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NEW CYBER PHYSICAL SYSTEM ARCHITECTURE FOR THE MANAGEMENT OF DRIVING BEHAVIOR WITHIN THE CONTEXT OF CONNECTED VEHICLES

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Abstract. In this paper, we address the problem of managing driving behaviours within the context of Connected Vehicles (CVs). In contrast with the existing related solutions, we are proposing a Cyber Physical System (CPS) architecture that ultimately enables the continuous acquisition and processing of driving data and then the assessment and classification of driving performance according to a welldefined set of driving states. The transitions between these states are decided based on current and previous driving records. In addition to their use for the generation of the appropriate feedback to the driver, the driving states could be used to identify relevant data to be shared with the CVs in the vicinity. They could also be used to recommend personalized trainings to the driver based on his/her driving performance.

Keywords: Connected vehicle, cyber-physical vehicle system, driving states

1 INTRODUCTION

Intelligent Transportation Systems (ITSs) have emerged as a promising solution to enhance the quality and quantity of road traffic flow as well as to improve access to transport and traffic information based on next-generation technologies [1]. Nevertheless, in spite of the huge progress in reaching these objectives, Road Traffic Crashes (RTC) continue to represent a serious public health issue. Indeed, the World Health Organization (WHO) and the International Transport Forum (ITF) have estimated the number of people killed due to RTCs to approximately 1.35 million and the number of injuries to around 50 million in 2018 [2, 3]. Studies have also reported that about 90 % of RTC fatalities are in low to middle-income countries, of which more than the half are among vulnerable road users (i.e. pedestrians, cyclists, and motorcyclists) [4]. Due to the critical situation caused by RTCs, current trends have revealed that if appropriate preemptive measures are not implemented, then, by the year 2030, road traffic injuries are predicted to be the seventh leading cause of death across all age groups [3]. In order to address these problems, several studies have intensively investigated the causes of RTCs that result from the deficiencies of ITS components, including vehicles (e.g., [5]), road infrastructure (e.g., [6, 7]), road users (e.g., [8, 9]), and regulations (e.g., [10, 11, 12]). These studies have particularly highlighted the need to leverage the interactions between the different components of an ITS (i.e. V2V, V2I, V2R, etc.) in order to share relevant traffic information at the right time with the right beneficiaries. They have also highlighted that these objectives could be reached thanks to the emerging concept of Connected Vehicle (CV).

CV refers to the technologies, services, and applications that connect a given vehicle to its surroundings (including external devices, neighbouring vehicles, road infrastructure elements, and networks). It is expected to play a major role in enhancing traffic safety through unleashing the true potential of the joint collaboration between vehicles as well as the sharing of precise, timely data among them. It is also expected to have a significant positive impact on capacity and traffic operations, travel demands and habits, and mobility behaviours [13]. Furthermore, several studies (e.g., [14, 15]) have predicted that CV technologies will have a positive impact on drivers' behaviours, particularly those that have been identified as main causes of RTCs. More specifically, the authors in [16] have claimed that CV applications can address about 81 % of unharmed driver crashes in highway, particularly since vehicles can sense and communicate the hazards around them. These applications would ultimately help drivers to improve their driving behaviours, particularly when it comes to making informed decisions to avoid road traffic hazards [17, 18]. The use of welldefined CV-based awareness solutions would help in reaching this objective [19, 20, 21, 18, 22, 23]. However, although intensive studies have focused on investigating the relation between RTCs and driving behaviours with conventional cars (e.g., [24, 25, 26]), very little efforts has been made so far to carry out such studies within the context of CVs. As the global CV market is predicted to jump from $ 63.03 billion in 2019 to $ 225.16 billion by 2027 [27], we argue that substantial efforts are still needed to support this growth. These efforts should particularly develop a better understanding of the relationship between driving behaviours, RTCs, and CV features and technologies. We address in this paper this untapped research field and propose a new Cyber Physical System (CPS) architecture for the management of driving behaviour within the context of CVs. We call our solution a Framework for Automated Driving States Identification (FADSI). It includes flexible mechanisms for acquiring the right driving data, performing the right data analytics, generating the right feedback to the driver, and sharing the right data with the neighbouring vehicles. Our contributions in this paper include a new CPS architecture for driving behaviour monitoring as well as a new solution for the management of driving states based on driving performance.

In the remainder of this paper, Section 2 highlights the current literature concerning the management of driving behaviours within the context of CVs. Section 3 sheds light on our new CPS architecture as well as on the proposed solution for the management of driving states. Section 4 presents a case study focusing on the mapping of our solution into an existing regulatory framework. Section 5 outlines the challenges and opportunities to our solution. Section 6 concludes the paper.

2 RELATED WORK

The ultimate aim of CVs is to enhance mobility, improve traffic safety, reduce environmental impact, and provide road users with the right services at the right time in the right location. To meet this end, several CV technologies are being used in a wide range of applications, including parking assistance, infotainment, roadside assistance, traffic safety and efficiency, remote diagnostics, and autonomous selfdriving. In addition to their positive impact on freeways capacity [16], these technologies are expected to reduce the costs related to RTCs all over the world. Indeed, according to the National Highway Traffic Safety Administration (NHTSA), CV technologies would annually prevent 439 000 to 615 000 crashes with the adoption of full V2V communications [28]. In addition, the combination of CV and Automated Vehicle (AV) technologies are capable of minimizing drivers' errors, which are considered as major cause for more than 94 % of traffic crashes [29]. These statistics need additional thorough investigations to assess and compare driving behaviours of both CVs and conventional vehicles, particularly since the efficiency of CV-related systems closely depends on the adhesion of drivers to their recommendations [30, 31, 32]. In this regard, intensive research works have focused on understanding, identifying, detecting, and predicting the driving behaviours [33], mainly by investigating human factors.

Human factors have been categorized into six major classes; namely physiological factors, driving skills, driving desires, personality traits, imperfect driving, and socioeconomic factors [34]. They have been used to detect potentially dangerous driving situations, based on image and video processing techniques whereby drivers' faces are captured and analyzed [35]. In order to investigate driving behaviours, four main sources of data have been used so far:

1. Self-reporting questionnaires (the Manchester Driver Behaviour Questionnaire, DBQ [36], is one of the commonly used instruments in traffic psychology for measuring self-reported driving style and investigating the relationship between driving behaviour and accident involvement);
2. Video and image processing;
3. Instrumented cars (i.e. cars equipped with dedicated sensors and tools to record data on behaviours of interest, like lanechange or acceleration); and
4. Dedicated mobile apps implemented on smartphones.

Regardless of their sources, data being collected represent the cornerstone of several solutions that have ultimately aimed to classify and predict driving behaviours as well as prevent their impact. These solutions, which are increasingly relying on machine learning tools (e.g., [42, 43, 54]), have different architectures. In this regard, Toledo et al. [44] have proposed a four-layer structure, including data management, manoeuver detection, behaviour analysis and prediction, and feedback. Salvucci [45] has proposed and integrated driver model based on an Adaptive Control of Thought-Rational (ACTR) cognitive architecture. The architecture is, basically, a framework for identifying computational behavioural models that reflect human cognitive performance. It includes monitoring, control, and decision-making processes for the management of driving behaviours in the context of a multilane highway. Silva and Analide [46] have proposed an architecture that associates the emotional state of mind of drivers with gamification techniques in order to improve drivers' performance. The ultimate goal of the architecture is to enhance safety by identifying and avoiding hazards that would result from dangerous driving behaviours. Bergasa et al. [47] have described an architecture for the detection of inattentive drivers, the scoring of their driving performance, and the generation of appropriate feedback, accordingly. The architecture, which is deployed on smart devices, relies on pattern recognition techniques as well as on sensing and computer vision tools to identify if a given driver is distracted or drowsy. The authors in [48] have proposed and architecture for Driver Behaviour Modeling (DBM) that outlines the advances of smartphone and in-vehicle sensing capabilities and communication. The architecture includes a sensing layer, an application layer, and future systems layer. The authors in [49] have presented an architecture that ultimately aims to reduce the number of road accidents and fatalities. The architecture includes a human target-oriented behaviour module (i.e. knowledge-based, rule-based, and skill-based behaviours), a transport mission structure, the vehicle and its features, and the driving environment.

Furthermore, some researchers (e.g., [50, 53, 37]) have proposed architectures that rely on the paradigm of Cyber Physical Systems (CPS), where the operations of the physical and engineered systems are integrated, coordinated, controlled, and monitored by means of communication and computing core [51]. The integration of CPS within the vehicular realm (Figure 1) has resulted into dedicated architectures evolving around the concept of Cyber-Physical Vehicle System (CPVS). CPVS solutions have been identified to improve road safety, essentially when autonomous vehicles are used [50, 52, 38]. These solutions are swiftly evolving thanks to continuous advances in real-time control, computing, and artificial intelligence. Their architectures roughly rely on three basic components [52]:

1. Lowest level reactive layer (consists of low-level tight control of physical actuators typically employing feedback control technique);
2. Control or acting layer (translates higher-level plans into reference trajectories or sequences of actions for the reactive layer); and
3. Guidance or sequencing layer (also called a high-level planning or deliberation layer. It includes task and/or motion planning/scheduling algorithms).

Examples of CPVS-related architectures include the solution proposed by [53]. In this paper, the authors have, indeed, presented a V-Cloud architecture that includes an in-car CPVS, V2V communications, and V2I layers to enhance road safety. Furthermore, the authors in [37] have described a CPVS-based solution that deploys mobile ground autonomous vehicles (known as DORSI robot) to support ongoing military operations.

In spite of the promising results of current CPVS solutions, we argue that additional investigations are still needed in order to intelligently assess driving behaviours and performance and generate relevant feedbacks to the driver as well as to other drivers in the vicinity.

3 A NEW CYBER-PHYSICAL SYSTEM FOR DRIVING BEHAVIOUR ASSESSMENT

3.1 Motivating Scenario

Driving behaviours have long been investigated by the research community. Several studies (e.g., [24, 25, 26, 41]) have, indeed, proposed tools and methodologies in order to define these behaviours, identify them, classify them, detect their causes, as well as investigate their impact on road safety, mobility, and the environment. However, due to the increasing dependency on technology as well as the advent of new concepts (such as CVs), further investigations are necessary. In this regard, and with the increasing popularity of the V2X paradigm, we are still in need for new approaches that enable the exchange of the right traffic information at the right time between vehicles as well as with the right ITS actors/components in their environments. This is the case, for example, of a driver driving down a hill without

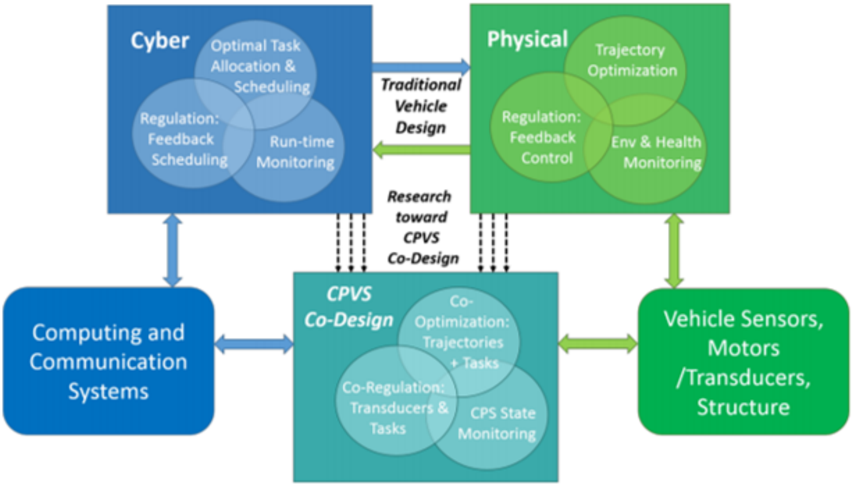

Figure 1. An evolution toward integrated CPVS run-time codesign [52]

being perfectly capable of maneuvering safely his vehicle due to bad road conditions (e.g., slippery). In this situation, it is important to report this fact and any relevant related information to the follower vehicles as well as to the vehicles coming from the opposite direction within a specific range. These vehicles would adjust their speeds to avoid any potential crashes. To this end, the driving performance of every individual driver should be known as well as any effect that could be incurred due to the specificities of the current location and the ongoing events. It is also important to possess the right tools to assess the relevance of the information received from any ITS peer component as well as its authenticity. Furthermore, as current technologies are prone to security breaches, the existing solutions still need to implement mechanisms that protect the drivers' data and safeguard their privacy. For this reason, a legal framework is needed, particularly to identify and classify driving behaviours. A more comprehensive framework is also needed to define what data should be exchanged in the specific context of CV, with which vehicles, when it should be exchanged, and where it should be exchanged. The right feedback must then be decided and provided to drivers to make sure that inappropriate, unsafe, and/or illegal behaviours are highlighted and, ultimately, avoided in the future. In order to respond to these needs, we propose in what follows a new CPS-based solution for the management of driving behaviour within the context of CVs.

3.2 Proposed Architecture

In order to manage driving behaviours, we propose in this paper the CPS architecture depicted in Figure 2. The data can be collected using Internet of Things

(IoT) devices, mobile apps, and/or any other dedicated device onboard of the vehicle. In our cyber layer, four modules are available: Beliefs, Actions, Feedback, and Applications. The Actions module aims at analyzing the data pushed out from the physical layer (e.g., acceleration/deceleration, braking, overpassing, etc.) and identifying the driving behaviour classes (i.e. safe/unsafe, legal/illegal) and states (see Figure 3). In order to achieve these tasks, several data repositories in the Beliefs module will be used/updated accordingly. More specifically, the Beliefs module includes personal beliefs repositories (i.e. driving behaviour, driving performance, etc.) as well as shared beliefs repositories (i.e. road network data, environmental data, policies, etc.). The data in the Beliefs repositories as well as new driving data will be particularly used to assess driving performance and calculate any related driving penalties. Driving performance and penalties can then be used to potentially impose specific driving restrictions on the driver (see Figure 3). Furthermore, the Action module aims to predict driving performance and identify the right data that could be shared with neighboring CVs at the right time. Finally, the Feedback module aims to identify and fire the right alerts based on the current driving data and traffic flow. It also aims to recommend specific trainings to the driver based on his/her driving performance. Feedback as well as results of the processing in the Actions module can be used in dedicated driving behaviour-related applications to improve road traffic safety and mobility.

The interactions between the different components of our CPS architecture will particularly allow us to identify and manage the driving states of the drivers. In other words, driving performance will be mapped into a regulatory framework through which drivers would be rewarded or penalized for their actions. We shed light in what follows on the proposed framework for driving states as well as on its transitions (see Figure 3).

3.3 Framework for Automated Driving States Identification – FADSI

In the context of CVs, it will be very important to automatically identify driving behaviours and then take appropriate legal actions and generate appropriate warnings, accordingly. However, to the best of our knowledge, these behaviours have not yet been mapped into any dedicated regulatory framework that explicitly define the driving states as well as their inter-relations. In order to address this matter, we propose a new Framework for Automated Driving States Identification (FADSI). FADSI (Figure 3) includes the following six states that reflect the situations into which a driver could fall based on his/her driving behaviour:

Normal. In this state, driving is bound to the ongoing road traffic policies.

Restitution. Based on the driving actions, if any road traffic policy is violated then the driving will transit to a Restitution state. In this case, the violation is assessed and classified. A recidivism level is calculated in order to check when, where, and how many times the driver has violated the same policy. If the

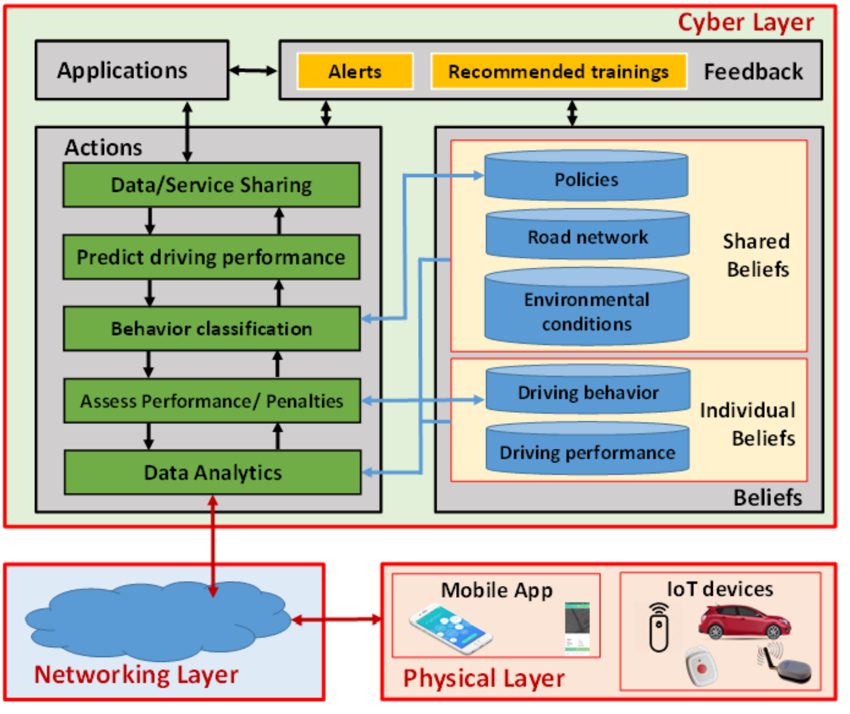

Figure 2. Proposed CPS architecture

fines related to the policy infraction is paid then the driving state will return to Normal. If, as per the policymakers, the recidivism level exceeds a given threshold or if the policy infraction is classified to be highly dangerous then the driving state will become Incapacitation. The driving could also transit to a Rehabilitation state based on the analysis done during the Restitution state. In order to decide on the next transition from the Restitution state, we propose to calculate driving penalties as follows:

$$f_u(x) = f_{u-1}(x) + \sum_{i=1}^{n} c_i * r_i * \sigma_i \tag{1}$$

where $f_u(x)$ is the cumulative penalty until commute u, $f_{(u-1)}(x)$ is the cumulative penalty until commute $u - 1$, the parameter n is the number of policies, c_i denote the cost of violating the policy i, r_i denote the recidivism factor for policy i, and $\delta_i = 1$ if policy i is violated during commute u and $\delta_i = 0$ otherwise.

Incapacitation. In this state, the driver is prevented from driving for a given period of time as per the rules specified by the policymakers.

Rehabilitation. Once the incapacitation period is over, the driving will transit to a Rehabilitation state wherein personalized policies will be applied. During this state, the driving behaviour is assessed and a decision to return to the Normal state is made accordingly.

Rewarding. Drivers who have exemplary driving behaviours (as defined by policymakers) during a given period of time will be rewarded. Reward could, for example, be in the form of insurance rebates.

Demerit. For severe or repeated infractions, a demerit point system is going to be used in order to reflect the corresponding penalties. For example, the driving license of a driver could be cancelled or suspended based on the number of demerit points accumulated by him/her over a period of time. Once the points of the new penalty are calculated, the driving could transit either to Incapacitation or to Rehabilitation.

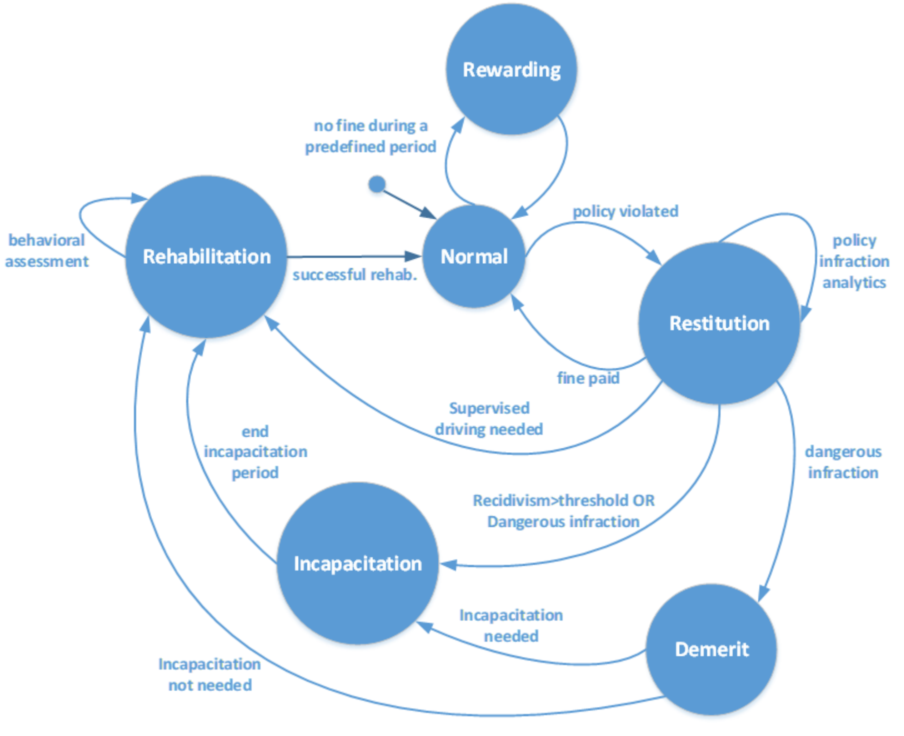

Figure 3. Framework for Automated Driving States Identification (FADSI)

3.4 Markov Decision Process

Our FADSI framework defines the legal states into which a driver may be at given time. The transitions between these states will depend on the behaviour of the driver. In order to predict these transitions, we are proposing the use of Markov Decision Process (MDP). MDP [56] could be defined with the following elements:

- A set of states ($s \in S$),
- A set of all possible actions ($a \in A$),
- A transition model ($P(s' \mid s, a)$) that will reflect the probability of going to state s' after taken action a in state s,
- A reward function ($R(s)$), and
- A discount factor (γ).

In our case, data about the performance of any given driver will be collected over time. A transition matrix could then be created, where the probabilities of transitions from one state to another could be calculated and updated with new feed about driving behavior. This matrix will then be translated to create a diagram similar to the one depicted in Figure 4. On this diagram, there is a reward r_i (alternatively a penalty) for the driver for being in the state s_i. The driving state could shift to the next state s_{i+1} if an action a_{i+1} is undertaken. This action has a probability p_i. The driver will get a reward (or a penalty) r_{i+1} once he/she transits to state s_{i+1}. The importance of this approach will lay on its use for the prediction of driving states and, therefore, generating the appropriate feedbacks to the driver.

4 CASE STUDY: MAPPING THE OMANI DRIVING LEGAL FRAMEWORK INTO THE PROPOSED FRAMEWORK

In order to showcase the relevance of our framework, we propose in this section to perform a mapping with an existing regulatory framework. More precisely, we consider the specific case-study of the regulatory framework in the Sultanate of Oman. We refer in this paper to this framework with ORTRF (ORTRF stands for Omani Road Traffic Regulation Framework). We summarize this mapping in Table 1.

Based on the mapping depicted in Table 1, we can say that our FADSI framework covers all the traffic road regulations in Oman. However, no existing regulation covers the aspects of rehabilitation and rewarding. For this reason, we argue that it is very important to extend the current ORTRF for the following reasons:

- Several infractions are caused by repetitive driving misbehaviors that need to be carefully addressed with legal supervision. This supervision will assess the improvement of driving behavior and ensure norecidivism.

						FADSI					
#	**Offence**	**Max. fine (OMR)**	**Penalty points**	**Procedure**	**Court actions**	**Normal**	**Restitution**	**Demerit**	**Incapacitation**	**Probation**	**Rewarding**
1	Driving under the influence of alcohol	50	3	Driver jailed for 48 hours max. Vehicle seized for 2 weeks max	Driving license could be cancelled under specific conditions				X		
2	Causing death by driving as result of dangerous driving or making damage to others' properties	50	3	Imprisonment for 48 hours (obligatory)	Refer to public prosecution for more investigation			X			
3	Escaping from scene of fatal accident or falling to report an accident	50	3	Impoundment of the vehicle (2 weeks) with possible imprisonment for 48 days	no actions			X			
4	Driving in a manner which is considered dangerous	50	3	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (recommended)	no actions			X			
5	Exceeding the speed limit by more than 75 KM	50	3	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (recommended)	no actions			X			
6	Driving car race on the road without permission	50	3	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (recommended)	no actions			X			
7	Driving outside the marked lanes	35	2	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (obligatory)	no actions			X			
8	Truck or bus overtaking in prohibited location or making a dangerous action	35	2	no actions	no actions			X			
9	Falling to identify motor bike as a result of covering the plate number	50	3	impoundment the vehicle(2week)with Imprisonment for 48 days (recommended)	no actions			X			

10	Using hand-held mobile phone or any other electronic device	15	2	If action repeated during 3 months, impoundment of the vehicle (not obligatory)	Maximum 10 days imprisonment and maximum 300 Rial fine				X		
11	Ignoring a red light	50	3	First time: sign a pledge not to repeat it	no actions			X			
				If repeated within the next 24 months then imprisonment for 48 hours and 2 weeks impoundment of the vehicle				X			
12	Falling to stop for police or runaway from location	35	1	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (recommended)	no actions			X			
13	Driving vehicle with none or expired insurance	50	0	Impoundment of the vehicle (2 weeks) with imprisonment for 48 days (recommended)	no actions		X				
14	Failing to identify driver as a result of covering the face	50	3	no actions	no actions		X				
15	Changing lanes illegally	35	2	no actions	no actions			X			
16	Making an illegal U-turn	0	10	no actions	no actions		X				
17	Driving a learner vehicle without a permit	2	35	no actions	no actions			X			
18	Following ambulances on roads	2	35	no actions	no actions			X			
19	Using films that affect glass transparency and reduce vision by more than 30%	0	10	no actions	no actions				X		

Table 1. Mapping the Omani road traffic regulation framework to FADSI

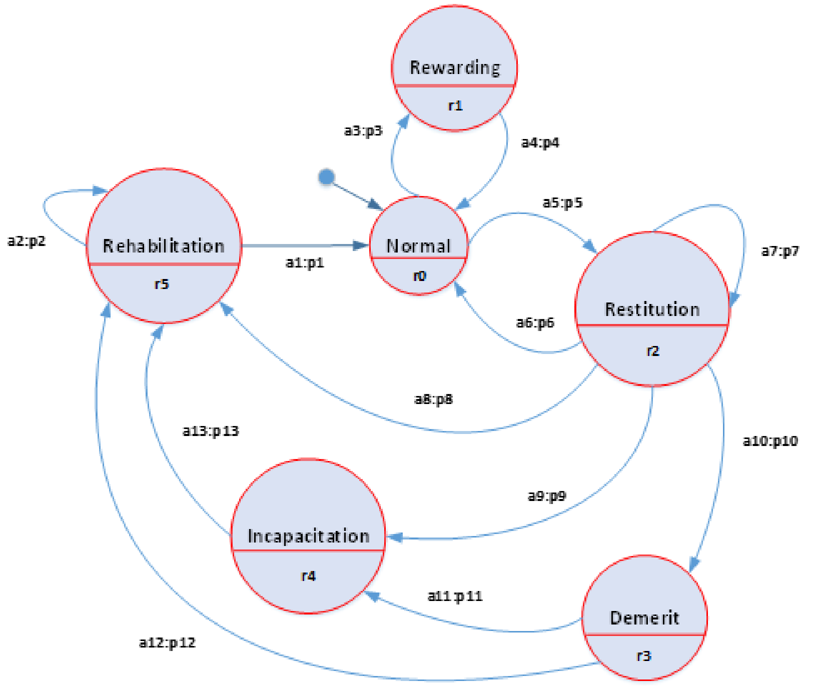

Figure 4. MDP mapped into our framework FADSI

- Regulatory frameworks around the world are commonly imposing fines for wrong driving behaviours. We argue that exemplary behaviours must be rewarded. This will particularly encourage drivers to selfregulate their driving. Road traffic risks may, therefore, decline.

5 CHALLENGES AND OPPORTUNITIES

Based on our thorough literature review, we remark that current approaches addressing driving behaviour management in the context of CVs are sharing several features. These features include data processing capabilities and behaviour detection mechanisms. Meanwhile, they differ on other features, such as behaviour prediction and feedbacks generated to drivers. Furthermore, in spite of the increasing popularity and capabilities of CPS and V2X fields, we argue that some emergent related technologies would bring great advantages to the solutions of driving behaviour management. In order to highlight the relevance of our solution, we present in what follow its related opportunities via a seamless integration with emerging technologies. Before this, we present the different challenges that must be addressed in order

Challenge	Description
Technology-related	• Availability of technology • Readiness of technology to establish stable and secure communications
Regulatory-related	• Absence of regulations for data and privacy protection • Absence of regulations to identify and assign reliabilities, particularly when technology is a major player and human lives are in stake • Absence of regulations related to rewarding exemplary behaviours • Some feedback solutions are not approved by local regulations
Human-related	• Discomfort of drivers of having their behaviours tracked and monitored by a third party • Discomfort of drivers with the exchange of data with unknown vehicles in the vicinity • Discomfort of drivers with the use of specific technologies for feedback
Implementation-related	Several modules of the proposed solution are not easy to implement as they require very complex coding

Table 2. Categories of challenges

to implement the proposed solution.

	Category of challenges			
	Technology	Regulatory	Human	Implementation
Driving data acquisition	X		X	X
Belief management				X
Driving behaviour classification				X
Driving states management		X		
Data sharing	X	X	X	
Feedback generation	X	X	X	X

Table 3. Challenges related to the implementation of our CPS solution

5.1 Challenges

In order to implement the proposed solution, several challenges must be overcome. These challenges could be classified into technology-related, regulatory-related, human-related, and implementation-related (Table 2). Firstly, the technology-related challenges mainly concern the readiness of current vehicle technologies in collecting and processing the right data and generating the right decision within acceptable timeframes (that may be very short when it comes to making real-time decisions to avoid road traffic crashes). In addition, not all current vehicles are necessary equipped with the right tools to establish stable and secure communications with the different components of an ITS. Secondly, regulatory related challenges mainly concern the absence of the right regulations to support the fast development of CVs and its related technologies. In this regard, several studies (e.g., [39, 54]) have highlighted serious issues concerning privacy and data protection. These concerns are major hindrances for the implementation of our architecture and its related vision. The case study of the ORTRF (see Table 1) already highlighted some shortcomings of an existing regulatory framework in supporting the proposed solution, particularly in terms of incapacitation and rewarding. Thirdly, the human-related challenges basically concern the readiness of drivers to rely on some advanced technologies that would continuously track their performance, especially since they continue to worry about their privacies. Lastly, implementation-related challenges are about the high complexity of developing the necessary software modules for the functions/services highlighted in our architecture (see Figure 2). In Table 3, we map the main aspects of our solution into these challenges as well as into the other challenges highlighted above.

5.2 Opportunities

In addition to the new CPS architecture, our solution includes a regulatory framework that explicitly specifies the driving states and their inter-related transitions. These states and transitions are identified based on previous and current driving performance, environmental conditions, road traffic flow, and CVs in the vicinity. We argue that our solution would create a well-structured framework where driving data could be thoroughly investigated and shared at the right time with the right components of an ITS, particularly within the context of CV. In Table 4, we highlight relevant opportunities that we are planning to investigate.

6 CONCLUSION

In this paper, we addressed the issue of managing driving behaviours. Intensive research works have investigated this issue and proposed a wide range of solutions that mainly allow for the collection of driving data and the assessment of related performance. In contract with these solutions, we proposed a new Cyber Physical System solution that implements a regulatory framework whereby driving states are assessed and classified and then the appropriate transitions are applied to drivers based on their driving performance. In the paper, we highlighted the importance, the challenges, and the opportunities related to our solution.

Our future works will focus on identifying and deploying the relevant emergent technologies to implement the different parts of our solution. More specifically, in addition to investigating data processing theories for an enhanced identification and classification of driving behaviors, we will work on implementing an intelligent

Technology	Opportunities
Internet of Things (IoT)	The proposed solution relies on our capability to gather real-time data about vehicles, driving behaviors, and the road traffic conditions. To meet this goal, the use of IoT is currently the obvious and unavoidable option. In addition, IoT will provide the solution with the necessary actuators to act of some ITS components (including vehicles) and could, therefore, ensure appropriate transitions to the driving state of demerit, incapacitation, and rehabilitation (see Fig. 3)
Big Data	IoT will allow the acquisition of huge amounts of, potentially real-time changing, data. Current Big Data-related technologies are quite advanced to process these data. The use of such technologies is mandatory to allow for the expected performance from the proposed solution. The use of Big Data analytics is particularly very important to get the right insights on driving behaviours as well as on road traffic conditions.
Machine learning	In order to process optimize the processing cost (in terms of resources and time), machine learning (and more specifically deep learning) will be an important option for the identification and the classification of driving behaviours. It will be also an important option for the generation of the right feedback to the drivers. In this regard, machine learning mechanisms could be combined with selected existing approaches (e.g. [41]) in order identify the right timing and format of delivering the feedback to the driver.
Blockchain	In the context of CVs, communications among vehicles must be secure and maintain the privacy of the interacting parties. The advent of blockchain is providing new means and techniques to achieve these goals while enabling to trace any data exchanges as well their legal/authorized senders and receivers. In additional to drivers, other stakeholders could benefit from a blockchain-based solution, including police, insurance companies, and car repair shops.
Immersive technologies	Immersive technologies are basically used to create distinct experiences to users by combining the physical world with a simulated or a virtual reality. These technologies are of paramount importance to our solution at two levels: (1) Providing the appropriate feedback to the driver while minimizing his/her interaction with the vehicle during commutes; and (2) Providing the driver with the appropriate tools to enhance the success of personalized trainings, based on driving performance.

Table 4. Seamless integration with emerging technologies

solution for the identification and the management of driving states. This solution will then be applied in a real-world scenario.

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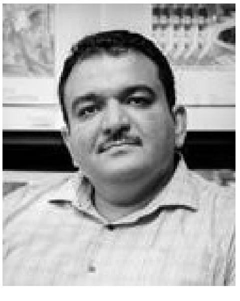

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