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Research Article

An IoT Architecture for Assessing Road Safety in Smart Cities

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The Safe System (SS) approach to road safety emphasizes safety-by-design through ensuring safe vehicles, road networks, and road users. With a strong motivation from the World Health Organization (WHO), this approach is increasingly adopted worldwide. Considerations in SS, however, are made for the medium-to-long term. Our interest in this work is to complement the approach with a short-to-medium term dynamic assessment of road safety. Toward this end, we introduce a novel, cost-effective Internet of Things (IoT) architecture that facilitates the realization of a robust and dynamic computational core in assessing the safety of a road network and its elements. In doing so, we introduce a new, meaningful, and scalable metric for assessing road safety. We also showcase the use of machine learning in the design of the metric computation core through a novel application of Hidden Markov Models (HMMs). Finally, the impact of the proposed architecture is demonstrated through an application to safety-based route planning.

1. Introduction

In its Global Status Report on Road Safety – 2015, the World Health Organization (WHO) noted that the worldwide total number of road traffic deaths has plateaued at 1.25 million per year, with tens of million either injured or disabled [1]. Different initiatives, such as the United Nations' initiative for the 2011-2020 Decade of Action for Road Safety, have led to improvements in road safety policies and enforcements. However, the WHO notes that the progress has been slow and has maintained the call for urgent action to reduce these figures [2].

Added to the losses in human lives and wellbeing, considerable monetary losses are incurred in medical expenses, infrastructure repair, and production downtime. While the worldwide figures have plateaued, the Global Status Report does indicate higher road fatalities and injuries in low-income countries. Such disparity, as noted in [3], signals a barring-limitation in low-income countries to improve road-safety by adopting solutions implemented in high-income countries.

The WHO describes different measures that can be implemented with minimal economic impacts in its "Save LIVES: Road Safety Technical Package" [4]. A cornerstone of these steps is realizing economic systems for "monitoring road safety by strengthening data systems". Meanwhile, a key theme in the package is motivating the adoption of a Safe System approach, which is a holistic approach to road safety that parts from traditional management solutions by emphasizing safety-by-design.

1.1. The Safe System Approach. The Safe System (SS) approach to transport networks originated with the "Safe Road Transport System" model developed by the Swedish Transport Agency. In its essence, the approach migrates from the view that accidents are largely and automatically the driver's fault to a view that identifies and evaluates the true causes for accidents. Through the categorization of safety into the safety of three elements (vehicle, road, and road user), SS minimizes fatalities and injuries by controlling speeds and facilitating prompt emergency response. The model has been widely adopted since its introduction and is currently motivated by the WHO as a basis for road safety planning, policy-making, and enforcement.

An illustration of the model is provided in Figure 1. A central emphasis is given to speed in the SS approach as it is the strongest and most fundamental variable in the

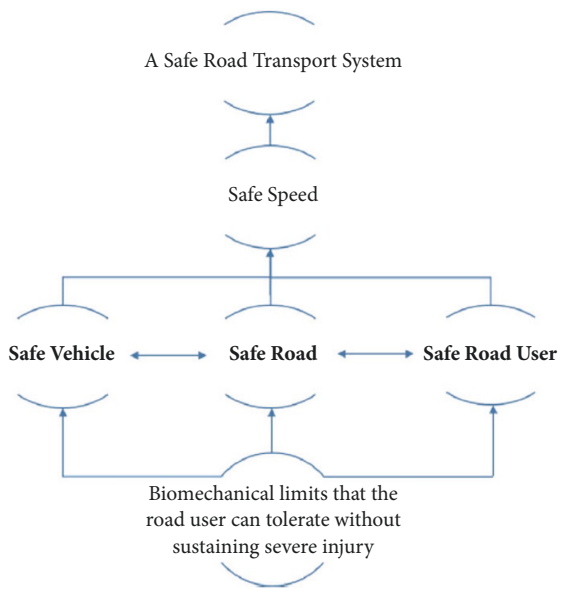


Figure 1: The Safe-System-based Safe Road Transport Systems, with its elements: safe vehicle, safe road, and safe road user [5].

outcome of fatality. The fragility of the human body makes it unlikely to survive an uncushioned impact at a speed of more than 30 km/h, with lower speeds resulting in either death or serious injury [3, 4]. The objective of the SS approach is that the three model elements should be designed and monitored to proactively prevent deadly speeds from happening and allow for a reduced emergency response time in the event of an accident.

Elements of the SS approach are as follows.

(1) Safe Vehicle. Emphasis on vehicle safety is verified through mandated regulatory testing and rating, as well as technologies such as electronic stability control. Beyond this, enforced checks (e.g., upon license renewals) combined with on the road reporting work to review the status of vehicle safety.

(2) Safe Road. The assessment of road (or road network) safety is multifaceted. Road inspection enables clear and direct observation of the state of the road and assesses the need for repairs or modifications. The structure of the road network is amenable to safety assessment through partitioning into what is called "Traffic Analysis Zones (TAZs)" [8]. In addition, considerations for crash data and other supporting data offer further insights into general safety assessment.

In 2011, the European Road Assessment Programme (EuroRAP) generated the European Road Safety Atlas for EU countries [9]. The atlas indicated the safety level of roads with a star rating based on specially equipped vehicles for multimedia-based data aggregation [10]. The EuroRAP efforts continue to implement an SS approach across the EU, along with several other national programmes within the International RAP, or iRAP, initiative [11].

(3) Safe Road User. There are several aspects to road user safety, including measures for education and awareness, travel distance, exposure, licensure, enforcement, and sober driving [5]. The need for such characterization rises substantially as the findings of crash report analysis in cities typically note a critical dependence on either driver behavior or driver awareness [12]. A great need is further established in these studies for innovative mechanisms to instill safe driving at the licensing and post-licensing stages.

1.2. Contributions. Figure 2 illustrates elements of assessing road safety. It can be seen in the figure that the scope of consideration in the SS approach is medium-to-long term, facilitating by design, systemic actions that are made to ensure the safety of the road network. While the use of "data monitoring systems" is motivated in [4] and can be utilized for shorter term scopes, the general emphasis is maintained at the medium-to-long term reaction cycles.

Our interest in this work is to extend SS to the short-to-medium term through exploiting recent advances in the context of the Internet of Things (IoT) and Intelligent Transport Systems (ITS) [13, 14]. This fits the outlook for Smart Cities where automation is emphasized to address the increasing dynamic nature of city elements [15].

Toward this, our contributions in this work are as follows:

(i) This work offers a comprehensive, IoT-based architecture with the objective of assessing the safety of the transportation road network.

(ii) In doing so, the proposed architecture is aligned with the SS approach in its entirety.

(iii) It also complements the SS approach by addressing the void in its short-to-medium scope of considerations, making the approach further fitting to the dynamic nature of smart cities (note the scopes illustrated in Figure 2).

(iv) Finally, the proposed architecture showcases the viability of an economic road safety monitoring through advances in IoT and ITS, especially those aimed at realizing smart cities.

The proposed architecture involves a novel use of machine learning as part of its road safety assessment core. This application facilitates assessments that are both dynamic and robust. We also showcase an application of the developed core aimed at safety-based route planning in smart cities.

1.3. Paper Organization. The remainder of this work is organized as follows. Section 2 reviews related work and motivates and positions the contributions made herein. Section 3 introduces the dynamic road safety assessment, with descriptions on architectural considerations, while Section 4 elaborates on the dynamic assessment core. Section 5 details an application of the developed assessment core in the context of route planning. Section 6 validates the dynamic assessment core together with a demonstration for route planning. Finally, Section 7 concludes this work.

2. Related Work and Motivation

This section reviews related works within the context of IoT and ITS, and their integrations within the more general

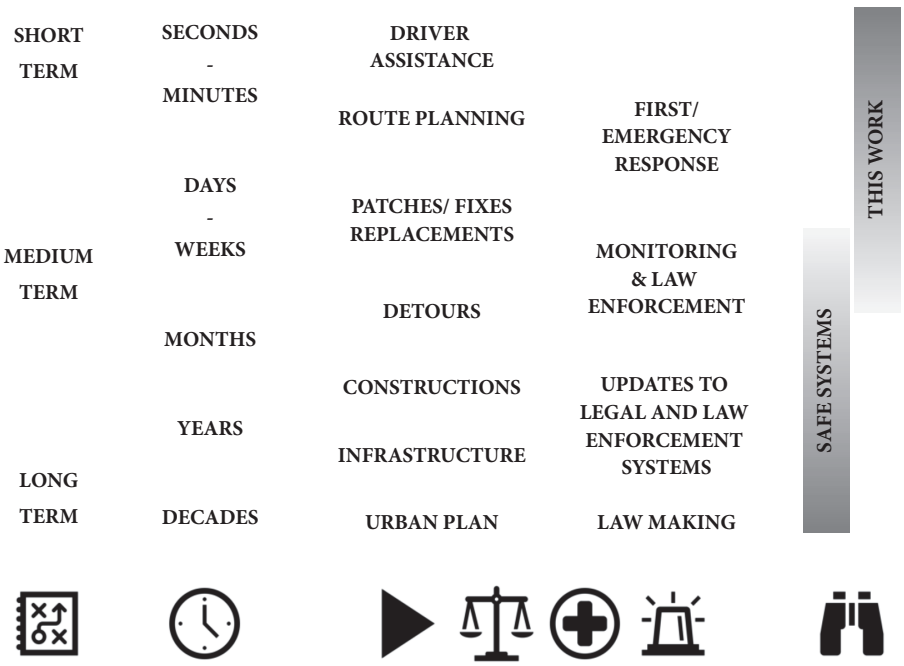


Figure 2: Safe System (SS) elements across different time considerations, i.e., short-, medium-, and long-term.

context of smart cities. The reviewed works have been categorized and presented per their relevance to elements of the adopted SS approach, i.e., in terms of facilitating safety in vehicles, roads, and drivers.

2.1. Safe Vehicle. As noted above, regulatory enforcements frame a substantial aspect of ensuring that vehicles traversing a city's road network are safe and reliable. Considerations for the short-to-medium term, however, require a more "real-time" monitoring of the vehicle status. Telematics allows for such monitoring within the IoT/ITS context and is facilitated by several options. The first includes having dedicated sensors, such as accelerometers, Carbon Monoxide (CO) level sensors, etc., mounted on the vehicle to gather and log information [15]. Such setups can be augmented with a communication module so that the collected data can be transferred to a local unit or to the cloud.

An alternative telematic approach involves accessing a vehicle's Controller Area Network (CAN), which is the network that interconnects a vehicle's computing and sensing capabilities [16]. Such access is made possible by a North American standard ratified in 1996, namely, the second-generation On-Board Diagnostics, or OBD-II. Since their introduction, OBD-II dongles have come a long way, with some models offering a mix of connectivity including Bluetooth, WIFI, and cellular (e.g., [17]). Through the OBD-II, various real-time and diagnostic information can be accessed, logged, and communicated, including RPM, speed, pedal position, coolant temperature, etc. This has allowed for applications such as TorquePro [18], which monitors a vehicle's fuel efficiency, and advises the driver more fuel-efficient driving behavior. More relevant here, another application has made it possible to identify when maintenance is required for a vehicle [19]. Meanwhile, OBD-II manufacturers, such as MUNIC [17], offers cloud-based portals for aggregating, processing, and visualizing sensed data, and that can be access for further processing by users.

The viability made by the above setups provides a key thrust to this work, especially as they enable an immediate assessment of a vehicle's safety. As will be demonstrated below, the introduction of smartphones allowed for more accessible in-vehicle monitoring that can be functional to various degrees, regardless of how the phone is mounted in the vehicle. Smartphones have also been used on their own or in a combined in-vehicle sensing unit including either dedicated sensors, OBD-II dongles, or both.

Many of these applications targeted the assessment of either road status or capturing driving behavior and are thus further elaborated on in the following two subsections.

2.2. Safe Road. As aforementioned, especially equipped vehicles within the xRAP programmes are optimal in how they facilitate exhaustive road inspections and ratings. Alternative approaches, however, have been sought using various cost-effective setups.

For example, in [20] an embedded device is realized to support various sensing techniques in road surface monitoring. Meanwhile, the system in [21] is proposed for the detection of wet-road conditions based on images captured by cameras mounted on the rear-view mirror of a vehicle. Specifically, the system employs image analysis for extracting features related to water and snow on the road. Other systems require the addition of simple hardware to such vehicles to widen the scope of the detection applications. For instance,

the pothole patrol [22] depends on the deployment of 3-axis accelerometers on board of vehicles for detecting such road conditions through monitoring vibration. Another example proposed in [23] is a system that detects ice on roads by analyzing tire-to-road friction ultrasonic noise detected by a transducer installed behind the front bumper.

Several works have also employed sensing features in smartphones and tablets. For example, the work in [24] aims at recognizing road surface anomalies through the combination of accelerometers and GPS data on a tablet, allowing for ease of data aggregation and reduced cost.

A smartphone system of note is *Nericell*, which utilizes smartphone accelerometers, microphones, and GPS to detect events related to the quality of the road, e.g., potholes and bumps [25]. Vibration thresholds are used to decide on detecting such road conditions, and to detect events linked to traffic including braking and vehicles' noise. Deceleration thresholds that are sustained for a predefined time interval are used to detect braking events, while microphones are used for detecting the noise levels. Another threshold-based inference implementation is proposed in [26]. The sensor measurements, accelerometers and photometers, are compared against a set of empirical thresholds and the anomaly is then detected when all thresholds are satisfied in a given road. The values of the thresholds are chosen based on measurements that indicated the existence of true anomalies within their values, while making sure that no anomalies are outside these intervals.

In [17], Bayesian inference and Unscented Kalman Filter (UKF) are used to determine the probability that a reported sequence of wheel measurements during nominal durations of time correspond to a pothole in the associated location. Bayesian inference is also applied for cooperative applications such as weather condition monitoring in [27]. The system aims to detect the foggy and icy conditions that would increase the probability of car accidents. Particularly, given the measurements of fog (from a thermal imaging camera) or icy conditions (from the temperature or the car stability), a belief function is calculated for each of these two conditions.

It has been advised that general caution should be exercised in relying on smartphones for sensing as some of their characteristics may limit sensing accuracy [28]. These characteristics include the smartphone's orientation, as well as its relative position inside the vehicle. Smartphones may further be limited in being able to directly capture a vehicle's external context, e.g., weather or visibility. Other sources may thus be needed to validate or augment the smartphone's view.

For example, the viability of crowdsourcing for smartphone users facilitates a further advantage, especially when it comes to validation. The system in [29] resolves the low accuracy stemming from the exclusive use of smartphones and relies on applying crowd-sourcing and on using sheer numbers to combat the presence of false positives. Meanwhile, authors in [30] consider pothole detection using a large dataset collected through implicit crowdsourcing, i.e., crowdsourcing without repeated user prompt/input. Thresholds are used on the phone's z-axis acceleration, with empirical data used for differentiating potholes from speed breakers.

Careful consideration should be made in evaluating the quality of aggregated data. For example, the work in [31] notes that various errors are introduced when crash data is reported by enforcement or insurance agencies. Meanwhile, validation mechanisms need to be introduced for any data aggregation measures based on common, i.e., nondedicated, technologies such as smartphones.

2.3. Safe Road User. Driver Behavior Modelling (DBM) [32, 33] is an area of road safety management that is concerned with the characterization of driver behavior. This characterization is enabled through the analysis of various inputs from either the transportation infrastructures, e.g., on-road CCTV cameras, speed-sensors; other infrastructures, e.g., smartphones, reporting to services such as Waze or Google Maps, registrations to cellular-base stations; or an in-vehicle sensing setup. Combined or separated, baselines for "safe" or "responsible" driving can be synthesized, against which counter driving behaviors are identifiable. Meanwhile, considerations for driver awareness or alertness can also be realized to extend identification to behaviors exhibited when driving under fatigue, distraction, or influence.

A smartphone-based driver activity recognition system is proposed in [34] with the objective of preventing drivers from texting while driving. The system identifies whether a smartphone holder (a) has entered a vehicle; (b) has boarded the vehicle from the left or the right; (c) sat in the front or back seat; and (d) is texting. Another system that differentiates drivers from passengers is offered in [35]. The system in [36] employs fuzzy logic and utilizes the acceleration, gravity, magnetic, and GPS sensors to estimate driving aspects such as jerk, orientation rate, speed variation, and bearing variation. A fusion module is then employed to distinguish activity such as hard/sudden acceleration or overspeeding.

The work in [37] exploits smartphone cameras to monitor the driver's alertness through recognizing head position and body orientation. It also utilizes the smartphone's back camera to process the driver's lane-change. Additionally, the system assists the user in detecting vehicles in the driver's blind-spot and alerts the driver if a lane change is undertaken while another vehicle is occupying the blind-spot.

Smartphone sensing is also utilized in [38] using both accelerometers and cameras to identify unsafe stopping behavior in busses. Meanwhile, a smartphone-based system is provided in [39] to identify aggressive driving styles.

Applications of combined smartphone and OBD-II sensing are provided in [40, 41], enabling the detection of different driving styles, and classifying whether the style is safe or unsafe. Particularly in [41] where engine load, RPM, speed, and pedal position are fused with smartphone data to assess driving behavior.

While much of the DBM has focused on human drivers, the general arguments presented herein are applicable to both human and autonomous driving agents. The model synthesized in [33], for example, considers human driving, assisted driving, and autonomous driving. The model synthesized is based on the Naturalistic Driving Study within the Second Strategic Highway Research Program (SHRP2-NDS).

The extensive data set relied on sensed data from in-vehicle setups synced with information on traversed roads, utilized vehicles, traffic conditions, and weather conditions. Through this comprehensive model, it is possible to identify behaviors such as "exceeded speed limit", "rolling stops", "drowsy", "sleepy", "asleep", and "fatigued". The model also enables characterizing distracted driving, as well as the nature of distraction, e.g., "cell phone, texting", "cell phone, holding", and "passenger in interaction seat – interaction".

2.4. Motivation. Achieving road safety is a multiterm and multifaceted objective, and the above discussion indicates strong emphasis in the SS approach on the medium-to-long term whereby road safety is achieved by design. Our interest in this work is to complement SS with a framework for a dynamic assessment of road safety. Our objectives are to first accommodate the dynamic nature of city traffic, especially in cases of major events and/or crisis. Secondly, it is to showcase the viability of an economically attractive alternative to monitor road safety using ubiquitous technologies and advances in IoT. This becomes critical to overcome any barring limitations, especially for low-to-medium income countries.

3. An IoT Architecture for Assessing the Safety of a Dynamic Road Transport System

In reviewing the related works in the previous section, we showcased how various advances are enabling the assessment of safety of vehicles, roads, and drivers. The objective of this section is to introduce a novel and adaptive IoT architecture that enables the assessment of safety in a city's road network. We elaborate on the assessment elements and how they can be used to synthesize a single, meaningful indicator for safety. We also describe the architecture components and their interrelationships, including a robust computational core for safety assessment.

3.1. Assessment Elements. The way the SS approach comprises the three elements of safe vehicle, safe road, and safe driver facilitates a hierarchical safety assessment approach whereby the safety of the individual elements can provide a collective indicator of safety for the road network, as illustrated in Figure 3. In turn, this indicator can be concatenated from the assessment of individual road segments, to routes, to the road network.

For vehicles, the assessment core would rely on inferences from the vehicle's Vehicle Identification Number (VIN) (thus establishing car make, manufacturing, and base safety rating); regulator's information (e.g., the outcome of the last regulatory check); and the updated information from an OBD-II unit.

For roads, the reliance on both historic and newly sensed data can facilitate an understanding of the road context, the road network map, and establish severity of turns, the presence of shoulders, and whether the road is on a hillside. Identifying a vehicle's location through an on-board GPS (whether dedicated or through a smartphone) would thereby provide for a first level of this understanding. Meanwhile, in-vehicle sensing can be utilized to report road anomalies (e.g., potholes). Sensing based on the OBD-II interface can also help identify instances of skidding, which in turn can be correlated with weather or reports. Weather, together with time of the day (ToD) and reports on the availability and/or state of road-lights, can be combined to ascertain visibility. Moreover, basic traffic information can indicate congestion levels, as well as road/segment criticality, i.e., repeated selection in route plans generated within a short span of time.

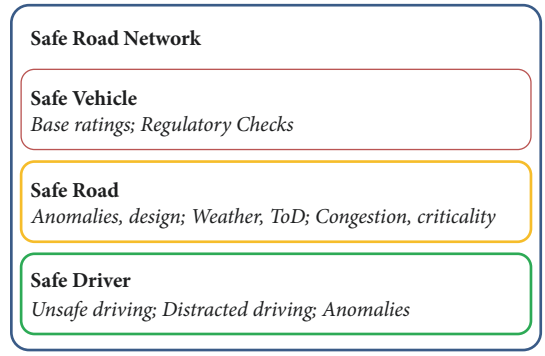


Figure 3: Elements in assessing the safety of the road network based on the safe systems approach.

As for drivers, the growing maturity of DBM will facilitate identifying unsafe or distracted driving behavior. It will also enable the recognition of localized driving behavior anomalies, facilitating the identification of emerging incidents, e.g., several swift lane changes to avoid a new obstacle in the road due to a falling tree trunk or other road debris.

It is possible to consider a meaningful safety metric based on the live (or real-time) status of the road. For example, the safety level of a certain segment/road depends on the aggregate safety of vehicles currently traversing it, combined with the number of potholes and/or the wetness or how slippery is the road, in addition to safety/alertness of the drivers on the road.

In designing our architecture, we exploit three important dependencies. The first is between the SS elements, e.g., how well a car can handle a certain road, or how some drivers exhibit safer behavior in instances of higher visibility. The second dependency is in between consecutive segment/roads, especially in terms of traversing vehicles and drivers. The third dependency is like the second but is established in time. Abrupt changes in safety levels can thus be viewed as an anomaly (outlier) or inferred as indicator to a substantial change in the road context.

3.2. Architecture Considerations. An illustration of architecture consideration is provided in Figure 4. At the core of the proposed architecture is a computational core that operates in two tiers. The first is concerned with dynamically assessing the safety of each aspect in SS. The second utilizes the outcome of these three assessments to generate a single rating for the road.

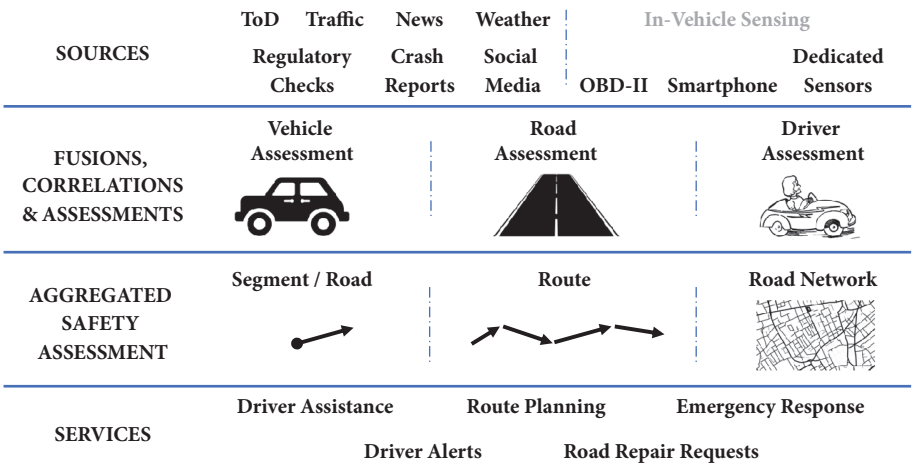


Figure 4: Architecture considerations for dynamic assessment of road network safety.

Figure 5: An example breakdown of fusion, correlation, and assessment for a Safe System component.

The individual assessments rely on a wide array of sources that generally fall into two categories. The first is sourced through in-vehicle sensing, while the second through sources that establish the general context of the road. These include traffic problems, regulatory checks, crash reports, processing of news and social media, weather updates, and time of day.

As aforementioned, inferences and assessments in each of the three elements of SS can utilize the same sources. This motivates the placement of the data fusion and correlation element in the architecture, as shown in Figure 5. In data fusion, sources that yield to the same knowledge synthesis are combined to enhance its reliability, while correlation is concerned with cotiming and colocation of sensed data, as well as cross-validation of input knowledge streams.

Based on the output of the three assessment modules, a live representation of a segment's safety to traverse can be made. We elaborate on a model for generating this representation below. Once the aggregated safety assessments have been generated, the values can be provided to several services that include driver-assistance modules and generating requests for road repair or emergency response.

In the following section we demonstrate how this assessment core can be utilized in a safety-based route planning application.

3.3. In-Vehicle Sensing. A possible setup for in-vehicle sensing comprises three elements: an OBD-II dongle, a dedicated sensor, and a smartphone. We evaluated two OBD-II interface alternatives: munic.box's Munic3 4G-cat4-WBT dongle and ScanTool's OBDLink MX Bluetooth. Both performed as desired on the tested vehicles. The dedicated sensor was Aaronia's GPS logger, which combines sensors for GPS localizations, compass, accelerometer, gyroscope, and altimeter with pressure sensor. The logger does not have wireless communication capabilities but can be connected to a PC through USB. Meanwhile, recent iOS and android-based phones were utilized for both their communication and sensing caspabilities.

While an objective of the work is to realize a cost-effective solution for dynamic assessment, the purpose of the setup described above was designed for both exploratory and validation purposed. Where the sensing elements were able to connect to the cloud repository directly, e.g., as in the case of the munic.box dongle, or the smartphone, the connection was allowed. Otherwise, a connection was established indirectly through another device, e.g., the logger through the PC laptop or ScanTool's dongle through the smartphone.

For the backend, sensed data and be transferred and stored on a PostgreSQL 9.6 built on a Red Hat Enterprise Linux Developer OS. This setup would allow for an Apache web portal access, facilitating quick prototyping and ease of simultaneous data reports from multiple sources.

3.4. The Assessment Core. Road networks comprise a complex, living structure, and thus require care in modeling any of their aspects. This is especially the case in cities and high density urban areas where traffic dynamics becomes further involved and further engaged with other planes of city activity.

In remarking on dependencies above, we noted that a reasonable model to assess a road network's safety should

mind the interelement dependencies in SS, as well as the dependencies in both space and time. It should also facilitate the quantification of these interdependencies without substantial overhead.

The design of such assessment core is elaborated upon in the next section.

4. Designing a Dynamic Assessment Core

Recent thrust into machine learning and its different variants (supervised, unsupervised, and reinforcement-based) has made addressing high processing demands in solving various problems possible. The operational requirements highlighted in Section 3.4 above position the target assessment core as a typical candidate for machine learning considerations. In what follows, we showcase an example modeling to the road network that can facilitate a robust and dynamic processing.

Hidden Markov Modelling (HMM) is a powerful statistical tool for modelling time-series systems that can be characterized to represent probability distributions over a sequence of observations. The tool thus lends itself easily to the nature of data gathering found in IoT and smart cities applications. It further stands as a potential base model for several machine learning approaches, including Bayesian or Mixture Density Network inferences.

Our interest herein is in a novel application HMMs to our problem. Specifically, a first-order, time-homogeneous, and discrete HMM is employed to identify the degree to which traversing a certain road link is safe, thereby realizing a safety metric.

The HMM at hand can be formally defined by the five-tuple $\Phi = (S, M, P, \delta, \pi)$, where S is an array of links' states; M is the emission symbols that characterizes observations per each state; P is the states' transition probabilities; δ is the emission (or output) probability matrix; and π is the initial state distribution array. We assume that the road link state in terms of safety, denoted S_t, is hidden from the observer. We also assume that the current hidden state of a certain road link depends only on the preceding state of the same road, i.e., that the Markov property is satisfied.

In what follows we elaborate on the tuple elements.

States, S: the hidden states of the road link status, which describe the safety of the road link. For example, and without loss of generality, two-states can be utilized, whether safe or not. Further in-between states can be added.

Emission Symbols, M: the observations from which the hidden states can be deduced. Examples of possible observations are road link congestion rate; road condition metric; road infrastructure type, e.g., number of road link lanes, type side or highway link; or road infrastructure characteristic; e.g., road visibility, etc. A metric utilizing a combination of two or more of these and other observations can also be synthesized.

For illustration, M can be made to capture road link congestion, with $M_i(t) = 0, 1, 2, \ldots, m-1$, representing m levels of congestion. If $m = 4$, the congestion can be digitized into 4 levels at $0, 25\%$, 50%, 75%, all relative to the link's maximum capacity. If we define the random variable $q_n(t)$ as the congestion of road segment, n at time, t, then, $M_n(t)$, as a function of road segment congestion, can be defined to be as follows.

$$M_n(t) = \begin{cases} 0, & 0.25 > q_n(t) \geq 0 \\ 1, & 0.5 > q_n(t) \geq 0.25 \\ 2, & 0.75 > q_n(t) \geq 0.5 \\ 3, & 1 \geq q_n(t) \geq 0.75 \end{cases} \quad (1)$$

It is essential to note, however, that the limits of these levels would need to be normalized to usefully reflect actual links congestion levels.

Transition Probabilities, P, is the probability of transition among the two states in the HMM.

Probability of Emission, δ (or output probabilities), is equal to $P(M_i/S_1)$ and $P(M_i/S_2)$ given the current state is S_1 (safe) or S_2 (unsafe) road link, respectively. Extending the illustrative example above, δ_i can be calculated if we know the probability distribution of $q_n(t)$, an empirical distribution interpolated from the sensory data. The empirical distribution can be approximated into the best standard distribution, if possible, taking into consideration the trade-off between accuracy and complexity.

Initial State Distribution, π, specifies the initial probability distribution of the states. While typically initialized using a uniform distribution assignment, there are generally no assumptions needed regarding prior distribution.

Three traditional algorithms can be employed to efficiently compute an HMM, namely, the Viterbi algorithm, the Forward-Backward algorithm, and the Expectation-Maximization algorithm [42]. This is particularly advantageous in the computation of link safety for our purposes. Furthermore, once the HMM is determined, the state of the links (as well the state of regions) can be identified and utilized using various services, including route planning, as will be discussed in the next section.

5. Safety-Based Route Planning

Route planning has become widely used in both personal and commercial use, resulting in an increasing dependence on its reliability. Various applications employ efficient algorithms for route planning [43]. Trip time and cost, e.g., for tolls, have been the typical metrics for route planning applications, but other metrics, however, have been utilized, e.g., for fuel emission/consumption or energy requirements of electric vehicles.

Using the dynamic safety assessment proposed above, it is now possible to route vehicles across cities based on a safety. In this manner, drivers can be directed through routes that minimizes their overall risk in traversing the road network. Meanwhile, enforcement can distribute vehicles across different paths to distribute risk of the network and avoid having critically unsafe links or routes within the network. It is furthermore possible to target auxiliary mechanisms for safety-control across the network by controlling and redirecting traffic based on user driving behavior or in-response to incidental changes in the road network.

An advantage of the assessment core proposed above is that a routing algorithm can be operated directly on its generated values. In what follows we describe a direct application for routes assumed to be traversed shortly after the route have been computed, and that require a traversal time sufficiently less than transition time in the HMM. These assumptions are without loss in generality and can be relaxed with easy modifications to the route planning formulation presented below.

Consider a graph (V, E), with V comprising $n+1$ nodes (vertices), and E comprising the edges in the graph. Nodes represent starting, ending, and midway stops for the vehicle, and our interest is in routing a vehicle from a source node (s) to a destination node (d). Vertices are further identified by numbers, with vertex 0 identifying the source node and $0 < i < n$ identifying possible target destinations. Nonsource nodes make the set $V^* = V - \{0\}$.

The set of edges $E = \{(i, j) : i, j \in V; i < j\}$ represents the set of $n \cdot (n+1)/2$ links between the $n+1$ nodes. Each edge has an associated traversal cost $c_{ij} > 0$, which may be either symmetric ($c_{ij} = c_{ji}$) or asymmetric ($c_{ij} \neq c_{ij}$). Herein, this cost can be inversely proportional to a link's safety assessment.

Considering the above, a formulation can be presented as shown in Table 1. The formulation minimizes the expended cost. The first four constraints suffice for a general (uncapacitated) shortest-path problem. The first constraint mandates that a stop along the chosen route is visited only once. The second constraint specifies that, except for the source and the destination, each stop has as many ingoing as outgoing traversals. The third and fourth constraint mandate single departure from the source and a single arrival at the destination.

The above formulation is an integer-programming instance, making the essential route planning problem NP-hard. Meanwhile, when engaging the computation core, as specified by the formulation above, the core is supplied with the updated "costs" and the "capacities" of the edges. This *updating*, while facilitating more relevant solutions, results in solutions that are at best critically stable. Dealing with probabilistic coefficients or constraint thus becomes inevitable when extending considerations for more realistic modelling. Such coefficients and limits, however, only add to the problem complexity.

The application of the road-safety assessment core introduced in Section 4 above overcomes this complexity aspect by simplifying the handling of the probabilistic. Enumerations. Specifically, the formulation can be revised to be applied over the HMM abstraction of the road-network, allow an end-to-end path selection based on safety.

Table 1: Formulation for the route planning problem.

$$\min \sum_{k \in F} \sum_{\substack{i,j \in V \\ i \neq j}} c_{ij} x_{ij}$$

Subject to: -

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in V$$

$$\sum_{k \in F} \sum_{i \in V} x_{ij} = 1 \quad \forall j = V^*$$

$$\sum_{i \in V} x_{iu} - \sum_{j \in V} x_{uj} = 0 \quad \forall u \in V \setminus \{s, d\}$$

$$\sum_{i \in V} x_{iu} - \sum_{j \in V} x_{uj} = -1 \quad \text{if } u = s, \ \forall u \in V^*$$

$$\sum_{i \in V} x_{iu} - \sum_{j \in V} x_{uj} = +1 \quad \text{if } u = d, \ \forall u \in V^*$$

6. Results and Validation

We validate the work through a case study based on data available for New York County, NY, USA. Maps and shapefiles were sourced from Open Street Maps (OSM) [6], United States Census Bureau [7], and David Gleich's US Roads extracts [44]. We utilized collisions data sourced from the New York City (NYC) OpenData portal [45]. Notwithstanding, the model applicability extends to all localized data. Core processing were performed in Matlab [46], with some preprocessing made in Geomatica 17 [47].

Figure 6(a) shows the map of the target area of analysis, while Figure 6(b) shows the road network as extracted from OSM shapefile. We note the longitude and latitude limits in Figure 6(b) as they dictate our focus for the results to follow.

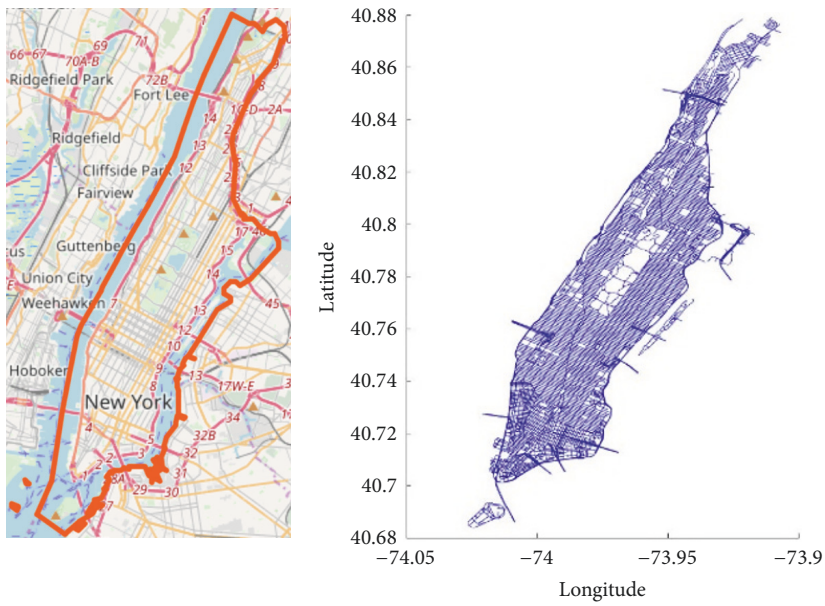
The NYC OpenData collisions dataset, as detailed in [45] specifies collision date, time, longitude, latitude, and address (street and/or intersection). The dataset also qualifies collisions based on deaths and injuries for motorists, pedestrians, and cyclists, as well as other contributing factors and vehicle types. The data is dated starting December 2, 2013, and populated until the date of download. An example of collision overlay on the road network is shown in Figure 7, where the red dots denote collision location. The extract in Figure 7 is partial for the map for the date June 23, 2018 during the hours 06:00 to 07:30.

Close analysis of the data details further characterization of collision distribution in terms of time and space. Here, we isolated the data for 2018 (starting January 1, 2018) and reviewed their space and time characteristics.

Figure 8 shows an overlay between location aggregate and the County's street network. This showcases a higher number of collisions in areas mapped to the County's main ingress/egress points (i.e., the Lincoln Tunnel, Manhattan Bridge, etc.), while the remainder of County area have on average near-equal collision numbers.

A second view is availed through reviewing collision distribution in time, which is shown in Figure 9. The histogram shows a drop in average daily collisions during the hours 00:00 (i.e., midnight) to 06:00, with a substantial but piecewise rise in collision counts during the hours 06:00 to 18:00.

Based on the above, we proceeded to feed the road network's HMM. In doing so, we mapped the network' edges to the HMM's nodes. We also considered four six-hour time windows, namely, the hours 00:00 to 06:00; 06:00 to 12:00; 12:00 to 18:00; and 18:00 to 24:00. We note, however, that a closer categorization of collision might be needed after isolating weekdays from weekends. Notwithstanding, the choice of windows does not result in loss of generality for results.



(a) (b)

Figure 6: Extracts for New York County from Open Street Maps (OSM): (a) overall map extract [6]; and (b) extract of the New York County road network [7].

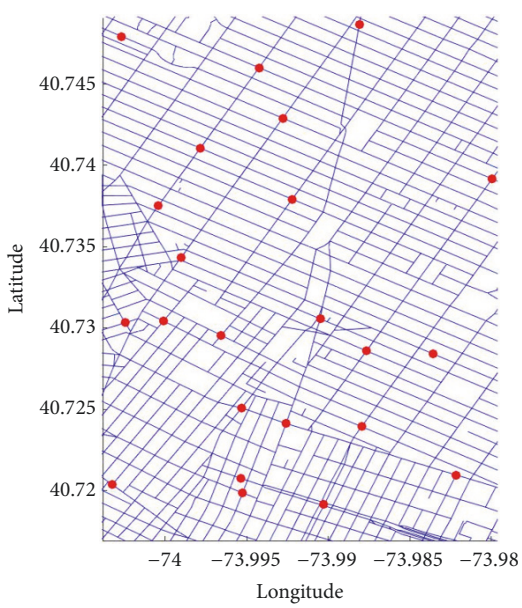


Figure 7: Collisions during the hours 06:00 to 07:30 on June 23, 2018, overlaid on a partial map of the New York County road network, with collision locations shown in red dots.

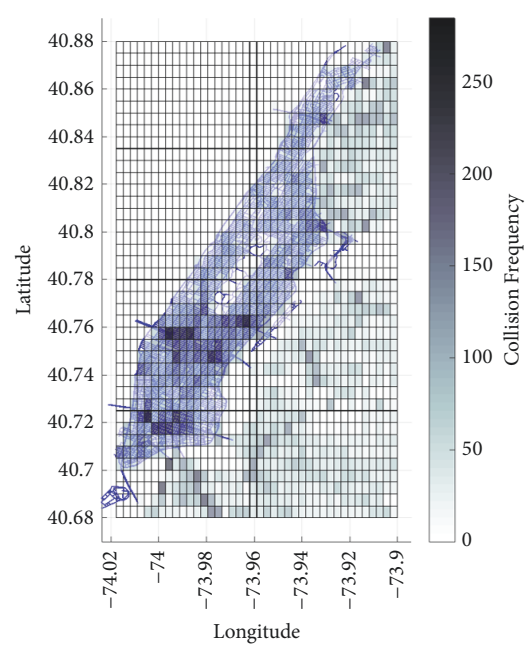


Figure 8: Overlay of New York County street network and collisions for 2018 (January 1, 2018 onward). Darker regions indicate higher collision frequencies.

Safety level was graded into four levels. Emission was normalized across County area in a manner like the description in Section 4. The HMM was initialized with uniform distribution.

We implemented the HMM using Matlab as per the description offered in Section 4. In doing so, we mapped the state of safety to the edge weights in the County road network. Figure 10 shows the route plan between two points on the road network, with the red highlighting the shortest path based on distance, and the green based on safety. The shortest path algorithm followed the description provided in Section 5.

7. Conclusions

This work illustrates the viability of an economic road safety monitoring and assessment solution through exploiting advances in the Internet of Things (IoT) within the context

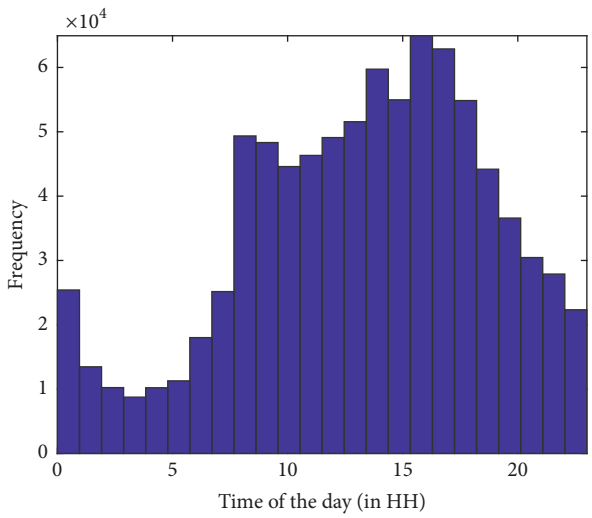


Figure 9: Collision distribution in time for the New York County street network and collisions for 2018 (January 1, 2018 onward).

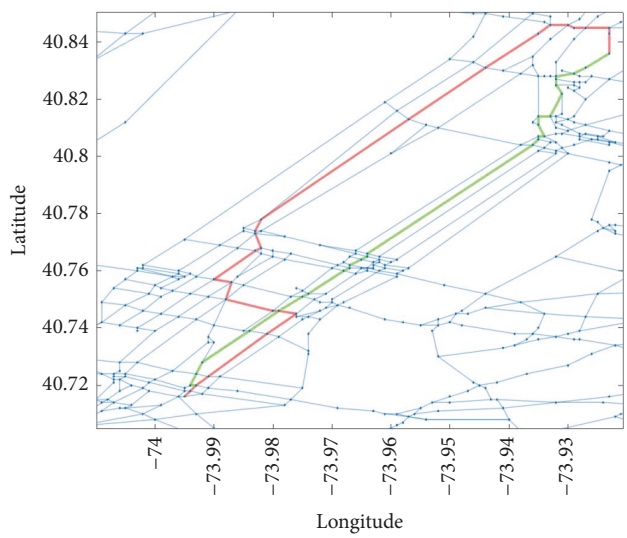


Figure 10: Route planning between two points on the New York County road network, with the red based on the shortest path, and the green based on safety.

of smart cities. The introduced architecture facilitates robust and dynamic road safety assessment that complements the Safe System approach motivated by the World Health Organization (WHO), which has been increasingly adopted worldwide. An application of the dynamic assessment framework for route planning is also demonstrated.

Future work involves exploring further applications, especially in the context of raising driver awareness of the road safety conditions during their trips.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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