmatrix} f_1 \\ \vdots \\ f_N \end{bmatrix} \in R^N; r = \begin{bmatrix} r_1 \\ \vdots \\ r_N \end{bmatrix} \in R^{2N}.$$

It can be seen that equations (4) – (5) represent the group dynamics of the concerned CAVs approaching an intersection. This is the standard state space equation where the fault vector f is in a generic form that can represent either actuator, system, sensor or controller faults of a CAV.

To ensure a safe movement of this group of CAVs, it is imperative that the following condition (or constraints) on safe distance between any two vehicles should be satisfied all the time.

$$\|x_i - x_j\| > \delta; \quad i \neq j \tag{6}$$

where $\delta > 0$ is a pre-specified minimum safe distance between any two CAVs.

In addition, to maximize the throughput of all CAVs, the speed of each needs to be maximized, this means that the concerned collaborative fault tolerant control should be to design the set-point $r_i, (i = 1, 2, \dots, N)$ so that the longitude speed of each CAVs is maximized so long as it does not exceed the required speed limit on the road, namely,

$$\max_r \dot{p}_i; \quad (i = 1, 2, \dots, N) \tag{7}$$

subjected to the speed limitation

$$\|\dot{p}_i\| < M; (i = 1, 2, \dots, N) \tag{8}$$

To summarize, when a fault occurs the purpose of collaborative fault tolerant control design is to select the set-points to each CAV in the group so that the following multi-objective constrained optimization is achieved:

$$\max_r \dot{p}_i; \quad (i = 1, 2, \dots, N)$$

s.t.

$$\|x_i - x_j\| > \delta; \quad i \neq j$$

$$\|\dot{p}_i\| < M; (i = 1, 2, \dots, N) \tag{9}$$

To solve such a problem, one needs to perform FD(see Figure 3) and FTCin a logical order. This will be described in the next sections.

To better formulate the optimization problem, one can group all the position variables together in representing the system dynamics in (4). For this purpose, we can define the following position vector

$$z = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$$

Then the state vector can be defined as

$$v = \begin{bmatrix} z \\ \dot{z} \end{bmatrix}$$

Under these definitions, equation (4) can be transferred into the following form

$$\dot{v} = \begin{bmatrix} \dot{z} \\ \ddot{z} \end{bmatrix} = \begin{bmatrix} 0 & I \\ A_{21} & A_{22} \end{bmatrix} v + \begin{bmatrix} B_{11} \\ 0 \end{bmatrix} r + \begin{bmatrix} E_{11} \\ E_{21} \end{bmatrix} f \tag{10}$$

where the parameter matrices $\{A_{21}, A_{22}, B_{11}, E_{11}, E_{21}\}$ can be obtained from the original parameter matrices given in equation (4).

The problem can be transferred into making the speed of each vehicle to be as close as possible to its maximum allowable speed M with respect to a time interval average. In this case the objective function in (7) can be transferred into the following optimization problem

$$\min_r \frac{1}{T_2 - T_1} \int_{T_1}^{T_2} (M - \dot{x}_i)^2 \, dt \quad .$$

where interval $[T_1, T_2]$ is the time during for the ith CAV to pass through the intersection. This looks like a linear quadratic problem, where one can further minimize the following

$$\min_r \sum_{i=1}^N \int_{T_1}^{T_2} (M - \dot{x}_i)^2 \, dt = \min_r \int_{T_1}^{T_2} \tilde{x}^T \tilde{x} dt \, .$$

where it has been denoted that

$$\tilde{x}^T = [M - \dot{x}_1, M - \dot{x}_2, \dots, M - \dot{x}_N]$$

On the other hand, one needs to constrain the changes of the set-point to each CAV to avoid unnecessary speed variations for a smooth movement, this would lead to the following optimization problem

$$\min_r J = \{ \int_{T_1}^{T_2} (\tilde{x}^T \tilde{x} + \vartheta \Delta r^T \Delta r) dt$$

s.t.

$$\|x_i - x_j\| > \delta; \quad i \neq j$$

$$\|\dot{p}_i\| < M; (i = 1, 2, \dots, N) \tag{12}$$

where $r = r^* + \Delta r$, r^* is the set-point vector to the CAVs when there is no fault in the concerned CAV group, and Δr is the incremental value of the set-point vector when there is a fault occurring in a CAV, $\vartheta > 0$ is a pre-specified weighting coefficient. In this case, Δr is the signal variation of the set-point vector to CAVs and is related to the estimated fault in fault detection and diagnosis. This is a finite-time linear quadratic control problem subjected to the relevant constraints, where standard optimal control theory can be readily applied ([19]).

IV. FAULT DIAGNOSIS OF EACH CAV

In this section we will formulate an adaptive observer-based fault diagnosis ([12]) for each CAV represented by equation (2). For this purpose, the following adaptive diagnostic observer is constructed.

$$\dot{\hat{X}}_i = A_i\hat{X}_i + B_i r_i + \sum_{i\neq j}^{N} C_{ij}\hat{X}_j + E_i\hat{f}_i + + L(x_i - \hat{x}_i) \tag{13}$$

where $\hat{X}_i$ is the estimate of X_i and $\hat{f}_i$ is the diagnosed (i.e., estimated) result of f_i, L is a gain matrix to be selected. Define the state estimate error and the fault estimation error as

$$e_i = \hat{X}_i - X_i$$
$$\tilde{f}_i = \hat{f}_i - f_i \tag{14}$$

Then the following fault diagnosis result can be obtained, where the detailed formulation, including the selection of the gain matrix L, can be found in [16] where the formulation uses the well-known Lyapunov stability theory.

$$\frac{d\hat{f}_i}{dt} = -\mu_i(\hat{x}_i - x_i) \tag{15}$$

where $\mu_i > 0$ is a pre-specified adaptive gain. Note that this observer is only for the purpose of estimating the fault. Other fault diagnosis methods can also be applied here to formulate the required fault diagnosis algorithm.

V. COLLABORATIVE FAULT TOLERANT CONTROL - AN APPROXIMATED SOLUTION FOR OPTIMIZATION PROBLEM (12)

Using the fault diagnosis result given in equation (15), a collaborative fault tolerant control that ensures the sub-optimality of the combined optimization (12) will be formulated and described in this section.

A. *Collaborative Fault Tolerant Control Structure*

For the fault case where the speed variation of the faulted CAV takes place in a way that does not violate the linear model format, a state feedback based position trajectory set-point adjustment for Δr can be formulated so that the information of other CAVs will be used in a feedback way to tune the position set-point of other concerned CAVs.

Assuming that the i_*th CAV has developed a fault, then the collaborative fault tolerant control for other healthy CAVs would be to tune their set-point slightly to ensure a safe movement in line with the optimization given by equation (12). This will lead to the following form

$$r_{j\neq i_*} = r^*_{j\neq i_*} + \Delta r_{j\neq i_*} \tag{16}$$

where the incremental change of set-points for healthy CAVs are represented as $\Delta r_{j\neq i_*}$ which is given by

$$\Delta r_{j\neq i_*} = \sum_{j\neq i_*} \theta_j \hat{f}_i X_j \tag{17a}$$

where θ_j is a set of feedback gain matrices via the communication to all the healthy CAVs. This means that we need to select θ_j so that the optimization problem (12) can be solved, and the solution to (12) becomes a parametric solution under (17a). For the faulty ith CAV, the set-point tuning should be zero, i.e.

$$\Delta r_i = 0 \tag{17b}$$

It can be seen that if there is no fault then $\hat{f}_i = 0$, this leads to $\Delta r_{j\neq i_*} = 0$ in equation (17). The structure of (17) thus guarantees the necessary compensation to the set-points of other healthy CAVs if there is a fault. When no fault occurs, there is no need to apply the tuning to the set-points.

C. *Approximated Solution to Optimization Problem (12)*

To select θ_j so that the optimization problem (12) can be solved, one can substitute (16) and (17) into (12) to start with, then we can obtain the explicit expression of the performance index J with respect to θ_j by using the generic solution of linear time-invariant state space model to obtain $\tilde{x}^T$ as a function of θ_j . This can be achieved using the available parameters in equation (10) for a given interval $[T_1, T_2]$. In this context, this time interval is divided into a number of sub-intervals and within each sub-interval $\Delta r_{j\neq i_*}$ is kept as a constant in line with the use of zero-order holder. This provides **an approximated solution** of θ_j to (12) rather than using standard LQR algorithm.

As for the constraints, a simple switching mechanism can be used, where if the constraints are satisfied then the above obtained setpoint tuning in (17) will be used, otherwise the collaborative fault tolerant control would set $\theta_j = 0$.

For large fault (i.e., an accident in a CAV), other healthy CAVs need to again control their passing through movements safely and this may need to change their position and speed in a large range. In this case, nonlinear control strategies should be used. This belongs to the future study where collaborative fault tolerant control will be formulated in a nonlinear control way with the following rule.

$$\Delta r_{j\neq i_*} = \sum_{j\neq i_*} h(X_j) \tag{18}$$

where *h(.)* is a nonlinear control strategy for the set-point tuning as a result of the optimization in (12).

VI. A SIMPLE SIMULATION EXAMPLE

A simple simulated case study has been considered, where 10 identical CAVs have been included as an example to demonstrate the proposed method with the time interval $[T_1, T_2] = [0, 100s]$. The safe distance limit is set to $\delta = 1.8$ meters and the maximum speed limit is 30MPH. The dynamics of each car has been discretized at 0.01 second sampling interval., this is the sampling rate for the control algorithm implementation as given in equation (17).

The simulation results for two CAVs' responses are shown in Figures 5 – 8, where Figure 5 shows the fault diagnosis effect, Figure 6 gives the speed profile, Figure 7 shows the set-point tuning and Figure 8 displays the distance between the two concerned CAVs. It can be concluded that desired results have been obtained.

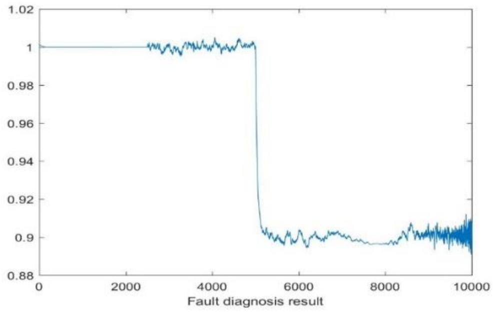


Fig. 5. Fault diagnosis result.

Note that the simulation is carried out for 10000 sample point which equals to 100 seconds. The fault is a small actuator fault and the vertical axes of figure 8 has a unit of 0.1 meter.

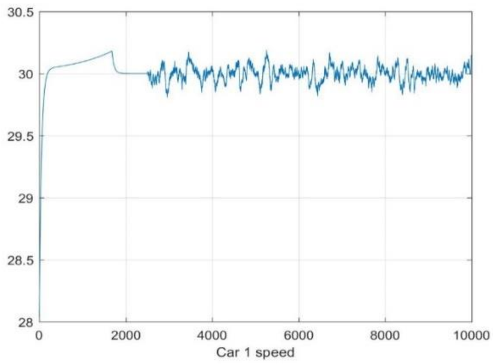


Fig. 6. Keeping maximum speed when passing through the intersection.

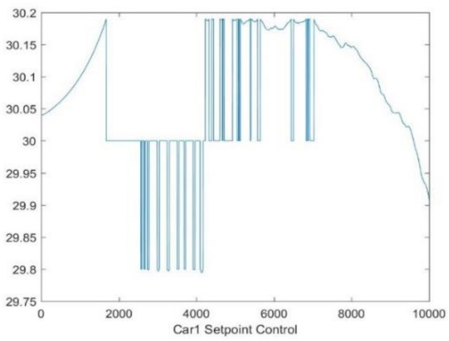


Fig. 7. Set-point incremental tuning $\Delta r_{j \neq i_*}$.

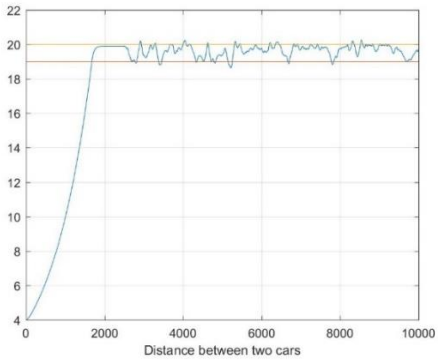


Fig. 8. Keeping a safe distance

VII. STOCHASTIC FEATURE IN COMPUTING OPTIMAL CONTROL AND ROBUSTNESS ISSUES

The formulation so far is performed in the deterministic dynamics domain. However, there are various uncertainties and randomness for such a system. These will be further discussed in this section.

A, Random number of CAVs to be considered

As the number of CAVs entering the non-signalized intersections are generally random, the number of the objective functions is also a random number. This means that the optimization index N is a random integer. In this context, the size of the optimization is random from time to time and the implementation of the algorithm should consider this effect and its impact to the real-time computing for the collaborative fault tolerant control among healthy CAVs.

B. Communication issues

CAVs use wireless communication as a major feature to exchange information of their state with other vehicles. Albeit wireless communications are being improved there are still issues related to the reliability of communication channels. For example, the common features of packet-drops and delays in communications would still exist and will therefore present impact to the modelling and control quality. In these cases, the communication packet-drops and delays are random. This indicates that the coefficients C_{ij} in equation (4) are random numbers. These random coefficients make the original system (4) a stochastic system subjected to random parameters. Therefore, the optimization should be solved in stochastic optimization sense. For example, optimization (12) should now be read as

$$\min_{r} J = \text{Mean}\{ \int_{T_1}^{T_2} (\tilde{x}^T \tilde{x} + \vartheta \Delta r^T \Delta r) dt \}$$

s.t.

$$\|x_i - x_j\| > \delta; \quad i \neq j$$

$$\|\dot{p}_i\| < M; (i = 1, 2, \dots, N) \tag{19}$$

where $Mean\{.\}$ is the mathematical expectation operator applied to the integration, and the above optimization problem should be subjected to the following stochastic dynamic constraints in Ito stochastic differential equation form

$$dX_i = (A_i X_i + B_i r_i + \sum_{i \neq j}^{N} \rho_{ij} C_{ij} X_j (t - \tau_{ij}) + E_i f_i) dt + \sigma_i(t) d\omega \tag{20}$$

where ρ_{ij} is a random switch taking values of 1.0 and zero. If there is a communication packet-drop then its value is zero, otherwise its value is 1.0, τ_{ij} represents the random time delays on the communications between the ith and the jth CAVs.

In this context, the problem set-up looks similar to networked control systems subjected to random delays and communication faults, where the rather rich literature on this subject can help to obtain effective solutions to stochastic optimization problem of descriptions (19) – (20). For example, in terms of fault diagnosis, rather than using an adaptive observer-based approach in equation (15), the well-known Kalman filtering or minimum entropy filtering should be used to obtain the fault estimation ([20] – [21]). In terms of set-point adjustment to healthy CAVs, similar structured optimization effect given in equations (17) and (18) can still be applied. This defines the scope of the optimization.

C. Robustness consideration

The models used to characterize CAV dynamics is quite simple and a linear model has been used for all the involved CAVs. In practice, realistic models for vehicles should be considered. For example, one can consider using a full dynamic model that involves air drag forces and road surface roughness. In this context, the following open loop dynamics of CAVs should be firstly used to obtain the closed loop CAVs control.

$$\dot{X}_i = A_i X_i + B_i r_i + \sum_{i\neq j}^{N} C_{ij} X_j - \frac{1}{2}\sigma D_i H_i X_i^2 + E_i f_i \tag{21}$$

where the quadratic term is the air dragging term and other symbols are constants. This would lead to the following non-linear dynamics in matrix form

$$\dot{x} = Ax + Br + \aleph(x) + Ef \tag{22}$$

where $\aleph(x)$ groups all the nonlinear components for the system.

D. Full energy consideration

The energy consideration here is reflected by the constrained changes of the incremental values Δr_{ij} , where the idea is to minimize the variations of the set-point as they will impact the acceleration and de-acceleration of CAVs. Alternatively, one can use the data provided by CAVs to value the energy consumption in a much more accurate manner. In this case, in line with the motion dynamics, the following energy calculation for the ith CAV can be included.

$$E_{i,CAV} = \int_{T_1}^{T_2} P_{i,CAV} dt \tag{23}$$

$$P_{i,CAV} = M_i \dot{x}_i \alpha_i + \frac{1}{2}\sigma C_D H \dot{x}_i^3 + M_i g \frac{dh_i}{dt} + d_i M_i g \dot{x}_i \tag{24}$$

where M_i is the mass, σ is the air density, C_D is the air resistance coefficient, H is the projected area of CAV, g is the gravity coefficient, $\frac{dh_i}{dt}$ is the difference of elevation, d_i is the rolling resistance coefficient. $P_{i,CAV}$ is the power of the ith CAV.

Therefore, the total energy consumed around the non-signalized intersection is given by

$$Energy\ (r) = \sum_{i=1}^{N} E_{i,CAV} \tag{25}$$

Adding the above energy into the performance function would lead to the following comprehensive index

$$\min_{r} J = \text{Mean}\{ \int_{T_1}^{T_2} (\tilde{x}^T \tilde{x} + \vartheta \Delta r^T \Delta r) dt + Energy\ (r) \} \tag{26}$$

subjected to the following full constraints.

$$\| x_i - x_j \| > \delta; \quad i \neq j$$
$$\| \dot{p}_i \| < M; (i = 1, 2, \dots, N)$$
$$\dot{x} = Ax + Br + \aleph(x) + Ef$$

This is a complicated dynamic multi-objective optimization and implementation onto the concerned CAVs requires certain computing power.

E. Integral interval issues

In the optimization, the interval is defined as $[T_1, T_2]$. Whilst T_1 can be fixed, T_2 does vary with the speed of the concerned CAVs. Moreover, the duration of each CAVs passing through the non-signalized intersections are different. This means that one need to consider the optimization for each CAVs with variable integral durations, where the actual optimization should be multi-objective with the following performance index for each CAV simultaneously

$$\min_{r_i} J_i = \frac{1}{T_2(\dot{x}_i) - T_1} \int_{T_1}^{T_2(\dot{x}_i)} [(M - \dot{x}_i)^2 + \vartheta_i \Delta r_i^2] dt + \\ + E_{i,CAV}$$

$$E_{i,CAV} = \int_{T_1}^{T_2(\dot{x}_i)} P_{i,CAV} dt$$

with $i = 1, 2, \dots, N$. In this context, effective real-time solution to such an optimization exercise is needed in the future study ([22]).

VIII. CONCLUSIONS

With 100% CAVs penetration on the road, intersection controls can be realized in a non-signalized way. In this case, the CAVs can control themselves to pass through the concerned intersection, where safety and smooth passage become an important issue when a CAV develops a fault. In this paper, a simple collaborative fault tolerant control is proposed which makes a full use of V2V information among all the concerned CAVs near an intersection. Assuming each CAV is well-controlled as a linear closed loop system with set-point as its position trajectory, then a simple state space model that takes into account V2V information among the concerned CAVs group has been formulated with a generic fault injection format as shown in equation (2). Using such a model, a fault diagnosis and collaborative fault tolerant control has been obtained, where an optimization problem is formulated as shown in (12) with an approximated solution that tunes the position set-points of other healthy CAVs. Simulation results have been obtained showing the effectiveness of the proposed method.

The feature of collaborative fault tolerant control means to use healthy CAVs to control the whole system performance. The faulty CAVs can also be controlled in a self-fault tolerant way, where the existing fault tolerant control can be directly applied. This would lead to a total fault tolerant effect where the system is not only controlled by healthy CAVs but also operated by faulty CAVs. This presents a future perspective.

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