Tiguan: Energy-Aware Collision-Free Control for Large-Scale Connected Vehicles

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***Abstract*—Traditional transportation systems in metropolitan areas always suffer from energy inefficiencies, evidenced by its uncoordinated behaviors such as system capacity and traffic demand change. With the advanced networked sensors are prevalent deployed into the autonomous vehicles, the information of system status and traffic demand can be collected in real-time. These information provides the potential to perform different types of coordination and control for autonomous vehicles in large-scale intelligent transportation systems.**

In this paper, we design a coordination-based energy-aware control method for large-scale connected vehicles, named Tiguan. Tiguan enables an iterative scheme to compute a practicable solution, which all vehicles are controlled on different trajectory paths of ground traffic network while achieving the close to the optimal performance. Safety is guaranteed by enabling vehicle to autonomously coordinate with other vehicles for a road traffic resource, and thus determine which vehicle needs the resource most. Experimental results show that Tiguan can effectively generate a feasible control solution with collision avoidance, and minimizing the energy consumption.

I. Introduction

With the recent advances in electronics, sensors, and communication techniques are increasingly deployed in the large-scale intelligent transportation systems, autonomous driving techniques has made significant progress during the past decade. These advances in autonomous driving vehicles have fueled to apperceive the environment with their own sensors, and also communicate with other vehicles and surrounding infrastructures for vehicle safety and transportation efficiency. There are many companies and academic institutions have started experimenting with autonomous vehicles on intelligent transportation systems. While research on energy-efficient driving trajectory paths, such as eco-driving, has already witnessed numerous efforts [1], it is still a grand challenge to design an autonomous transportation system, which each vehicle can autonomously coordinate with other vehicles and drive itself on a road in energy-efficient with a safety guarantee.

An intelligent transportation system in metropolitan areas generally involves the following phases. First, users send their requests through the clients installed in their vehicles to the cloud servers. This requests, also called orders, mainly include the current locations and destinations. After receiving these orders, the system will generate a feasible solution based on current network status and traffic demand in a holistic environment. And at meanwhile, the corresponding trajectory path of each vehicle will be published through wireless networks. With the changes in network status, the system will update the solution in real-time for vehicle safety and transportation efficiency. Although such system has provided great convenience for vehicle driving, it still exists several non-negligible shortcomings. For instance, the choices are not always the most energy-efficient ones.

It is non-trivial to accurately estimate the energy consumption of large-scale connected vehicle in intelligent transportation systems [2]. Energy consumption should be estimated on each of the different road segments in ground traffic networks. Macroscopic and microscopic models are broadly applied to estimate the vehicle energy consumption [3]. In microscopic models, the vehicle acquires a larger amount of driving data to decide a statistical cost on each road segment. In macroscopic models, the vehicle only considers the driving time and road grade, which are typically easier to obtain through free or commercial historical databases. Specifically, the road-based macroscopic models rely on the longitudinal dynamics of the vehicles and are easier to calibrate using vehicle construction parameters [4]. In this paper, we focus on the macroscopic road-based energy consumption model to control vehicle driving from one road segment to the adjacent ones.

To utilize large-scale real-time information of the intelligent transportation system, we present Tiguan, a computational efficient, coordination-based performance-driven energy-aware control framework. In Tiguan, an iteration algorithm that balances the competing goals of eliminating collision between vehicles and minimizing the energy consumption of trajectory paths in this framework. Initially, all vehicles are allowed to share the identical ground traffic resources, but subsequently must coordinate with other vehicles to determine which vehicle needs the shared resource most. The emphasis of our control approach is to adjust the energy costs of traffic resources in a gradual, semi-equilibrium fashion to achieve an optimum distribution of resources. The contributions of this work are as follows,

- To the best of our knowledge, we are the first to design an energy-aware framework for large-scale vehicle controlling.
- We formulate the energy-efficient driving of road vehicles as a control problem and design a close to the optimal algorithm.

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- Experimental results show that our approach effectively converges a feasible solution with collision avoidance and maintains the energy-efficiency.

The rest is organized as follows. The preliminaries are in Section II. The energy-aware control method is presented in Section III. The results are given in Section IV. Related work is shown in Section V, followed by the conclusion in Section VI.

II. Preliminaries

A. Vehicle Control and Associated Terminology

Control is an important process for large-scale connected vehicles in intelligent transportation systems. It consists in assigning ground traffic resources to each vehicle of the transportation system in order to connect its current location to the destination. The resources in a road traffic network and their connections are represented by a graph $G = (V, E)$. The set of vertices V corresponds to the road segments in the ground traffic network and the edges E to the feasible links that connect these nodes.

In conventional vehicle driving graphs, the weight associated with each node n is either the length of the segment or vehicle travel time. In this energy-aware framework, each node of the graph is assigned a weight that represents the travel energy expenditure. Thus, we define a weighting function $w : V \rightarrow W$, which associates each node of the graph with a weight.

Given a vehicle i in the ground traffic network, the vehicle trajectory path T_i is the set of terminals including the source terminal s_i and destination d_i. T_i forms a subset of V. A feasible solution to the control problem for vehicle i is the trajectory path T_i mapped onto the graph G and connecting s_i with its d_i.

B. Vehicle Energy Consumption Model

To develop an energy-efficient scheme, we mainly focus on the autonomous electric vehicles. Thus, the energy consumption model is required to capture regenerative braking and electric drive efficiency. In general, the vehicle longitudinal dynamical model may be written as [5].

$$m\dot{v}(t) = F_w - F_a - F_f - F_s \tag{1}$$

where m is the vehicle mass, $\dot{v}(t)$ is the vehicle acceleration, F_w is the force at the wheels, F_a denotes the aerodynamic force, F_f represents the rolling resistance force, and F_s is the gravity force. Thus, we have the vehicle model

$$\begin{cases} \dot{x}(t) = v(t) \\ m\dot{v}(t) = F_w - \frac{1}{2}\rho_a A_f c_d v(t)^2 - mgc_r - mgsin(\alpha(x)) \end{cases} \tag{2}$$

where ρ_a is the external air density, A_f is the vehicle frontal area, c_d is the aerodynamic drag coefficient, c_r is the rolling resistance coefficient, $\alpha(x)$ is the road slope as a function of the position, and g is the gravity.

Note that the sum of aerodynamic and rolling frictions, named road load force, is generally approximated as a second order polynomial in the speed v. Thus, we have

$$F_a + F_f = a_2 v(t)^2 + a_1 v(t) + a_0 \tag{3}$$

where a_0 , a_1 and a_2 are the constant parameters identified for a considered vehicle. Thus, the force at the wheels can be also expressed as followed.

$$F_w = m\dot{v}(t) + a_2 v(t)^2 + a_1 v(t) + a_0 + mgsin(\alpha(x)) \tag{4}$$

For each node $n \in V$ of the graph, it is possible that we can obtain road segment length l_n and average traffic speed $\overline{v_n}$ of vehicle on this road. Because we can obtain the time of the day, and the road grade $\alpha_n(x)$, both of which varies within the used road segment depending on the position.

Specifically, due to the time-variant speed or acceleration profile is not available, the energy consumption model cannot be directly used to assign the weights to each node of the graph. Thus, we use average traffic speed $\overline{v}$ to replace the time-variant speed $v(t)$. All the vehicles on node n are supposed to travel at average traffic speed $\overline{v_n}$. While it exists difference, it can efficiently reflect real driving conditions. The previous work also give a validation analysis to verify the accuracy [6]. Thus, the force expression in (4) is modified for each node n as follows:

$$\overline{F}_{w,n} = a_2 \overline{v}_n^2 + a_1 \overline{v}_n + a_0 + mgsin(\alpha_n(x)) \tag{5}$$

with no acceleration term. The torque requested from the electric motor to meet the force demand at the wheels is given as:

$$\overline{T}_{m,n} = \begin{cases} \frac{\overline{F}_{m,n} r}{\rho_t \eta_t}, & \text{if } \overline{F}_{w,n} \geq 0 \\ \frac{\overline{F}_{m,n} r \eta_t}{\rho_t}, & \text{if } \overline{F}_{w,n} < 0 \end{cases} \tag{6}$$

where r is the wheel radius, ρ_t and η_t are the transmission ratio and efficiency, respectively. The electric motor rotational regime is also constant over time if constant speed is assumed:

$$\overline{w}_n = \frac{\overline{v}_n \rho_t}{r} \tag{7}$$

Thus, the mechanical power available at the electric motor is written as followed.

$$\overline{P}_{m,n} = \begin{cases} T_{m,max} \cdot \overline{w}_n, & \text{if } \overline{T}_{m,n} \geq T_{m,max} \\ \overline{T}_{m,n} \cdot \overline{w}_n, & \text{if } T_{m,min} < \overline{T}_{m,n} < T_{m,max} \\ T_{m,min} \cdot \overline{w}_n, & \text{if } \overline{T}_{m,n} \leq T_{m,min} \end{cases} \tag{8}$$

In the following we assumed that the saturation torque is independent from the motor regime. Finally, the power demand at the battery of the electric vehicle, considering the electric drive efficiency η_b constant, can be written as:

$$\overline{P}_{b,n} = \begin{cases} \frac{\overline{P}_{m,n}}{\eta_b}, & \text{if } \overline{P}_{m,n} \geq 0 \\ \overline{P}_{m,n} \cdot \eta_b, & \text{if } \overline{P}_{m,n} < 0 \end{cases} \tag{9}$$

and ultimately, we have the battery energy consumption over the generic travel time T_n.

$$\overline{E}_{b,n} = \int_0^{T_n} \overline{P}_{b,n} dt = \overline{P}_{b,n} T_n \tag{10}$$

where $T_n = l_n / \overline{v}_n$ is the travel time on segment node n when traveling at the average traffic speed $\overline{v}_n$.

C. Problem Formulation

The objective of this work is to design an energy-efficient control framework for large-scale connected vehicles on the road transportation networks. Thus, the weight assigned to each node of the graph represents only the associated energy consumption. Furthermore, the framework can be easily extended to consider also travel time, and the optimization would search then for a tradeoff solution between energy consumption and travel time minimization. In this paper, we solely focus on energy aspects.

The control problem of road vehicles consists in the actual minimization of the energy consumption to drive from a selected origin to a destination in the road network with collision free. Minimization of an energy cost in a graph can be solved by means of a standard shortest path algorithm. However, it is challenge to mitigate the collision between vehicles in the same time to guarantee the safety.

Notice that vehicle control is a technology-specific variation of the disjoint path problem from graph theory, which is one of Karp's original NP-complete problems [7]. In a graph, two trajectory paths are disjoint if they share no vertices or edges.

III. Methodology

In this section, we present a control algorithm to minimize the energy consumption and guarantee the collision free between vehicles.

A. Overview

The design scheme of the proposed energy-aware control for large-scale connected vehicles is summarized in Fig. 1.

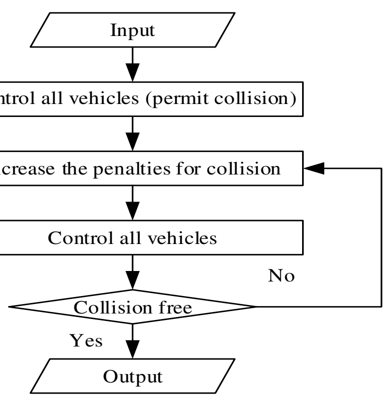

Fig. 1. Overview.

First, Tiguan enables all vehicles in a transportation network to be controlled in the best manner possible to minimize the energy resource consumption. Meanwhile, Tiguan permits the collision between the vehicles, which means that two different vehicles may use the same resource[1] on the network. After initial solution, each vehicle is controlled with its ideal trajectory path, while it is infeasible owing to the collisions. Then, the penalties associated with collisions are increased, and the driving of vehicles is re-controlled with consideration of the increased penalties. The process of increasing the penalties for collisions and re-controlling the vehicle driving continues iteratively until all collisions are removed and the solution is feasible.

In essence, the vehicles coordinate with each other to determine which vehicle gets to keep a shared resource.

B. Energy-Aware Control Algorithm

Controlling a vehicle driving involves assigning road resources such that the destination are reachable from the source. When controlling a set of vehicles sequentially, the order in which the vehicle driving are controlled may be critical since some road resources needed by a vehicle may be occupied by other vehicles.

The principal idea of Tiguan algorithm is to permit unlimited sharing of road resources initially and then repeatedly re-control the vehicle driving until no resources are shared. By assigning collision costs to the shared road resources, and increasing these costs with each iteration through the vehicles, the control algorithm encourages alternative trajectory paths to be explored until all the collisions are resolved.

Here we impose the cost of each road resource n inspired by PathFinder [11]. In Tiguan algorithm, this cost has three terms, which can be adjusted to eliminate the collision between vehicles.

$$c_n = (b_n + h_n) \times p_n \tag{11}$$

where b_n is the base cost of using road resource n, which can be used to reflect the energy of the road resource. A reasonable choice for b_n is the intrinsic energy e_n of the node n, since minimizing the energy consumption of a vehicle is equivalent to minimize the road resources of a vehicle in nature. In the remainder of our work, we set $b_n = e_n$.

The first-order collision term p_n is the number of vehicles that are presently occupying the same road resource. The second-order collision term h_n is related to the history of collision on a road resource n during previous iterations. This history cost h_n grows monotonically with each iteration in which the road resource is shared. In fact, the h_n increases by a fixed amount each time when a vehicle is re-controlled through an already occupied node.

The implementation details of the Tiguan are shown in Algorithm 1. This algorithm can be divided into three nested iterations. In outermost iterations, Tiguan enables the vehicles to coordinate with each other to decide who will make a detour around the collisional resource nodes, until all the collisions are resolved to obtain a complete legal control solution. In middle iterations, the sequential control loop starts at step 8. The vehicle trajectory path T_i from the previous outermost iterations is erased and initialized to the vehicle source. and at the meanwhile, it will invoke the shortest-path algorithm, which computes a path from the source to the sink in the network resource graph. In innermost iterations, it employs the single source shortest path algorithm, which is implemented by Dijkstra's algorithm. After a sink is found, all nodes along

[1] In practice, the occupation of same resource must be less than or equal to the capacity to guarantee the collision avoidance.

a backtraced path from the sink to source are added to T_i, and at last, if the solution is feasible, the algorithm is complete.

Algorithm 1 The vehicle control algorithm

Tiguan(vehicles $\{i\}$, network $G = \langle V, E \rangle$)
while control incomplete or collision exists **do**
  Sequential-Control($\{i\}$)
  update history costs $\{h_n\}$ of the nodes in V
end while
end Tiguan

Sequential-Control(vehicles $\{i\}$)
for each uncontrolled or collision vehicle i **do**
  erase T_i if exists
  $T_i \leftarrow \{s_i\}$
  $T_i \leftarrow$ **Find-Shortest-Path**(T_i, d_i)
  update present costs $\{p_n\}$ of the nodes in T_i
end for
end Sequential-Control

Find-Shortest-Path(T_i, d_i)
for each node n in T_i **do**
  enqueue n onto Q with key 0
end for
while a sink of d_i has not been found **do**
  dequeue node, p with lowest key from Q
  if p was not previously dequeued **then**
    for each neighbor n of p **do**
      enqueue n on Q with cost of n + key of p
    end for
  end if
end while
backtrace from sink to a node of T_i that is reached
return this path
end Find-Shortest-Path

Specifically, the energy of the points chosen by this algorithm is a challenge problem. However, finding the optimal or even near-optimal points is not essential in the Tiguan algorithm. The key of algorithm is successfully feasible in adjusting costs to eliminate the collision between vehicles to drive itself on a road with a safety guarantee.

C. Energy and Collision Tradeoffs

To introduce energy into Tiguan algorithm, we redefine the cost of using node n when controlling a vehicle i driving from source s_i to sink d_i.

$$C_n = \sigma_i e_n + (1 - \sigma_i) c_n \tag{12}$$

where c_n is defined in (11) and σ_i is the balance ratio.

$$\sigma_i = E_i / E_{max} \tag{13}$$

where E_i is the longest trajectory path from s_i to d_i, and E_{max} is the maximum over all trajectory paths, and here, we call *critical trajectory path energy*. Thus, $0 < \sigma_i \leq 1$. The first term in equation (12) is the energy-sensitive term, while the second term is the collision-based term. Note that the long trajectory path will produce more energy consumption for vehicle driving. Fig. 2 shows the vehicle may drive on the alternative path due to the collision in the shortest path.

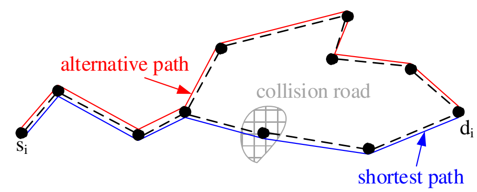

Fig. 2. Trajectory path selection.

Equations. (12) and (13) are the crucial to provide the appropriate mix of *minimum-energy* and *minimum-cost* trajectory path. If a source-sink pair relies on the critical trajectory path, then $\sigma_i = 1$ and the cost for using node n is simply energy term. Thus, a minimum-energy control will be used and collision will be ignored. If a source-sink pair belongs on a trajectory path whose energy is much smaller than the critical trajectory path energy, its σ_i will be small and the collision term will dominate, resulting in a solution which avoids collision at the expense of extra energy.

To accommodate energy, the Tiguan algorithm is changed as follows. First, the σ_i are initialized to 1. Thus, the Tiguan searches the minimum-energy trajectory path for every vehicle during the first iteration. The σ_i are recomputed in each subsequent iteration. Second, the destination are reached in decreasing σ_i order. Third, the priority queue is initialized to T_i at cost $\sigma_i e_i$. The control effect of this initialization is that nodes that are already in the partial trajectory path will have only a energy component. These modifications will be refered in our Tiguan algorithm.

The Tiguan completes when no more collisional resources exist. Note that by recomputing the σ_i, we have kept a tight reign on the critical trajectory path. Over the process of iterations, the critical trajectory path increases only to the extent that requires to resolve the collision. Our approach first reduce the energy consumption and then attempt to resolve the collision by re-controlling vehicle driving.

D. Energy Consumption Analysis

In this section, we present the energy consumption analysis of the Tiguan algorithm.

We consider that if h_n is constrained by e_n, then Tiguan algorithm will produce a worst case trajectory path energy, which is equal to the minimum-energy path of the critical trajectory path. It means that Tiguan algorithm converges the fastest implementation in the transportation network graph.

In practice, h_n is allowed to increase gradually until a complete solution is found. While the h_n maybe exceed e_n in very collisional transportation networks, Tiguan still comes very close to this constraint in practice.

THEOREM 1. *If $h_n \leq e_n$ for all nodes of graph, then the energy of any vehicle path consumed by Tiguan algorithm* *is constrained by E_{max}, the energy of the longest minimum-energy path in the ground traffic graph.*

Proof. When Tiguan algorithm terminates successfully, the p_n term in equation (12) is 1 and thus, $c_n = e_n + h_n$. Let R represents the most critical used path and S denotes the shortest path energy for R. The cost of S is given by:

$$C_S = \sum_{n \in S} C_n \tag{14}$$

$$= \sum_{n \in S} (\sigma_i e_n + (1 - \sigma_i)(e_n + h_n)) \tag{15}$$

$$= \sum_{n \in S} e_n + (1 - \sigma_i) \sum_{n \in S} h_n \tag{16}$$

According to our assumption $h_n \leq e_n$,

$$C_S \leq \sum_{n \in S} e_n + (1 - \sigma_i) \sum_{n \in S} e_n \tag{17}$$

$$= E_i + (1 - \sigma_i) E_i \tag{18}$$

$$= (2 - \sigma_i) E_i \tag{19}$$

$$= (2 - \sigma_i) \sigma_i E_{max} \tag{20}$$

Since $0 \leq \sigma_i \leq 1$, we have $0 \leq (2 - \sigma_i)\sigma_i \leq 1$ and

$$C_S \leq E_{max} \tag{21}$$

The cost of R must be less than the cost of S, thus, the energy of R must be less than the cost of S, which is less than E_{max}. $\square$

E. Performance Enhancements

We consider several enhancements to improve the runtime of Tiguan algorithm without adversely affecting the energy consumption of vehicle driving.

One enhancement is to employ the A^* algorithm into the shortest path search loop. A^* leverages lower constraints on road segment lengths to reduce the search space on traffic network graph. Alternately, A^* can be applied to the collision-avoidance energy-aware control algorithm, which adjusts the cost of minimum-energy trajectory paths from every node to the potential sink. During the first iteration, the search can be performed linearly in the number of nodes along a minimum-energy trajectory path. With iterations progress, increasing p_n and h_n make this lower constraint to prove more and more efficient, and the search continues. As a result, this algorithm remains less than a full space search and improve the runtime.

Another enhancement is to control only the vehicles, which are involved in the collisional road resources. This is because in large-scale transportation network, there exists more sufficient ground traffic resources compared to the collisional resources. While this strategy may lead to the energy consumption, the runtime will improve. To validate we have not seen any cases where controlling only collisional resources resulted in a more energy consumption. In our experience, the number of iterations increases, but the total runtime decreases.

In summary, these two techniques efficiently accelerate our control algorithm runtime, and improve the ability of real-time updating in intelligent transportation systems.

IV. Evaluation

A. Experimental Setup

The energy-aware control framework was implemented in the C++ programming language on a Intel Xeon E5-2430 processor at 2.2GHz and 32GB memory. The simulation study and the experimental campaign were conducted on ten different test cases, all of which are extracted from the ground traffic network of the California state (*i.e.*, about 1,965,206 nodes and 2,766,607 links) [17]. Because there exists no available free dataset about the road segment length, road grade, and current traffic conditions as previously discussed, we implemented a random algorithm to produce these information, including the corresponding average traffic speed of each vehicle, the number of vehicles with different origin-destination pairs in the considered network. By this way, we can compute the energy-consumption weight of each node in traffic resource graph while it is synthetic.

TABLE I
Road Network Information

Bench.	#Nodes	#Vehicles
case1	27120	788
case2	76386	1946
case3	43872	2380
case4	104176	3710
case5	110250	3953
case6	283792	5224
case7	305082	6606
case8	283338	7154
case9	311112	7474
case10	492570	8078

Table. I shows the extracted ground traffic network benchmark. Specifically, the size of road network is increased in a gradual manner, because the scalability of control algorithm is very crucial in the large-scale connected vehicles. In our simulation study, our mainly focus on the runtime and energy consumption of control algorithm. In general, we leverage the usage of road segment resources to evaluate the energy consumption.

B. Experimental Results

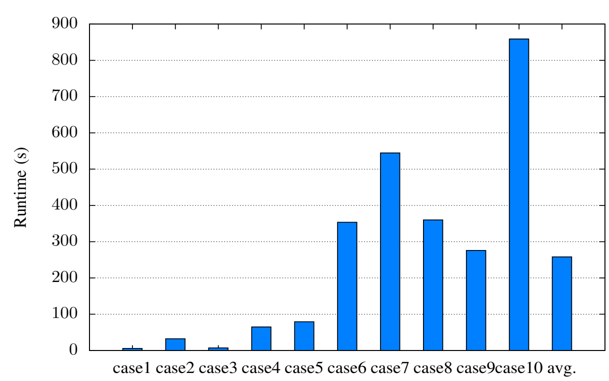

Fig. 3. Runtime of Tiguan algorithm.

Fig. 3 gives the total runtime of Tiguan algorithm for each case of large-scale connected vehicles on ground traffic networks. The convergence time of Tiguan algorithm will take the average 258 seconds to achieve a feasible solution, which all vehicles can drive itself on a road with a collision-free guarantee. Specifically, our Tiguan algorithm only takes about 5 seconds to find a practicable solution for the case1, it is close to the scale of a city. It is meaningful for large-scale intelligent transportation systems, which can be processed by region partitioning and coverage control so that coordinated vehicles can perform tasks in their specified regions [8], [9].

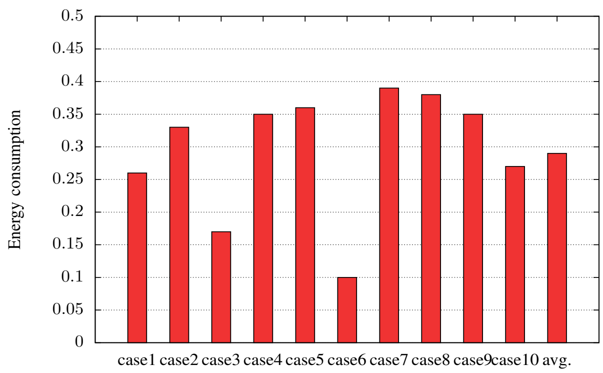

Fig. 4. Energy consumption of Tiguan algorithm.

To evaluate the energy consumption, we introduce an energy consumption ratio, which is between the total energy consumption of all vehicles and the available energy of ground traffic networks. Fig. 4 reports the probability distribution of the energy consumption ratio provided by Tiguan algorithm. On average, the energy consumption ratio is only about 29% using our energy-aware framework to control such a large-scale connected vehicles. In particular, our Tiguan algorithm only consumes about 10% energy to achieve a feasible solution for the case6. The proposed energy-aware control framework has the potential to implement the energy-efficient control for the large-scale connected vehicles in intelligent transportation systems.

V. Related Work

Existing efforts related to our work are multi-agent coordination and control. Different from our method, these works usually leverage the idea of region partitioning and coverage control to coordinate the agents to perform tasks in their specified regions [8], [9], [10]. Also, these works can not fully overcome the challenge of collision between multiple agents, and the scale of agents is small. Other related works include multiple vehicles routing without communications and robust traffic flow management under uncertainty [12], [13]. Their task models and design objectives are different from energy-aware control problem. Moreover, these works do not consider the advances in communication techniques to enable the vehicle to coordinate with each other to drive itself on a road with collision free. Recently, the model predictive control has also been widely used to solve the problem of process control, task scheduling, cruise control, and multi-agent transportation networks [14], [15], [16]. These works provide solid results for related mobility scheduling and control problems. However, none of these works incorporates both the current and historical mobility patterns into the large-scale connected vehicles control design, leveraging the iteration scheme to solve the collision between vehicles.

VI. Conclusions and Future Work

Control is an important process for large-scale connected vehicles in intelligent transportation systems. In this paper, we design an energy-aware collision-free control framework, namely Tiguan. Tiguan leverages an iteration scheme to guarantee the safety driving with collision avoidance between vehicles. At the meanwhile, energy-efficient is maintained by minimizing the usage of road segment resources. Specifically, Tiguan is the first energy-aware work with a safety guarantee. While the runtime of Tiguan algorithm is possibly length for very-large-scale connected vehicles, it is still practically meaningful for the autonomous transportation applications.

The future work is to leverage the parallelization techniques to accelerate this process.

VII. Acknowledgement

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