VEHICULAR 2025

The Fourteenth International Conference on Advances in Vehicular Systems, Technologies and Applications

ISBN: 978-1-68558-233-3

March 9th –13th, 2025

Lisbon, Portugal

VEHICULAR 2025 Editors

Eugen Borcoci, National University of Science and Technology POLITEHNICA Bucharest, Romania

VEHICULAR 2025

Forward

The Fourteenth International Conference on Advances in Vehicular Systems, Technologies and Applications (VEHICULAR 2025), held between March 9th, 2025, and March 13th, 2025, in Lisbon, Portugal, continued a series of international events considering the state-of-the-art technologies for information dissemination in vehicle-to-vehicle and vehicle-to-infrastructure and focusing on advances in vehicular systems, technologies and applications.

Mobility brought new dimensions to communication and networking systems, making possible new applications and services in vehicular systems. Wireless networking and communication between vehicles and infrastructure have specific characteristics from other conventional wireless networking systems and applications (rapidly changing topology, specific road direction of vehicle movements, etc.). These led to specific constraints and optimizations techniques; for example, power efficiency is not as important for vehicle communications as it is for traditional ad hoc networking. Additionally, vehicle applications demand strict communications performance requirements that are not present in conventional wireless networks. Services can range from time-critical safety services, traffic management, to infotainment and local advertising services. They introduce critical and subliminal information. Subliminally delivered information, unobtrusive techniques for driver's state detection, and mitigation or regulation interfaces enlarge the spectrum of challenges in vehicular systems.

We take the opportunity to warmly thank all the members of the VEHICULAR 2025 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to VEHICULAR 2025. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the VEHICULAR 2025 organizing committee for their help in handling the logistics of this event.

We hope that VEHICULAR 2025 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress in the field of vehicular systems, technologies, and applications.

VEHICULAR 2025 Chairs

VEHICULAR 2025 Steering Committee
Khalil El-Khatib, University of Ontario Institute of Technology – Oshawa, Canada
Éric Renault, ESIEE Paris, France
Xiaohong Peng, Birmingham City University, UK
Yuping He, University of Ontario Institute of Technology, Canada

VEHICULAR 2025 Publicity Chairs
Francisco Javier Díaz Blasco, Universitat Politècnica de València, Spain
Ali Ahmad, Universitat Politècnica de València, Spain
José Miguel Jiménez, Universitat Politècnica de València, Spain

Sandra Viciano Tudela, Universitat Politècnica de València, Spain

VEHICULAR 2025
Committee

VEHICULAR 2025 Steering Committee

Khalil El-Khatib, University of Ontario Institute of Technology – Oshawa, Canada
Éric Renault, ESIEE Paris, France
Xiaohong Peng, Birmingham City University, UK
Yuping He, University of Ontario Institute of Technology, Canada

VEHICULAR 2025 Publicity Chairs

Francisco Javier Díaz Blasco, Universitat Politècnica de València, Spain
Ali Ahmad, Universitat Politècnica de València, Spain
José Miguel Jiménez, Universitat Politècnica de València, Spain
Sandra Viciano Tudela, Universitat Politècnica de València, Spain

VEHICULAR 2025 Technical Program Committee

Vahdat Abdelzad, University of Waterloo, Canada
Nor Fadzilah Abdullah, National University of Malaysia (UKM), Malaysia
Mohammed Al-Ansi, University Malaysia Perlis (UniMAP), Malaysia
Sufyan T. Faraj Al-Janabi, University of Anbar, Ramadi, Iraq
Ali Alfoudi, Al-Qadisiyah University, Irak
Ala'a Al-Momani, Ulm University, Germany
Adel Aneiba, Birmingham City University, UK
Waqas Aman, Sultan Qaboos University, Oman
Muhammad Asim, Chung-Ang University, Seoul, South Korea
Hakan Aydin, Karadeniz Technical University, Turkey
Manlio Bacco, CNR-ISTI, Italy
Andrea Baiocchi, University of Roma "Sapienza", Italy
Paolo Barsocchi, ISTI (Institute of Information Science and Technologies) | Italian National Research Council (C.N.R.), Pisa, Italy
Paulo C. Bartolomeu, University of Aveiro, Portugal
Marcel Baunach, Graz University of Technology, Austria
Rahim (Ray) Benekohal, University of Illinois at Urbana-Champaign, USA
Sylvia Bhattacharya, Kennesaw State University, USA
Neila Bhouri, Université Gustave Eiffel, France
Konstantinos Blekas, University of Ioannina, Greece
Eugen Borcoci, National University of Science and Technology POLITEHNICA Bucharest, Romania
Alexandros-Apostolos A. Boulogeorgos, University of Piraeus, Greece
Christos Bouras, University of Patras, Greece
Alyssa Byrnes, University of North Carolina at Chapel Hill, USA
Roberto Caldelli, CNIT, Florence, Italy
Rodrigo Capobianco Guido, São Paulo State University (UNESP), Brazil
Antonio Carcaterra, Sapienza University of Rome, Italy
Pedro Cardoso, Universidade do Algarve, Portugal

Marcos F. Caetano, University of Brasilia, Brazil
Florent Carlier, Centre de Reserche en Education de Nantes / Le Mans Université, France
Juan Carlos Ruiz, Universitat Politecnica de Valencia, Spain
Rodrigo Castelan Carlson, Federal University of Santa Catarina, Brazil
Francois Chan, Royal Military College, Canada
Rui Chen, Xidian University, China
Gihwan Cho, Jeonbuk University, Korea
Adam Cohen, University of California, Berkeley, USA
Gianpiero Costantino, Institute of Informatics and Telematics (IIT) | National Research Council (CNR), Italy
Yousef-Awwad Daraghmi, Palestine Technical University-Kadoorie, Palestine
Gonçalo Homem de Almeida Correia, TU Delft, Netherlands
David de Andrés, Universitat Politècnica de València, Spain
Fawad Ud Din, McGill University, Canada
Liza Dixon, Independent Researcher, Germany
Konrad Doll, University of Applied Sciences Aschaffenburg, Germany
Zoran Duric, George Mason University, USA
Péter Ekler, Budapest University of Technology and Economics, Hungary
Mostafa Emam, University of the Bundeswehr Munich, Germany
Suzi Iryanti Fadilah, Universiti Sains Malaysia, University
Mariano Falcitelli, Photonic Networks & Technologies National Laboratory of CNIT, Italy
Abraham O. Fapojuwo, University of Calgary, Canada
Gustavo Fernandez Dominguez, Center for Digital Safety & Security | AIT Austrian Institute of Technology, Austria
Irene Fiesoli, University of Florence, Italy
Francesco Flammini, Mälardalen University, Sweden
Pierfrancesco Foglia, Università di Pisa, Italy
Clovis Francis, Arts et Métiers ParisTech, Châlons en Champagne, France
Miguel Franklin de Castro, Federal University of Ceará, Brazil
Tomonari Furukawa, University of Virginia, USA
Varun Garg, UMass Lowell, USA
Pedro Pablo Garrido Abenza, Universidad Miguel Hernandez de Elche, Spain
Malek Ghanes, Centrale Nantes, France
Lee Gillam, University of Surrey, UK
Apostolos Gkamas, University of Ioannina, Greece
Sezer Goren, Yeditepe University, Turkey
Alberto Gotta, National Research Council - Institute of Information Science and Technologies “A. Faedo” (CNR-ISTI), Italy
Heinrich Gotzig, Valeo, Germany
Javier Gozalvez, Universidad Miguel Hernandez de Elche, Spain
Abel Guilhermino da Silva Filho, Federal University of Pernambuco - UFPE, Brazil
Marco Häberle, University of Tuebingen, Germany
Rami Hamdi, Hamad Bin Khalifa University, Qatar Foundation, Qatar
Kyungtae (KT) Han, Toyota North America, USA
Petr Hanáček, Brno University of Technology, Czech Republic
Hong Hande, Huawei Technologies, Singapore
Fazirulhisyam Hashim, Universiti Putra Malaysia (UPM), Malaysia
Yuping He, University of Ontario Institute of Technology, Canada

Moritz Höser, Bauhaus Luftfahrt e. V., Taufkirchen, Germany
Javier Ibanez-Guzman, Renault S.A., France
Hocine Imine, IFSTTAR/LEPSIS, France
Uzair Javaid, National University of Singapore, Singapore
Dush Nalin Jayakody, Tomsk Polytechnic University, Russia
Terje Jensen, Telenor, Norway
Yiming Ji, Georgia Southern University, USA
Felipe Jiménez Alonso, Technical University of Madrid, Spain
Magnus Jonsson, Halmstad University, Sweden
Filbert Juwono, Curtin University, Malaysia
Thabet Kacem, University of the District of Columbia, USA
Chuyo Kaku, Jiangsu Chaoli Electric Co. Ltd., China
Gorkem Kar, Bahcesehir University, Turkey
Frank Kargl, Institute of Distributed Systems | Ulm University, Germany
Sokratis K. Katsikas, Norwegian University of Science and Technology, Norway
John Kenney, Toyota InfoTech Labs, USA
Norazlina Khamis, Universiti Malaysia Sabah, Malaysia
Asil Koc, McGill University, Montreal, Canada
Lisimachos Kondi, University of Ioannina, Greece
Spyros Kontogiannis, University of Ioannina, Greece
Anastasios Kouvelas, ETH Zürich, Switzerland
Zdzislaw Kowalczuk, Gdansk University of Technology, Poland
Francine Krief, Bordeaux INP, France
Reiner Kriesten, University of Applied Sciences Karlsruhe, Germany
Ryo Kurachi, Nagoya University, Japan
Gyu Myoung Lee, Liverpool John Moores University, UK
Lianggui Liu, Zhejiang Shuren University, China
M.Carmen Lucas-Estañ, Universidad Miguel Hernández de Elche, Spain
Dalila B. Megherbi, University of Massachusetts, USA
Zoubir Mammeri, IRIT - Paul Sabatier University, France
Sunil Manvi, REVA University, India
Mirco Marchetti, University of Modena and Reggio Emilia, Italy
Philippe Martinet, Inria Center at Côte d'Azur University, France
P. Takis Mathiopoulos, University of Athens, Greece
Rashid Mehmood, King Abdul Aziz University, Saudi Arabia
José Manuel Menéndez, Universidad Politécnica de Madrid, Spain
Maria Luisa Merani, University of Modena and Reggio Emilia, Italy
Lyudmila Mihaylova, The University of Sheffield, UK
Gerardo Mino Aguilar, Benemérita Universidad Autónoma De Puebla, Mexico
Naveen Mohan, KTH, Sweden
Bruno Monsuez, ENSTA ParisTech, France
Umberto Montanaro, University of Surrey, UK
Luís Moutinho, Escola Superior de Gestão e Tecnologia de Águeda (ESTGA) - University of Aveiro / Instituto de Telecomunicações, Portugal
Vasco N. G. J. Soares, Instituto de Telecomunicações / Instituto Politécnico de Castelo Branco, Portugal
Mena Nagiub, Valeo Schalter und Sensoren GmbH, Germany
Jose Eugenio Naranjo Hernandez, Universidad Politécnica de Madrid | Instituto Universitario de Investigación del Automóvil (INSIA), Spain

Ridha Nasri, Orange Labs, France
Keivan Navaie, Lancaster University, UK
Vincent Omollo Nyangaresi, Tom Mboya University College, Kenya
Tomas Olovsson, Chalmers University of Technology, Gothenburg, Sweden
Rodolfo Orjuela, IRIMAS-Université de Haute-Alsace (UHA), France
Patrik Österberg, Mid Sweden University, Sweden
Gerald Ostermayer, University of Applied Sciences Upper Austria, Hagenberg, Austria
Ciprian Paduraru, University of Bucharest, Romania
Ilias Panagiotopoulos, Harokopio University of Athens, Greece
Sugandh Pargal, IIT Kharagpur, India
Antonio M. Pascoal, Institute for Systems and Robotics - IST | Univ. Lisbon, Portugal
Al-Sakib Khan Pathan, United International University, Bangladesh
Robert M. Patton, Oak Ridge National Laboratory, USA
Xiaohong Peng, Birmingham City University, UK
Paulo J. G. Pereirinha, Polytechnic of Coimbra | IPC/ISEC | INESC Coimbra, Portugal
Fernando Pereñíguez García, University Defense Center | Spanish Air Force Academy, Murcia, Spain
Valerio Persico, University of Napoli Federico II, Italy
Ivan Petrunin, Cranfield University, UK
Paulo Pinto, Universidade Nova de Lisboa, Portugal
Ioannis Politis, Aristotle University of Thessaloniki, Greece
Srinivas Pulugurtha, University of Mississippi, USA
Mahmoud Rahat, Halmstad University, Sweden
Hesham Rakha, Virginia Tech Transportation Institute, USA
Mohd Fadlee A Rasid, Universiti Putra Malaysia, Malaysia
Éric Renault, ESIEE Paris, France
Martin Ring, Robert Bosch GmbH, Germany
Lidia G. S. Rocha, Federal University of São Carlos, Brazil
Geraldo P. Rocha Filho, University of Brasília, Brazil
Giulio Rossolini, Scuola Superiore Sant'Anna, Pisa
Aymeric Rousseau, Argonne National Laboratory, USA
Javier Rubio-Loyola, CINVESTAV, Mexico
João Rufino, Instituto de Telecomunicações - Pólo Aveiro, Portugal
Aduwati Sali, UPM, Malaysia
José Santa Lozano, Technical University of Cartagena (UPCT), Spain
José Santa, Technical University of Cartagena, Spain
Nico Saputro, Parahyangan Catholic University, Bandung, Indonesia
Marios Savvides, Carnegie Mellon University, USA
Barbara Schütt, FZI Research Center of Information Technology, Germany
Alireza Shahrabi, Glasgow Caledonian University, Scotland, UK
Rajan Shankaran, Macquarie University, Australia
Susmit Shannigrahi, Tennessee Tech University, USA
Prinkle Sharma, University of Massachusetts Dartmouth, USA
Shih-Lung Shaw, University of Tennessee Knoxville, USA
Dana Simian, Lucian Blaga University of Sibiu, Romania
Pranav Kumar Singh, Central Institute of Technology Kokrajhar, India
Michal Sojka, Czech Technical University in Prague, Czech Republic
Marko Sonkki, Ericsson, Germany
Chokri Souani, Higher Institute of Applied Sciences and Technology of Sousse, Tunisia

Copyright Information

Table of Contents

Context-Aware Collaborative Perception: Estimating Relevance through Knowledge Representation

Romain Tessier [1,2], Oyunchimeg Shagdar [2], Bruno Monsuez [1]

[1] *U2IS, ENSTA, Institut Polytechnique de Paris*, 828 Bd. des Maréchaux, Palaiseau, France
[2] *Ampere Software Technology*, 1 Av. du Golf, Guyancourt, France
Email: {romain.tessier, bruno.monsuez}@ensta.fr, oyunchimeg.shagdar@ampere.cars

***Abstract*—Automated driving systems have made significant strides in real-time perception and response to complex driving scenarios. However, these systems struggle when road users are beyond sensor range or obstructed by obstacles, limiting their ability to make informed decisions. Cooperative Intelligent Transport Systems (C-ITS) offer a promising solution by enabling vehicles to share real-time data with nearby vehicles and infrastructure. While this enhances collaborative perception, a major challenge is managing the high volume of sensor data exchanged, which are not always useful for the receiver. This can lead to data congestion, latency, and misinterpretation. Our solution addresses these issues by using an ontology to represent a vehicle's observable scene and assess information relevance. Additionally, the ontology serves as a knowledge base, facilitating semantic communication that allows more effective interpretation of received messages. This approach aims to improve both the safety and efficiency of cooperative systems in automated driving environments.**

***Keywords*-Collective Perception; V2X; Ontology; Context-aware; Semantic-Communication.**

I. INTRODUCTION

As the global number of vehicles on the road continues to rise, ensuring road safety remains a critical concern. According to the World Health Organization [1], approximately 1.2 million people died in 2023 due to road traffic crashes, with countless more suffering non-fatal injuries. In response to these alarming statistics, the automotive industry faces mounting pressure to improve vehicle safety systems aimed at preventing accidents and reducing fatalities. Automated driving technologies play a key role in this effort by enabling real-time perception, analysis, and response to complex driving environments. Despite these advancements, automated vehicles still face limitations when making decisions based on their own perception of the environment, particularly in scenarios where obstacles obstruct a vehicle's line of sight or where objects are out of sensor range [2][3]. To address these limitations, C-ITS have emerged as a promising solution [4]. By facilitating real-time information exchange among vehicles, infrastructure, and other road users, C-ITS enhances situational awareness beyond the capabilities of onboard sensors alone. Leveraging Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, C-ITS enables vehicles to access a broader array of information from nearby vehicles or RoadSide Units (RSUs), allowing them to make more informed decisions in critical situations. By sharing data on traffic conditions, potential hazards, and road infrastructure, C-ITS offers a proactive approach to accident prevention that goes beyond the limitations of non connected autonomous systems.

Integrating Collective Perception Services (CPS) within the C-ITS framework represents a crucial step toward achieving safer and more efficient roadways [5][6]. CPS allows vehicles to collaboratively perceive and interpret road users, significantly improving their global perception. The Collective Perception Message (CPM) is the standardized message format used to transmit aggregated data which contain information relative to the locally-detected elements. Particularly valuable is the ability to share data about occluded or out of sensor range objects in real time, which enhances a vehicle's capacity to anticipate and respond to hidden dangers. However, as the number of connected nodes—such as vehicles and infrastructure—continues to grow, so does the volume of data transmitted over communication channels. Given that each CPM usually includes data on the perceived elements, this exponential increase in data can lead to communication congestion, resulting in latency, energy over-consumption, and challenges in merging data across heterogeneous sources.

In the context of vehicular networks, effective communication hinges on the principle of transmitting relevant information efficiently, as conceptualized by Shannon's Information Theory. According to Shannon, information is defined as the reduction of uncertainty (entropy) [7][8]; thus, relevant data in vehicular systems is the one that significantly contributes to reducing uncertainty about the environment for the receiving vehicle. In this case, data relevance is not merely about the volume of information but about the usefulness of the transmitted data regarding the needs of the receiver. In CPM, the relevance of information is closely tied to the type of system consuming it and its specific context. For instance, an Automatic Emergency Braking (AEB) system requires highly precise data regarding very close predicted object trajectories to make immediate safety interventions; An Autonomous Driving (AD) system needs a broader understanding of the environment to plan longer-term maneuvers, such as anticipating the pedestrian's intention to cross the road. The solution utilizes an ontology to represent the vehicle's observable scene, enabling it to assess the relevance of the situation. This allows the system to adjust the frequency and priority of message transmissions according to its criticity. By enhancing semantic precision and contextual relevance, this approach aims to reduce data congestion, improve decision-making efficiency, and ultimately advance the safety and efficacy of C-ITS.

This paper is organized as follows: Section II provides an overview of congestion mitigation in Collaborative Perception and Semantic Communication. Section III presents a specific use case to introduce the issues of contextual and informational relevance. In Section IV, an ontology model is explored to describe the vehicle's knowledge base. Section V then discusses methods for using the ontology to assess the contextual relevance of situations. Finally, Section VI demonstrates how this knowledge can be shared among connected vehicles and integrated into the vehicle's C-ITS architecture.

II. Related Work

Mitigating channel congestion has been the main concern in a large number of research activities. For example, in [9], vehicles reduce the CPM generation frequency in high-density areas. Decentralized Congestion Control (DCC) techniques have been proposed to allow individual nodes to autonomously adjust their transmission rates based on channel congestion level observed locally [10]–[13]. While these congestion control systems effectively alleviate network congestion, they often lack explicit consideration of context. In critical scenarios, this can lead to potentially harmful information gaps. To address this, some solutions incorporate context-awareness. For example, [14] proposes limiting collaborative communication to the most relevant nodes by creating a matching score between nodes. However, in C-ITS, where actors change rapidly, this approach is incompatible with the handshake mechanism explained in Who2Com [14]. Consequently, other studies propose limiting communication within geographical zones to ensure a level of relevance. In Direct-CP [15], collaborative communication is monitored by infrastructure based on each vehicle's maneuver intent. In contrast, Where2Com [16] does not rely on infrastructure to manage communication; instead, it uses a spatial confidence map at each agent to facilitate pragmatic compression, guiding agents on what to communicate, with whom, and whose information to aggregate. Additionally, [17] introduces a protocol that takes context into account for CPM generation frequency by aggregating information about the communication channel and environmental context (e.g., other vehicles and road layout). However, these solutions do not ensure that transmitted messages remain semantically relevant to the receiver; in other words, they do not consider what information will be efficiently consumed. Consequently, the receiver must infer semantic information about the sender's context, which may lead to interpretation issues.

To tackle these challenges, recent studies advocate for semantic communication between vehicles, which aims to convey meaningful content with inherent contextual value. For instance in [18], the authors implemented collaborative perception by extracting semantic features that are gathered and computed by an edge server. This concept of communicating high semantic-value information is also explored in [19]–[22] where a semantic encoder/decoder achieves higher transmission efficiency. This approach is demonstrated in [23] for image segmentation: rather than sending a full image (6 MB), it can be advantageous to transmit only the semantic interpretation of the image (30.5 KB). However, in semantic communication, the data is not merely compressed; it is reduced to the essential meaning. Thus, both the sender and receiver must have some form of shared knowledge to encode and decode the information effectively. This notion of a knowledge base can be linked to situational context, as the context forms part of the vehicle's knowledge. Finally, [24] provides initial steps for implementing semantic communication in V2X, introducing a new layer between the application layer and the transport/network layer. The authors illustrate the benefits of semantic communication through use cases such as adaptive traffic light management and collaborative driving. In this work, we aim to advance these efforts by (i) enhancing context-awareness in collaborative perception to generate situationally relevant messages, and (ii) adding semantic precision to collaborative messages, thereby minimizing interpretation issues and improving decision-making capabilities.

III. Assessing Relevance

Let us imagine a scenario as shown in Figure 1. A vehicle (V1) is positioned on the left side of a straight road, while a pedestrian (P1) crosses the road, and a vehicle (V2) on the right is masked by a bus (O1). This "hidden pedestrian" situation is critical for accident prevention [25], emphasizing the need for collaborative perception between vehicles. In traditional CPS, V1 continually generates CPMs without fully accounting for the specific environmental context. While such messages are situationally relevant, they usually include pre-processed sensor data on all detected objects, such as their positions, speeds, and types. Consequently, the message would

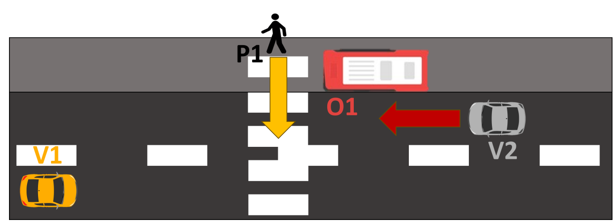


Figure 1. Use Case : Hidden Pedestrian Intending To Cross.

relay information about the pedestrian (P1), the bus (O1), the vehicle (V2), data that may not be entirely relevant to the vehicle (V2). This lack of context-awareness can lead to the transmission of unnecessary data, potentially impacting decision-making and response times. A more efficient solution involves integrating formalized knowledge into both vehicles. This way, the vehicle (V1) can communicate only the most valuable and situationally relevant information, while the other vehicle (V2), armed with a similar knowledge base, can interpret the context and make quicker decisions.

IV. Formalizing Knowledge

Ontologies—structured models in knowledge representation—enable this level of contextual relevance by defining sets

Copyright (c) IARIA, 2025. ISBN: 978-1-68558-233-3

of concepts, their attributes, and relationships within a specific domain [26]–[29]. Leveraging ontologies enables machines to process and share information with enhanced semantic precision. In autonomous vehicle systems, ontologies provide a standardized framework for consistently interpreting and integrating data across diverse systems—an essential capability for effective inter-vehicular communication and decision-making. Given the variety of data sources in autonomous driving, from real-time sensors to camera feeds, ontological mapping transforms raw data into semantically enriched formats. For example, to resolve the relevance assessment in the masked pedestrian scenario, an ontology must efficiently describe the situation. Here, the *Road-Segment* comprises two *Lanes* (*Lane-Left* and *Lane-Right*) and a *Crossing-Path*. *Vehicle-1*, classified as a *Car*, *isDriving* on *Lane-Right* and *hasDetected* *Vehicle-2*, *Pedestrian-1*, and *Bus-1*. Meanwhile, *Pedestrian-1* *intendToCross* via the *Crossing-Path*. *Vehicle-2*, also a *Car*, *isDriving* on *Lane-Left* and *hasDetected* *Vehicle-1* and *Bus-1* and also *intendToCross* via the *Crossing-Path*. This ontological

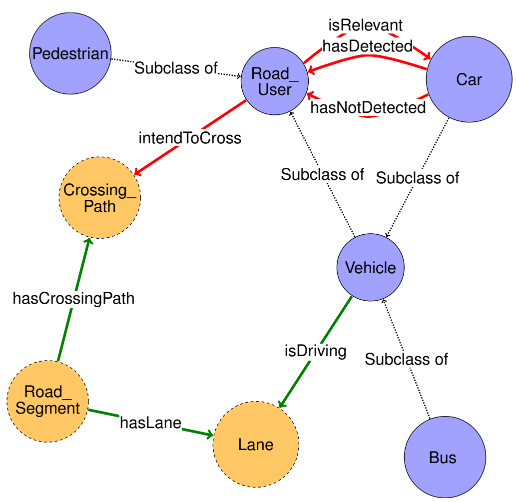


Figure 2. Example Ontology for Masked Pedestrian Use Case.

(Figure 2) representation of the scene allows the system to capture structural properties (green arrows) and functional properties (red arrows), supporting collaborative perception and enhancing safety-critical decisions.

V. Contextual Relevance Estimation

Relevance identification is performed by establishing a set of rules in the Semantic Web Rule Language (SWRL) format, which facilitates advanced reasoning over ontologies to infer new knowledge from existing information. SWRL rules consist of conditions and conclusions expressed in terms of ontological classes and properties, allowing for the formal representation of complex relationships and logical inferences. These rules can adhere to theoretical principles, defining relevance based on parameters, such as distance, state, or type, thereby creating a structured approach to understanding interactions within a given context. Alternatively, they can be scenario-specific, tailored to reflect particular conditions and requirements relevant to specific situations. Scenario-based relevance can be derived from accidentology studies that identify scenarios where the safety benefits of C-ITS have been demonstrated [25]. The SECUR results distilled 15 high-risk scenarios, with safety benefits estimated for each. Thus, relevance estimation can be achieved through scene recognition by determining if the vehicle's observable scene falls within a high-risk scenario. Scenario-based relevance, relies on predefined cases that may not generalize well to novel or evolving traffic situations. This approach risks overlooking edge cases or unexpected factor combinations that do not neatly fit within established categories but still pose safety concerns. Despite this, a scenario-specific definition ensures that information is relevant within the identified use cases but does not inherently imply irrelevance in other scenarios. In practice, a message deemed crucial in one context may still hold value in different, yet unaccounted-for, situations. Thus, rather than strictly matching predefined cases, it may be necessary to assess the degree to which the vehicle's current situation resembles known scenarios.

Another solution could be to find patterns from accidentology databases itself by employing machine learning techniques [27][26], to derive complex SWRL rules that are highly specific and adaptive to real-world conditions (see Figure 3). In this context, machine learning models not only facilitate the

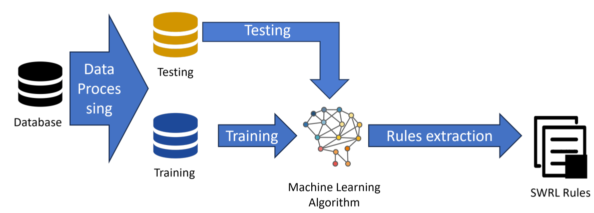


Figure 3. Rules Extraction Based On Accidentology Database.

extraction of patterns and trends from historical accident data but also enhance the precision of the SWRL rules generated. This integration allows for a continuous improvement loop, where the relevance criteria can evolve based on updated data inputs. After a training phase, the vehicle becomes capable of assessing the relevance of a situation in real time by using the ontology, which is updated through vehicle's perception layer, and by applying the SWRL rules. For each road users instantiated inside the knowledge base, the relevance is assessed in relation to the other road users.

For the pedestrian use case, we can define a simple SWRL rule to infer the relevance of the situation.

$$
\begin{aligned}
&\text{RoadUser}(?pedestrian) \wedge \text{Car}(?car) \\
&\quad \wedge \text{intendToCross}(?pedestrian, ?crossing) \\
&\quad \wedge \text{intendToCross}(?car, ?crossing) \\
&\quad \wedge \text{hasNotDetected}(?car, ?pedestrian) \\
&\quad \wedge \text{speed}(?car, ?carSpeed) \\
&\quad \wedge \text{swrlb:greaterThan}(?carSpeed, \text{SpeedThreshold}) \\
&\rightarrow \text{isRelevantTo}(?pedestrian, ?car)
\end{aligned}
$$

This set of rules defines when a road user is considered relevant to a vehicle. Specifically, it evaluates whether both a pedestrian and a vehicle intend to cross paths and ensures that the vehicle has not yet detected the pedestrian. It also checks the vehicle's speed against a predefined threshold, indicating that if the vehicle is already stationary, the information is not relevant. If these conditions are satisfied, the pedestrian data becomes relevant to the vehicle, prompting any vehicle that has locally-detected both elements to include the relevant information in a CPM.

VI. Knowledge Sharing

Knowledge sharing between vehicles can complement sensor data by providing additional context, which is critical for autonomous vehicles. Studies show that ontology and formalized knowledge representation improve decision-making [28]–[30]. Semantic-aware messages can be used to share knowledge between vehicles, adding valuable semantic details about the environment [18]–[20][23][24]. For example, in this use case, sender can generate a message about the pedestrian not just with its position, speed, and timestamp but also enriched with semantic details like "pedestrian on sidewalk," "pedestrian intending to cross," or "pedestrian hidden by bus." This enriched information allows the receiver vehicle to fuse data from multiple sources, such as RSUs and other vehicles, recognizing that they have detected the same pedestrian, even if the detection timing and precision differ.

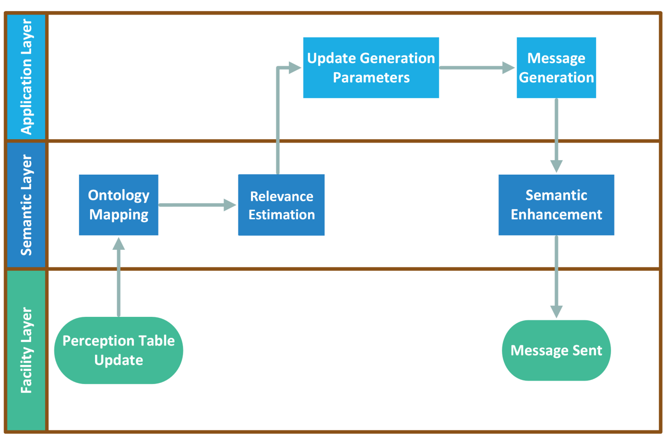


Figure 4. Integration of Semantic Layer For CPM.

In this use case, the vehicle (V1) observes a pedestrian (P1) crossing a straight road while a bus (O1) occludes another vehicle (V2) on the opposite side. The process begins with V1's sensors detecting and classifying entities within its environment. These entities—such as "Pedestrian", "Bus", "Crossing path", and "Vehicle"—are instantiated within the ontology (Ontology Mapping, Figure 4), each associated with specific properties like location, movement direction and link between instances (Section IV). Once these instances and properties are mapped in the ontology, an inference engine applies predefined rules to evaluate the scenario, SWRL rules (Section V) specify conditions under which an information relative to an element is relevant to another element (Relevance Estimation, Figure 4). Following this, the Collective Perception Application constructs a CPM containing only the relevant information, specifically prioritizing details about the pedestrian due to its potential impact on V2. Furthermore, the Collective Perception Application (CPA) dynamically adjusts the message transmission frequency based on the overall relevance of the situation. Based on the ontology instances and the sensors data, CPM message is enhanced with semantic properties like "intending to cross" (Semantic Enhancement, Figure 4). Upon receiving the enriched CPM, V2 utilizes its own ontological model to interpret the semantic information embedded within the message. This process allows the vehicle (V2) to integrate the contextual details about the pedestrian with its existing sensor data, effectively enhancing its understanding of the environment. For instance, recognizing that a pedestrian is "intending to cross" prompts the vehicle (V2) to prioritize its own response strategy, potentially preparing to yield or adjust speed. This capability to process semantic enrichment ensures that the receiver vehicle can act promptly and appropriately, even in complex driving conditions where visual information is compromised. This approach improves situational awareness and supports more accurate interpretation of the environment, thereby enhancing the value of information.

VII. Conclusion

C-ITS and the integration of CPS mark a significant advancement in enhancing road safety. By fostering real-time communication among vehicles and infrastructure, the proposed solution addresses critical limitations associated with traditional automated driving systems, particularly in terms of situational awareness and decision-making. The utilization of ontologies and semantic communication enables vehicles to share contextually relevant and semantically enriched information, thereby reducing data congestion and improving the accuracy of interpretations in dynamic environments. This research underscores the importance of situational pertinence and the value of information in collaborative perception, paving the way for safer and more efficient transportation systems.

In future work, relevance estimation will be implemented within a simulation environment, leveraging ontologies to support various consumers, such as Perception, Advanced Driver Assistance Systems (ADAS), and Automated Driving. This effort will involve the development of an ontology-based framework and a comparative analysis of two distinct approaches to defining relevance. The first approach will utilize machine learning algorithms for pattern extraction, employing data-driven techniques to derive relevance rules. The second approach will adopt a scenario-specific exploration, where relevance is defined based on predefined scenarios and expert-driven criteria tailored to specific use cases. By comparing these methods, this study aims to uncover their respective strengths, limitations, and areas of applicability, paving the way for more adaptive and effective relevance estimation strategies across diverse applications. Additionally, compar-

 ISBN: 978-1-68558-233-3

isons will be made with methodologies presented in recent literature [14][15][16] to benchmark and validate the proposed approaches. It is also crucial to address the challenges posed by ontology computation in real-time scenarios, ensuring its feasibility and robustness in practical implementations.

References

[1] *Global Status Report on Road Safety 2023*, en, 1st ed. Geneva: World Health Organization, 2023, ISBN: 978-92-4-008651-7.

[2] J. Ruan *et al.*, "A review of occluded objects detection in real complex scenarios for autonomous driving," en, *Green Energy and Intelligent Transportation*, vol. 2, no. 3, p. 100 092, Jun. 2023, ISSN: 27731537. DOI: 10.1016/j.geits.2023.100092.

[3] E. Marti, M. A. De Miguel, F. Garcia, and J. Perez, "A Review of Sensor Technologies for Perception in Automated Driving," en, *IEEE Intelligent Transportation Systems Magazine*, vol. 11, no. 4, pp. 94–108, 2019, ISSN: 1939-1390, 1941-1197. DOI: 10.1109/MITS.2019.2907630.

[4] J. Ko, J. Jang, and C. Oh, "Assessing the Safety Benefits of In-Vehicle Warning Information by Vehicle Interaction Analysis in C-ITS Environments," en, *Journal of Korean Society of Transportation*, vol. 39, no. 1, pp. 1–13, Feb. 2021, ISSN: 1229-1366, 2234-4217. DOI: 10.7470/jkst.2021.39.1.001.

[5] G. Yu, H. Li, Y. Wang, P. Chen, and B. Zhou, "A review on cooperative perception and control supported infrastructure-vehicle system," en, *Green Energy and Intelligent Transportation*, vol. 1, no. 3, p. 100 023, Dec. 2022, ISSN: 27731537. DOI: 10.1016/j.geits.2022.100023.

[6] S. Hu, Z. Fang, Y. Deng, X. Chen, and Y. Fang, *Collaborative Perception for Connected and Autonomous Driving: Challenges, Possible Solutions and Opportunities*, arXiv:2401.01544 [cs, eess], Jan. 2024.

[7] C. E. Shannon, "A mathematical theory of communication," *The Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948. DOI: 10.1002/j.1538-7305.1948.tb01338.x.

[8] J. V. Stone, *Information Theory: A Tutorial Introduction*, en, arXiv:1802.05968 [cs], Jun. 2019.

[9] S. Ishihara, K. Furukawa, and H. Kikuchi, "Congestion Control Algorithms for Collective Perception in Vehicular Networks," en, *Journal of Information Processing*, vol. 30, no. 0, pp. 22–29, 2022, ISSN: 1882-6652. DOI: 10.2197/ipsjjip.30.22.

[10] A. Mansouri, V. Martinez, and J. Harri, "A First Investigation of Congestion Control for LTE-V2X Mode 4," en, in *2019 15th Annual Conference on Wireless On-demand Network Systems and Services (WONS)*, Wengen, Switzerland: IEEE, Jan. 2019, pp. 56–63, ISBN: 978-3-903176-13-3. DOI: 10.23919/WONS.2019.8795500.

[11] A. Bazzi, "Congestion control mechanisms in ieee 802.11p and sidelink c-v2x," in *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, Nov. 2019, pp. 1125–1130. DOI: 10.1109/IEEECONF44664.2019.9048738.

[12] H.-J. Gunther, R. Riebl, L. Wolf, and C. Facchi, "Collective perception and decentralized congestion control in vehicular ad-hoc networks," in *2016 IEEE Vehicular Networking Conference (VNC)*, Columbus, OH, USA: IEEE, Dec. 2016, pp. 1–8, ISBN: 978-1-5090-5197-7. DOI: 10.1109/VNC.2016.7835931.

[13] M. H. Jabardi and A. S. Hadi, "Using Machine Learning to Inductively Learn Semantic Rules," en, *Journal of Physics: Conference Series*, vol. 1804, no. 1, p. 012 099, Feb. 2021, ISSN: 1742-6588, 1742-6596. DOI: 10.1088/1742-6596/1804/1/012099.

[14] Y.-C. Liu *et al.*, *Who2com: Collaborative Perception via Learnable Handshake Communication*, en, arXiv:2003.09575 [cs], Mar. 2020.

[15] Y. Tao, S. Hu, Z. Fang, and Y. Fang, *Direct-CP: Directed Collaborative Perception for Connected and Autonomous Vehicles via Proactive Attention*, arXiv:2409.08840 [cs], Sep. 2024.

[16] Y. Hu, S. Fang, Z. Lei, Y. Zhong, and S. Chen, *Where2comm: Communication-Efficient Collaborative Perception via Spatial Confidence Maps*, arXiv:2209.12836 [cs], Sep. 2022.

[17] A. Chtourou, P. Merdrignac, and O. Shagdar, "Context-Aware Content Selection and Message Generation for Collective Perception Services," en, *Electronics*, vol. 10, no. 20, p. 2509, Oct. 2021, ISSN: 2079-9292. DOI: 10.3390/electronics10202509.

[18] Y. Feng, H. Shen, Z. Shan, Q. Yang, and X. Shi, *Semantic Communication for Edge Intelligence Enabled Autonomous Driving System*, en, arXiv:2406.10606 [eess], Sep. 2024.

[19] W. Xu *et al.*, *Semantic Communication for Internet of Vehicles: A Multi-User Cooperative Approach*, en, arXiv:2212.03037 [eess], Dec. 2022.

[20] Z. Qin, X. Tao, J. Lu, W. Tong, and G. Y. Li, *Semantic Communications: Principles and Challenges*, en, arXiv:2201.01389 [cs, eess, math], Jun. 2022.

[21] S. Iyer *et al.*, "A Survey on Semantic Communications for Intelligent Wireless Networks," en, *Wireless Personal Communications*, vol. 129, no. 1, pp. 569–611, Mar. 2023, ISSN: 0929-6212, 1572-834X. DOI: 10.1007/s11277-022-10111-7.

[22] J. Lu *et al.*, *Generative AI-Enhanced Multi-Modal Semantic Communication in Internet of Vehicles: System Design and Methodologies*, en, arXiv:2409.15642 [cs], Sep. 2024.

[23] J. M. Gimenez-Guzman, I. Leyva-Mayorga, and P. Popovski, "Semantic V2X Communications for Image Transmission in 6G Systems," en, *IEEE Network*, pp. 1–1, 2024, ISSN: 0890-8044, 1558-156X. DOI: 10.1109/MNET.2024.3420214.

[24] T. Lyu, M. Noor-A-Rahim, A. O'Driscoll, and D. Pesch, *Semantic Vehicle-to-Everything (V2X) Communications Towards 6G*, en, arXiv:2407.17186 [cs], Jul. 2024.

[25] L. Dulewicz *et al.*, "Deliverable 1.2 : Accident parameters description for the chosen scenarios," SECUR Project Consortium (VUFO, UTAC, Volvo Cars, Continental, Renault), Europe, Project Deliverable D1.2, version 1.3, Apr. 2022, SECUR Project, WP1 – Accident Data Study.

[26] N. Shoaip *et al.*, "Alzheimer's Disease Diagnosis Based on a Semantic Rule-Based Modeling and Reasoning Approach," en, *Computers, Materials & Continua*, vol. 69, no. 3, pp. 3531–3548, 2021, ISSN: 1546-2226. DOI: 10.32604/cmc.2021.019069.

[27] H. E. Massari *et al.*, "Effectiveness of applying Machine Learning techniques and Ontologies in Breast Cancer detection," en, *Procedia Computer Science*, vol. 218, pp. 2392–2400, 2023, ISSN: 18770509. DOI: 10.1016/j.procs.2023.01.214.

[28] C. Schlenoff, S. Balakirsky, M. Uschold, R. Provine, and S. Smith, "Using ontologies to aid navigation planning in autonomous vehicles," en, *The Knowledge Engineering Review*, vol. 18, no. 3, pp. 243–255, Sep. 2003, ISSN: 0269-8889, 1469-8005. DOI: 10.1017/S0269888904000050.

[29] R. Regele, "Using Ontology-Based Traffic Models for More Efficient Decision Making of Autonomous Vehicles," en, in *Fourth International Conference on Autonomic and Autonomous Systems (ICAS'08)*, Gosier, Guadeloupe: IEEE, Mar. 2008, pp. 94–99, ISBN: 978-0-7695-3093-2. DOI: 10.1109/ICAS.2008.10.

[30] H. Bhuiyan, G. Governatori, A. Rakotonirainy, M. W. Wong, and A. Mahajan, "Driving Decision Making of Autonomous Vehicle According to Queensland Overtaking Traffic Rules," en, *The Review of Socionetwork Strategies*, vol. 17, no. 2, pp. 233–254, Oct. 2023, ISSN: 2523-3173, 1867-3236. DOI: 10.1007/s12626-023-00147-x.

Investigating Electric Vehicle Adoption Using Correlation and Prediction Analyses

Fahad S. Alrasheedi and Hesham H. Ali
Department of Computer Science
University of Nebraska at Omaha
Omaha, USA
e-mail: {falrasheedi, hali}@unomaha.edu

***Abstract*—The transportation sector, dominated by gas-powered vehicles, is a major contributor to carbon dioxide emissions that pose significant threats to both environmental and public health. To address this issue, Electric Vehicles (EVs) have emerged as a promising alternative aimed at achieving zero-carbon emissions. However, EV adoption faces several challenges, including high costs, insufficient charging infrastructure, range anxiety, and other barriers. To promote EV adoption, authorities responsible for the management of EVs have implemented various incentives, such as tax reductions, credits, and support for charging infrastructure programs. Despite these targeted management efforts, the adoption of EVs remains a complex issue that requires extensive analysis to understand the factors driving increases or decreases in adoption rates. In this study, we employ a two-pronged approach to examine EV adoption growth rates across counties in six U.S. states. Our methodology integrates correlation network analysis and statistical prediction-based analysis. The primary finding of these analyzes highlights the critical role of geographical features and practices of local management of EVs in influencing similar patterns of EV adoption among counties. Additionally, we identify two clusters exhibiting declines in EV adoption, underscoring the need for further investigation into the management strategies and underlying causes of these decreases.**

Keywords*- *electric vehicle; charging stations; electric vehicle adoption; graph modeling, correlation networks.

I. Introduction

The transportation sector is a major contributor to carbon dioxide (CO2) emissions, which pose a significant threat to life on Earth. For example, in the United States, 29% of CO2 emissions are caused by the transportation sector, which relies heavily on greenhouse gases such as gasoline. Light vehicles alone account for more than half of the transportation sector's emissions [1][2].

Electric Vehicles (EVs) are widely regarded as a replacement for gasoline-powered vehicles. However, EV adoption (represented by the number of EVs) faces several challenges, including high costs, insufficient charging infrastructure, range anxiety (i.e., the concern that the battery's remaining charge may not be sufficient to reach the next stop), and other barriers. Consequently, significant managment efforts have been made to transition the transportation sector toward electrification. For instance, U.S. authorities manage EV adoption by offering incentives such as tax reductions and credits for purchasing EVs and supporting various programs to enhance charging infrastructure.

Despite such management efforts to promote EV usage, the EV adoption remains a complex issue that requires in-depth investigation to provide insights into how adoption rates can be increased based on the characteristics of targeted populations.

In this study, we focus on counties in the U.S. We conduct our analysis at the county level rather than at the state or zip code level because states are too broad, while zip codes are too narrow to effectively capture differences in EV adoption behavior across regions. Therefore, an essential first step in addressing the complexity of EV adoption is to examine how different counties across various states in the U.S. are working to accelerate EV adoption.

We conducted two analyses as part of this effort: one using Graph Theory and the other employing statistical prediction analysis. Graph Theory has been applied in the EV domain as a method to optimize the distribution of charging stations [3]–[9]. On the other hand, statistical analyses have been used in studies to investigate the impact of charging stations and other factors on EV adoption [10]–[16]; however, these studies typically focus on one to three cities.

In our Graph Theory analysis, we leveraged a correlation network to build a network of counties and clustered them based on their correlations of EV growth rates. This approach identified several clusters of correlated counties. Counties within the same cluster exhibited similar EV adoption behaviors, opening avenues for future research to understand the reasons behind these shared behaviors.

The second analysis involved building various prediction models to forecast EV adoption in a county based on its demographic features. The best-performing model was selected, and further analyzed to identify significant features.

Our findings from the correlation network revealed that counties within the same cluster often belong to the same state and are geographically close to one another. This suggests that local managements and neighboring areas may play a significant role in EV adoption. Additionally, some clusters showed declines in EV growth rates, prompting the need for further studies to investigate the causes of these decreases.

In the statistical prediction-based analysis, the Gradient Boosting model emerged as the best-performing prediction model. Among the significant features identified in the best prediction model, the geographical feature 'Federal Information Processing Standards (FIPS)' stood out, aligning with the findings from the correlation network analysis. Hence, a local management's strategy for EV adoption may be influenced by both the characteristics of their own region and the strategies of neighboring regions in adopting EVs.

The remainder of this paper is organized as follows: Section II discusses our approach for employing Graph Theory to build the EV adoption correlation network and the development of

TABLE I. NUMBER OF COMPLETED COUNTIES BY STATE

No.	State	No. of Counties
1	Colorado	20
2	Minnesota	3
3	Montana	2
4	New York	48
6	Texas	30
7	Virginia	34
8	Total	137

prediction models. Section III discusses the results, followed by the conclusion and future work in Section IV.

II. Methodology

In this section, we describe the data collection process for this study, the application of Graph Theory in our analysis, and the development of prediction models.

A. Data Collection

1) EV Data: Atlas Hub [17] provides temporal data on EV registrations at the zip code level for several states in the U.S. For this study, we selected states that offered data from 2018 to 2023 and aggregated the data at the county level. We chose this time range based on data availability, as increasing the range results in a smaller number of states and counties, while decreasing the range shortens the time series and may negatively impact the analysis.

Consequently, we identified 137 counties from six states that provided a complete 12 months of EV registration data for each year within the study period. Table I presents the number of counties per state.

This study includes all EVs registered in each state, regardless of their usage purpose, such as personal or commercial, and whether they are light-duty or heavy-duty. The impact of usage purpose on EV adoption is worth further investigation in the future.

2) Charging Station Data: Charging station data is required as a predictor in the statistical prediction models. We collected the number of stations for each county of interest from the Alternative Fueling Station Locator [18]. Using the establishment dates for each station, we aggregated the number of stations established annually in each county. For the analysis, we used the number of stations as of 2022 to predict the number of EVs in 2023 (as explained in II-C), incorporating a one-year lag.

3) Demographic Data: This data was retrieved at the county level from the official Census Bureau of the United States [19]. The dataset, covering the period from 2017 to 2022, includes approximately 58 features categorized into the following groups: Population, Age and Sex, Race and Hispanic Origin, Population Characteristics, Housing, Families Living Arrangements, Computer and Internet Use, Education, Health, Economy, Transportation, Income Poverty, Business, and Geography.

B. The Correlation Network Method

First, we computed the month-to-month growth rates for each county in our study, resulting in 72 data points of growth rates per county. These growth rates were calculated using the equation:

$$\frac{Current\ Month - Previous\ Month}{Previous\ Month}$$

where *Current Month* means the cumulative number of EVs until the current month, and *Previous Month* means the the cumulative number of EVs until the previous month.

Next, since our data are not perfectly linear, we calculate the Spearman correlation [20] between counties, resulting in a 137 × 137 correlation matrix. Using this matrix, we created a correlation network where nodes represent counties and edges represent correlations that exceed a specified threshold. After testing several thresholds, we found that the optimal threshold for our case study was 0.72, which yielded clusters of correlated counties.

C. Statistical Prediction Analysis

Our second analysis leveraged the nature of our data, which includes 137 counties across multiple U.S. states, to build cross-sectional prediction models for estimating the number of EVs at the county level for a specific year. Specifically, we focused on predicting the number of EVs in 2023 using the following approach:

1) The target variable was the number of EVs in 2023.
2) The features included demographic data from the Census Bureau and the cumulative number of charging stations as of 2022, reflecting a one-year effect of charging stations on the number of EVs in 2023.
3) The statistical prediction models used included Linear Regression, Random Forest, Gradient Boosting, Decision Tree, Elastic Net, Lasso, and Ridge.

Finally, we identified the most significant features in the best-performing prediction model.

III. Results and Discussion

In this section, we present the outcomes of our analysis, including the identification of clusters based on EV adoption patterns and the evaluation of our prediction models. We highlight the most significant features identified in our Gradient Boosting model and discuss their implications.

A. Graph Theory Based Clustering

First, the number of counties meeting our correlation threshold is 40 out of 137 counties. Among the correlations between these counties, we identified four main clusters, as shown in the correlation network in Figure. 1. Table III shows the number of counties and their corresponding states for each cluster in the resulting correlation network.

We observed that the correlated counties in each cluster belong to a single state. For instance, the counties in clusters 1, 2, 3, and 4 are from Colorado, New York, Texas, and Minnesota, respectively. Hence, our primary finding in this analysis is

 ISBN: 978-1-68558-233-3

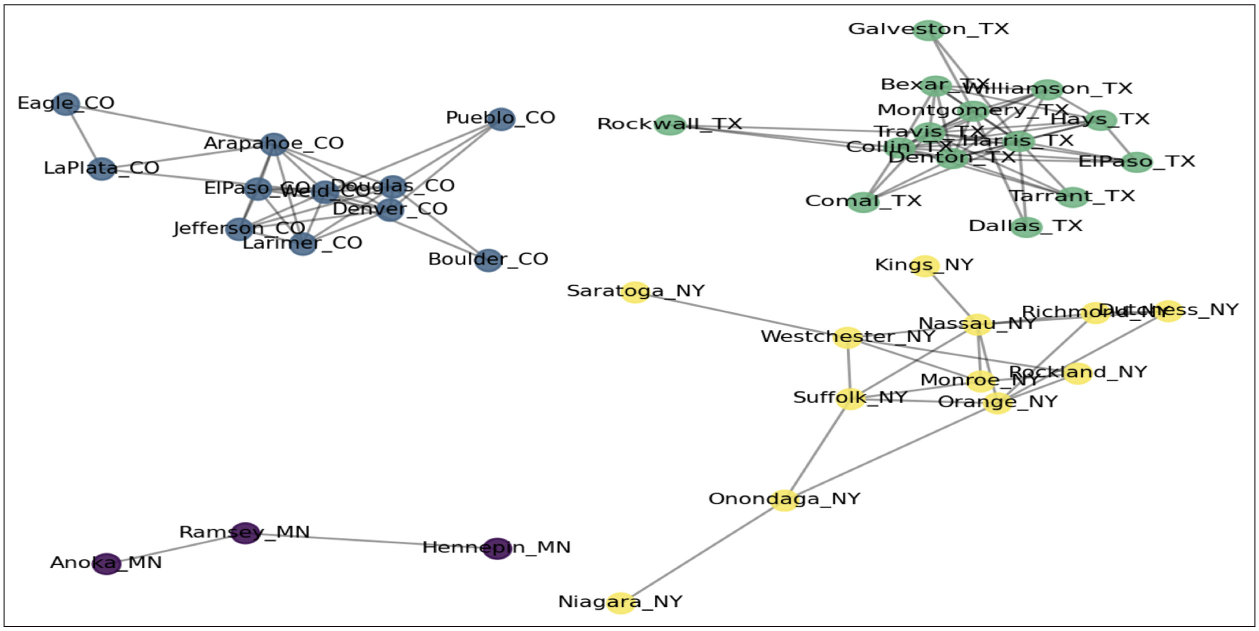


Figure 1. Correlation Network: Nodes represent counties, with labels indicating the county name appended with the state abbreviation, where colors distinguish different states (e.g., Saratoga_NY represents Saratoga County in New York). Edges correspond to correlations exceeding 0.72.

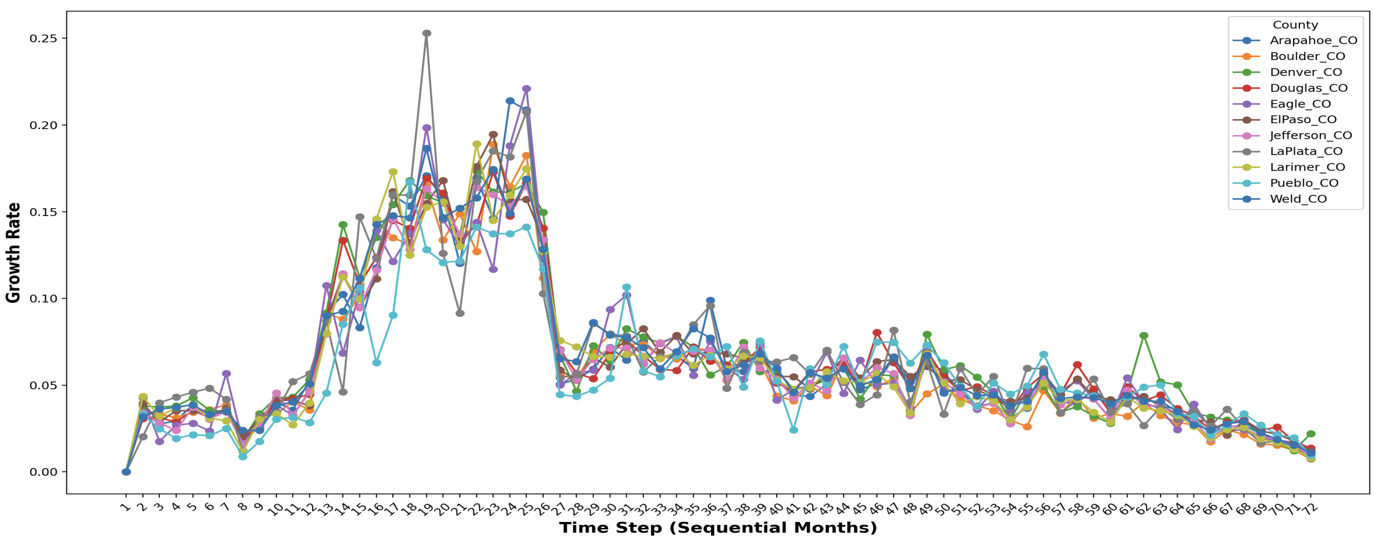


Figure 2. Growth rates of counties in cluster 1 (Colorado). The X-axis represents 72 months, from January 2018 to December 2023.

TABLE II. THE SEVEN MOST SIGNFICANT FEATURES IN THE GRADIENT BOOSTING MODEL

Feature	Group	Importance
Nonminority-owned employer firms, Reference year 2017	Business	5.26e-01
Living in same house 1 year ago, percent of persons age 1 year+, 2018-2022	Families & Living Arrangements	2.02e-01
Station Counts	Station data	4.96e-2
Total annual payroll	Business	4.75e-2
Men-owned employer firms, Reference year 2017	Business	4.60e-2
Women-owned employer firms, Reference year 2017	Business	1.66e-2
FIPS Code	Geography	1.05e-02

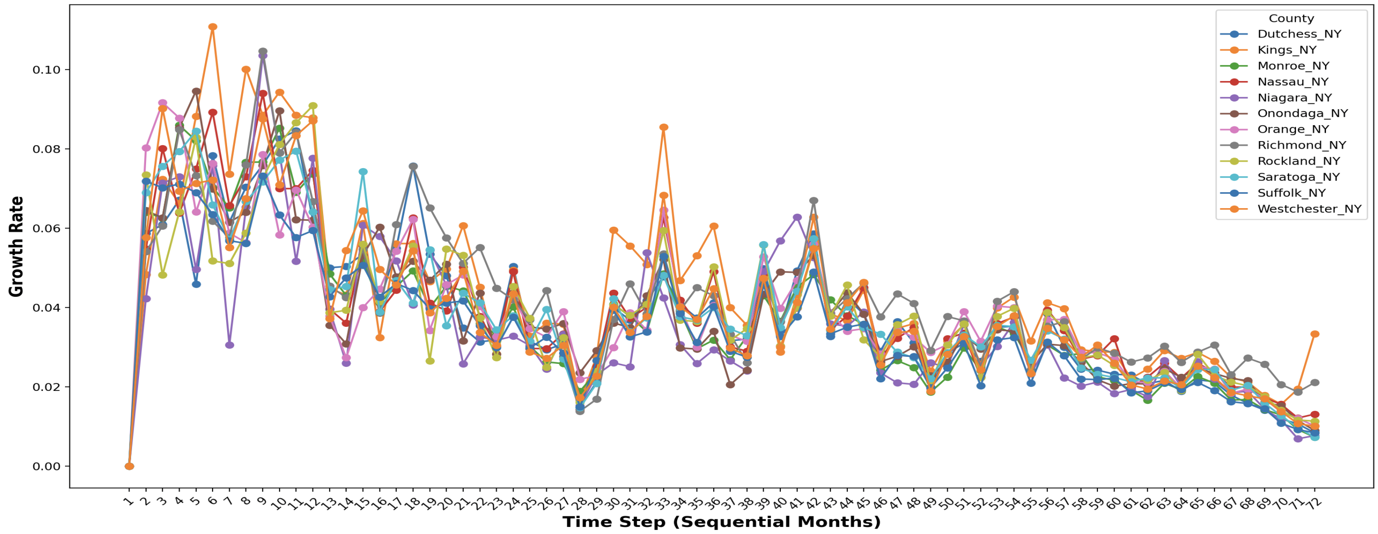


Figure 3. Growth rates of counties in cluster 2 (New York). The X-axis represents 72 months, from January 2018 to December 2023.

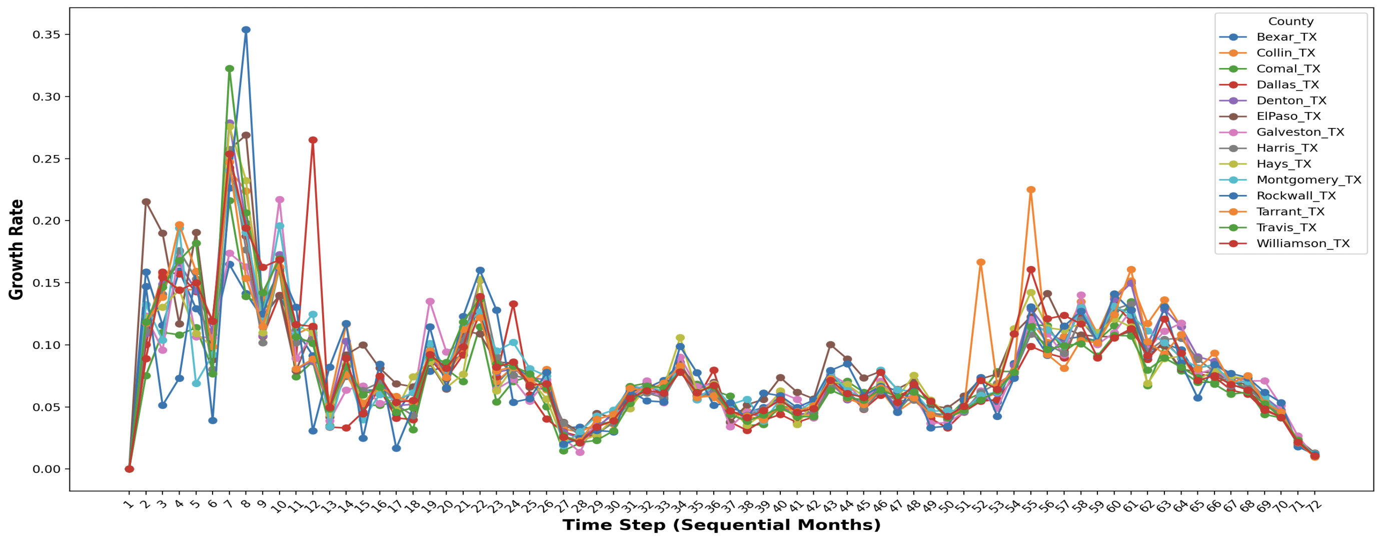


Figure 4. Growth rates of counties in cluster 3 (Texas). The X-axis represents 72 months, from January 2018 to December 2023.

that correlated counties tend to cluster geographically within individual states. Furthermore, beyond manual investigations, these correlated counties often appear to be neighbors within the same state. This suggests that the management strategies of neighboring regions and the geographical characteristics of counties may play a significant role in driving EV adoption.

Furthermore, we visualized the growth rates of the counties in Colorado cluster, Texas cluster, and New York cluster in Figures. 2, 4, and 3, respectively (we ignored the Minnesota cluster since it only contained three counties). These visualizations reveal the strength of correlations within each cluster. Interestingly, the growth rates in Colorado and New York tend to decline, highlighting the need for further investigation to understand the underlying causes in these counties. Such insights could help local authorities manage and address this decline in EV adoption more effectively.

TABLE III. The four clusters found in the correlation network, how many counties in each cluster, and the states of these counties

Cluster Code	No. of Counties	States
Cluster 1	11	Colorado
Cluster 2	12	New York
Cluster 3	14	Texas
Cluster 4	3	Minnesota

TABLE IV. Comparison of several ML models in predicting EV adoption

Model	MSRE	R-Squared
Linear Regression	101850027.5567	0.5377
Random Forest	69206289.8	0.6859
Gradient Boosting	**58108466.13**	**0.7362**
Decision Tree	141672157.654	0.357
Elastic Net	122403797.77	0.444
Lasso	98257697.207	0.554
Ridge	96591486.7415	0.5616

B. Prediction models

We applied statistical prediction models to predict the number of EVs at the county level. These models were evaluated using metrics such as mean squared regression error (MSRE) and adjusted R-squared. The models tested include Linear Regression, Random Forest, Gradient Boosting, Decision Tree, Elastic Net, Lasso, and Ridge Regression. Table IV compares the performance of these models, with Gradient Boosting emerging as the best performer. It achieved MSRE of 58108466.13, and adjusted R-squared of 0.7362, explaining 73.62% of the variability in EV numbers.

Finally, we prioritized features based on their importance in the Gradient Boosting model and identified the top seven features, as shown in Table II. Among these, the FIPS feature emerged as one of the most significant predictors of EV adoption at the county level. The FIPS feature, being geographical in nature, aligns with our findings in the correlation network, where counties from the same state tend to cluster together. This highlights the influence of local authorities and geographic location on EV adoption behavior.

IV. Conclusion and Future Directions

We presented a two-pronged analysis of EV adoption in counties across six U.S. states. The first approach utilized a correlation network from Graph Theory, where nodes represent counties and edges indicate correlations in their EV growth rates. We then clustered the counties based on these correlations. The second approach involved developing various statistical prediction models to forecast EV adoption in 2023 using demographic and charging station data as predictors. The best-performing model was selected and further analyzed to identify significant features.

Our key finding is that the geographical characteristics of counties, such as the state in which a county is located and its neighboring counties, play a significant role in EV adoption. This is evident in the correlation network, where counties within the same state exhibit similar EV growth rate patterns, and in the prediction model, where the FIPS feature (a geographical identifier) emerges as one of the most significant predictors in the best-performing model.

Additionally, we identified two clusters with declining EV growth rates, highlighting the need for further investigation into their underlying causes. Future research could enhance prediction models by incorporating political, environmental, and climatic factors while also expanding the dataset to cover more counties across states. More specifically, an in-depth exploration of how gas prices interact with EV adoption remains a promising area of study. Lastly, distinguishing between different types of EVs in future adoption analyses may yield valuable insights.

References

[1] United States Environmental Agency (Epa), *Inventory of U.s. greenhouse gas emissions and sinks*, en. North Charleston, SC: Createspace Independent Publishing Platform, Jul. 2018.

[2] O. Us Epa, "Fast facts on transportation greenhouse gas emissions", en, Aug. 2015.

[3] M. A. Moni and P. Liò, "Network-based analysis of comorbidities risk during an infection: Sars and hiv case studies", *BMC bioinformatics*, vol. 15, pp. 1–23, 2014.

[4] A. Gagarin and P. Corcoran, "Multiple domination models for placement of electric vehicle charging stations in road networks", *Computers & Operations Research*, vol. 96, pp. 69–79, 2018.

[5] E. M. Arkin, P. Carmi, M. J. Katz, J. S. Mitchell, and M. Segal, "Locating battery charging stations to facilitate almost shortest paths", *Discrete Applied Mathematics*, vol. 254, pp. 10–16, 2019.

[6] S. Funke, A. Nusser, and S. Storandt, "Placement of loading stations for electric vehicles: No detours necessary!", *Journal of Artificial Intelligence Research*, vol. 53, pp. 633–658, 2015.

[7] S. Funke, A. Nusser, and S. Storandt, "Placement of loading stations for electric vehicles: Allowing small detours", in *Proceedings of the international conference on automated planning and scheduling*, vol. 26, 2016, pp. 131–139.

[8] P. K. Agarwal, J. Pan, and W. Victor, "An efficient algorithm for placing electric vehicle charging stations", in *27th International Symposium on Algorithms and Computation (ISAAC 2016)*, Schloss Dagstuhl–Leibniz-Zentrum für Informatik, 2016, pp. 7–1.

[9] T. G. Altundogan, A. Yildiz, and E. Karakose, "Genetic algorithm approach based on graph theory for location optimization of electric vehicle charging stations", in *2021 Innovations in intelligent systems and applications conference (ASYU)*, IEEE, 2021, pp. 1–5.

[10] C. Ledna, M. Muratori, A. Brooker, E. Wood, and D. Greene, "How to support ev adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in california", *Energy Policy*, vol. 165, p. 112 931, 2022.

[11] R. Chen, Q. Meng, and J. J. Yu, "Optimal government incentives to improve the new technology adoption: Subsidizing infrastructure investment or usage?", *Omega*, vol. 114, p. 102 740, 2023.

[12] L. V. White, A. L. Carrel, W. Shi, and N. D. Sintov, "Why are charging stations associated with electric vehicle adoption? untangling effects in three united states metropolitan areas", *Energy Research & Social Science*, vol. 89, p. 102 663, 2022.

[13] H. A. U. Khan, S. Price, C. Avraam, and Y. Dvorkin, "Inequitable access to ev charging infrastructure", *The Electricity Journal*, vol. 35, no. 3, p. 107 096, 2022.

[14] G. H. Broadbent, C. I. Allen, T. Wiedmann, and G. I. Metternicht, "Accelerating electric vehicle uptake: Modelling public policy options on prices and infrastructure", *Transportation Research Part A: Policy and Practice*, vol. 162, pp. 155–174, 2022.

[15] U. Illmann and J. Kluge, "Public charging infrastructure and the market diffusion of electric vehicles", *Transportation Research Part D: Transport and Environment*, vol. 86, p. 102 413, 2020.

[16] B. Haidar and M. T. A. Rojas, "The relationship between public charging infrastructure deployment and other socio-economic factors and electric vehicle adoption in france", *Research in Transportation Economics*, vol. 95, p. 101 208, 2022.

[17] N. Nigro, *State EV registration data*, en, https://www.atlasevhub.com/materials/state-ev-registration-data/, Accessed: 2024-5-6.

[18] *Alternative fueling station locator*, en, https://afdc.energy.gov/stations, Accessed: 2024-5-6.

[19] United States Census Bureau, "United states census bureau: Data and statistics", 2024, [Online]. Available: https://www.census.gov (visited on 06/13/2024).

[20] C. Spearman, "The proof and measurement of association between two things", *The American Journal of Psychology*, vol. 15, no. 1, pp. 72–101, 1904.

Development and Validation of a 12-DOF Vehicle Model for Ride and Handling Analysis for Three-Wheeled Vehicle

Dumpala Gangi Reddy
TVS Motor Company Ltd
Hosur, India
e-mail: gangi.reddy@tvsmotor.com

Ramarathnam Krishna Kumar
Department of Engg. Design. IIT Madras
Chennai, India
e-mail: rkkumar@iitm.ac.in

***Abstract*—An accurate vehicle model is essential for effectively representing vehicle behaviour, particularly in the study of ride and handling dynamics. This work focuses on developing a comprehensive vehicle model to analyse vehicle behaviour in various driving conditions. A 12-Degrees-Of-Freedom (DOF) vehicle model is derived, incorporating ride, handling, and tire dynamics. Two types of tire models—Linear and Nonlinear (Magic Formula)—are implemented in Simulink, and their performance is evaluated by comparing simulation results with ADAMS outputs. The tire model that best aligns with the ADAMS results is integrated into the 12-DOF vehicle model. All assumptions considered in the model development are detailed. The proposed vehicle model is validated using an instrumented vehicle under different steering inputs. The deviations between simulated and experimental results, particularly in yaw rate, lateral acceleration, roll angle, and individual tire slip angles, are analysed and discussed.**

Keywords - Vehicle dynamics; Multibody simulation; Three wheeler; Constat radius cornering.

I. INTRODUCTION

A three-wheeled vehicle features a single front wheel, similar to a two-wheeler, and two rear wheels, resembling a four-wheeler. This unique configuration combines the advantages of both vehicle types, offering compactness and enhanced maneuverability in congested traffic and narrow roads. However, this design also introduces certain challenges in terms of stability and dynamic performance.

One of the primary concerns with three-wheeled vehicles is their inherently lower rollover stability compared to four-wheeled vehicles due to their asymmetric weight distribution and reduced lateral support [1][2]. The current design employs a trailing arm suspension at the rear, which maintains a fixed roll axis at ground level. Since there is no variation in camber or toe during wheel travel, the roll axis remains significantly lower than the Vehicle's Center of Gravity (CG). This results in a high roll moment, making the vehicle more susceptible to lateral instability and rollover, especially during sharp turns or evasive maneuvers [3].

Furthermore, the absence of an independent suspension system in most three-wheeled vehicles limits their ability to adapt to uneven road surfaces, affecting ride comfort and handling characteristics. The distribution of roll stiffness between the front and rear also plays a crucial role in the vehicle's dynamic behaviour, influencing parameters, such as understeer, oversteer, and load transfer. These factors must be carefully analysed to optimize the stability and safety of three-wheeled vehicles under various driving conditions.

The following sections of this paper are structured as follows: Section II presents the analytical formulation of a 12-Degrees-Of-Freedom (DOF) three-wheeled vehicle model, including the derivation of roll dynamics and an analytical representation of the tire model. Section III introduces a multibody dynamic model, incorporating flexible body dynamics for enhanced fidelity, and discusses the simulation of a step-steer maneuver and Constant Radius Cornering (CRC) simulation, with corresponding results plotted. Section IV details the experimental validation, where a physical prototype instrumented with sensors is used to measure key vehicle dynamics parameters, and a comparative analysis between experimental and simulation results is performed, with correlation graphs presented. Finally, Section V outlines the future work, highlighting planned improvements, further analysis, and potential extensions to refine the proposed models.

II. SCOPE OF THE WORK

Existing research papers primarily emphasize analytical expressions for evaluating vehicle dynamics, often neglecting the critical correlation between physical and virtual simulation results. Analytical models, due to their inherent simplifications, frequently yield results that underestimate experimental findings. In contrast, this study integrates three fundamental approaches: analytical modelling, 3D virtual simulation, and instrumented experimental testing. By incorporating all three dimensions, a stronger correlation between virtual and physical results is achieved, leading to more accurate vehicle dynamics assessments.

The developed virtual Multi-Body Dynamics (MBD) model includes real-time flexible body integration, replicating physical vehicle components with higher fidelity compared to conventional 2D analytical models. This enhancement significantly improves result accuracy, ensuring that the simulation model aligns closely with real-world vehicle behavior.

The high-fidelity MBD model considers key structural flexibilities, including suspension components, such as trailing arms, control arms, steering system elasticity, such as steering column compliance, axle housing deformation, and body-in-white stiffness properties. Virtual simulations account for real-world material properties by iteratively refining stiffness and damping parameters based on actual test data. A scaling factor is applied to material properties to ensure consistency with physical test results, improving the predictive capabilities of the model.

The primary goal of this work is to establish a complete 3D virtual simulation framework for comprehensive vehicle dynamics testing. This enables early-stage vehicle dynamics target setting, with parameter cascading down to the subsystem level, ultimately accelerating product development cycles. By reducing dependency on physical prototypes, both time and cost constraints associated with mule vehicle manufacturing are significantly minimized. Initial validation of the simulation model against physical test results provides confidence in early-stage vehicle performance assessment.

To enhance the reliability of virtual simulations, key assumptions are incorporated, including equivalent stiffness values for springs, dampers, and bushings, as well as realistic flexibility properties of major structural components. Material properties are iteratively refined using real-world data, ensuring an accurate representation of actual vehicle dynamics.

In this study, Step steer manoeuvring and Constant Radius Cornering (CRC) tests have been utilized for validation. However, additional dynamic test scenarios, such as fishhook, free steer, slalom, and ramp steer tests along with dynamics control systems are planned as future work to further reinforce simulation accuracy and reliability. Expanding the range of test cases will enhance confidence in virtual simulations, reducing dependency on physical testing while ensuring robust vehicle handling performance predictions.

III. THREE WHEELER VEHICLE MODEL

The vehicle dynamic model for a three-wheeled vehicle is developed as a nonlinear system with 12-Degrees-Of-Freedom (DOF). This model consists of both sprung and unsprung masses, with the vehicle body having six DOF: translational motions along the x, y, and z axes, and rotational motions (roll, pitch, and yaw) about these axes. Specifically, the roll, pitch, and yaw motions represent the rotations about the x, y, and z axes, respectively. Each wheel is modeled with translational motion in the vertical (z) direction and wheel spins about the y-axis. Additionally, the front wheel is capable of steering about the z-axis, which contributes to the vehicle's overall maneuverability.

In this study, the dynamic model of a typical three-wheeled passenger vehicle is developed, as shown in Figure 1. The model is constructed using Lagrangian mechanics, where the Equations Of Motion (EOM) are derived to describe the complex interactions between the sprung and unsprung masses. The coordinate system for the vehicle follows the Society of Automotive Engineers (SAE) International convention, and the relevant sign conventions are shown in Figure 2. The developed model incorporates both vehicle dynamics and the interaction between the vehicle body and the wheel assemblies, enabling a detailed analysis of the ride and handling characteristics of three-wheeled vehicles.

A. Equations of Motion

Governing equations of the Longitudinal, Lateral, and Vertical, Roll, Pitch and Yaw motions can be expressed as [2]:

Equation of motion for longitudinal motion

$$M_t\ddot{x} = Fx_{,f} + Fx_{,rl} + Fx_{,rr}$$
$$M_t(\dot{v_x} + \dot{\theta}v_z - v_y\dot{\psi}) = Fx_{,f} + Fx_{,rl} + Fx_{,rr} \quad (1)$$

Equation of motion for lateral motion

$$M_t\ddot{y} = Fy_{,f} + Fy_{,rl} + Fy_{,rr}$$
$$M_t(\dot{v_y} + v_x\dot{\psi} - \dot{\theta}v_z) = Fy_{,r} + Fy_{,rl} + Fy_{,rr} \quad (2)$$

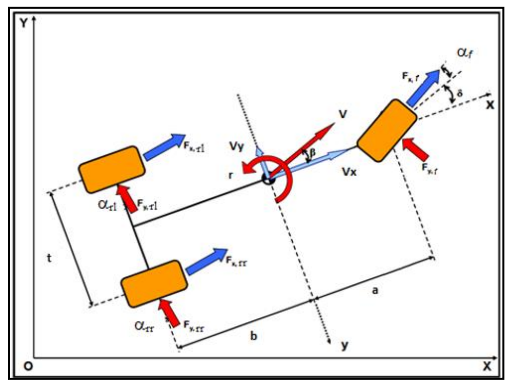


Figure 1. Six DOF Horizontal vehicle model.

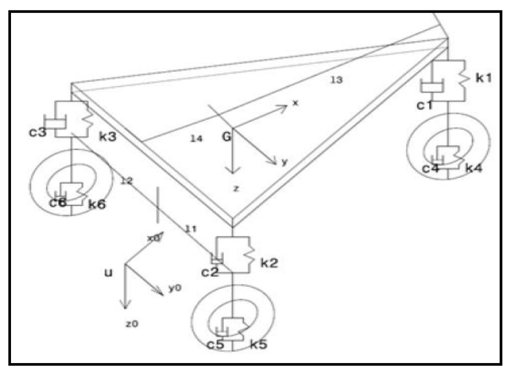


Figure 2. Six DOF Vertical vehicle model.

Equation of motion for sprung mass vertical motion

$$M_s\ddot{z} = Fz_{,f} + Fz_{,rl} + Fz_{,rr}$$
$$M_s(\dot{v_z} + v_x\dot{\psi} - \dot{\theta}v_z) = Fz_{,r} + Fz_{,rl} + Fz_{,rr} \quad (3)$$

Equation of motion for sprung mass roll motion

$$M_x = I_{sxx}\ddot{\phi} - (I_{syy} - I_{szz})\dot{\theta}\dot{\psi} = Fz_{,rl} - Fz_{,rr} \quad (4)$$

Equation of motion for sprung mass pitch motion

$$M_y = I_{syy}\ddot{\theta} - (I_{szz} - I_{sxx})\dot{\theta}\dot{\psi} =$$
$$(Fz_{,rl} + Fz_{,rr})b - Fz_{,f}\,a - ((Fx_{,f} + Fx_{,rl} + Fx_{,rr}) \quad (5)$$

 ISBN: 978-1-68558-233-3

Equation of motion for sprung mass yaw motion

$$M_z = I_{zz}\ddot{\psi} - (I_{xx} - I_{yy})\dot{\phi}\dot{\theta} = (Fx_{,rl} - Fx_{,rr})t/2 - (Fy_{,rl} + Fy_{,rr})b + (Fy_{,f}\ a) \quad (6)$$

where:

a = Length between the CG and front tire patch
V = Vehicle velocity vector
b = Length between the CG and rear tire patch
V_f = Front tire velocity vector
δ= Steer angle
V_r = Rear tire velocity vector
F_Y= Tire lateral forces
V_x = Vehicle velocity in the x-axis
Ψ= Yaw angle
V_y = Vehicle velocity in the y-axis
I_{zz} Vertical axis moment inertia
a_x, a_y=Longitudinal and Lateral acceleration

The horizontal vehicle model receives lateral and longitudinal forces from the tire model, which are crucial inputs for the vertical dynamics of the vehicle. Based on these forces, a 6 Degrees-Of-Freedom (DOF) vertical vehicle model is developed, as illustrated in Figures 1 and 2. The model incorporates a two-dimensional vertical dynamic system, representing a half-track vehicle model for pitch dynamics and a two-track half-vehicle model for roll dynamics. This approach allows for three DOF associated with the vehicle's mass center (vertical, roll, and pitch dynamics), along with three DOF for each wheel, focusing on the vertical dynamics of the wheels.

The primary dynamics analysed in this study are the yaw and roll motions, which play a crucial role in vehicle stability and handling. The yaw motion is essential for understanding the vehicle's directional control, while roll dynamics influence the lateral stability, particularly in cornering and evasive maneuvers [2]. These factors are critical for evaluating the overall ride and handling characteristics of the vehicle.

B. Roll Model

The roll equations are derived by decomposing the vehicle into sprung and unsprung masses within the y-z plane, as illustrated in Figures 3 and 4. Newton's Second Law, formulated for rigid body dynamics, is applied to analyze the roll motion. In this context, "inside" and "outside" refer to the respective sides of the vehicle relative to the direction of a turn.

The steady state roll model has been derived, by setting the acceleration and velocity dynamic states to zero. This simplification allows the roll angle to be expressed as a linear function of lateral acceleration. The approach assumes that the total roll stiffness remains linear and that the parameter d1 is constant, based on the small-angle linearization technique. Under these conditions, the roll response of the vehicle is primarily governed by lateral load transfer, roll stiffness, and suspension characteristics. This linearized formulation provides insights into the steady-state roll behavior, aiding in the evaluation of vehicle stability and handling performance.

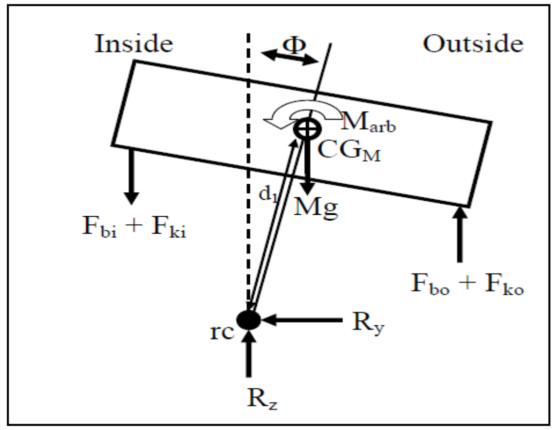


Figure 3. Roll FBD Sprung Mass.

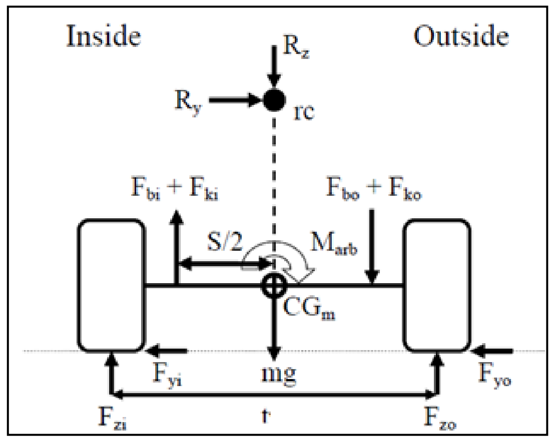


Figure 4. Roll FBD Un-Sprung Mass.

The forces, moment, and lengths in Figures 3 and 4 are defined as:

CG_M = Sprung mass center of gravity
M_{arb} = Anti-roll bar moment
CG_m = Un-sprung mass center of gravity
Φ= Roll angle
d_1 = Length between the rc and CG_M
rc = Roll center
F_b = Damper force (o – outside, i – inside)
R_y = Reaction force in the y-axis
F_k= spring force (o – outside, i – inside)
R_z = Reaction force in the z-axis
F_y= Tire lateral force
S = Length between the springs and dampers
F_z = Tire normal force,
t = Track width

The resulting roll angle equation, given by Equation (7), serves as a fundamental expression for analyzing roll dynamics in steady-state cornering conditions.

$$\Phi_{ss} = \frac{M_s d1}{k_{\Phi t} - M_s d1} \cdot a_y \qquad (7)$$

where:

a_y = *Lateral acceleration*
$k_{\Phi t}$ = *Total roll stiffness*
M_s = *Total sprung mass*

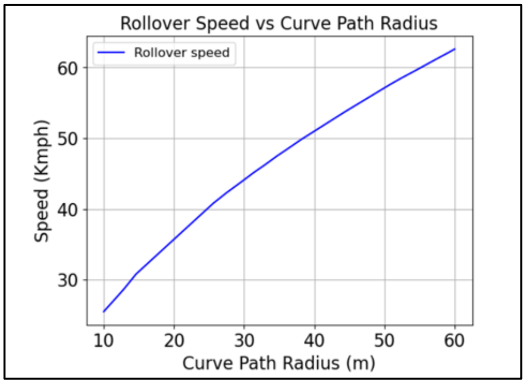


Figure 5. Rollover speed Vs Radius of turn.

C. Tire Model

In this study, the Pacejka Magic Formula [6] is used to model tire forces based on existing experimental data for the vehicle, as summarized in Table I. This widely used semi-empirical tire model captures the nonlinear behavior of tires by defining lateral and longitudinal forces as functions of slip angle and slip ratio, respectively [5]. Figure 6 illustrates the differences between the linear and nonlinear Magic Formula tire models.

TABLE I. PACEJKA PARAMETERS

a0 = 0.5;	a9 = 0.0;
a1 = -1300;	a10 = 0.0;
a2 = 2400;	a11 = 0.0;
a3 = -250;	a12 = 0.0;
a4 = -3;	a13 = 0.0;
a5 = -0.0024;	a14 = 0.0;
a6 = -1.6;	a15 = -0.1;
a7 = 1.6;	a16 = 0.0;
a8 = 0.0;	a17 = 0.2

The general form of the Pacejka Magic Formula for longitudinal, lateral, and aligning moment forces is expressed as [5]:

$$y = D \sin\left(C\, tan^{-1}\left(Bx - E\left(Bx - tan^{-1}(Bx)\right)\right)\right) \qquad (8)$$

Where:

y - represents the force or moment
x - represents the slip parameter
B - is the stiffness factor, controlling the shape of the curve
C - is the shape factor, determining the curvature
D - is the peak factor, representing the maximum force value
E - is the curvature factor, adjusting the asymmetry of the curve

The linear tire model assumes constant tire cornering stiffness with no saturation, meaning the lateral force increases proportionally with slip angle. In contrast, the Pacejka model accounts for non-linearities by varying the cornering stiffness dynamically.

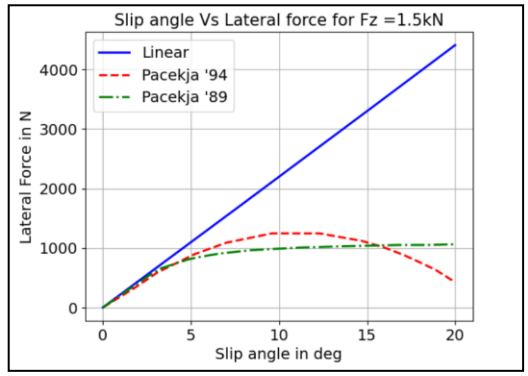


Figure 6. Comparison of Linear vs. Nonlinear Pacejka '89 and '94 Tire Models under a Normal Force of 1.5 kN.

As the slip angle increases, the lateral tire force initially rises, reaching a peak before gradually decreasing due to tire saturation. This behavior accurately represents real-world tire dynamics, particularly during aggressive cornering and limit-handling scenarios. The linear tire model provides a reasonable approximation of the nonlinear Pacejka model for small slip angles [5]. However, as shown in Table II, this approximation becomes increasingly inaccurate as the slip angle grows. The linear model assumes a constant cornering stiffness, leading to an overestimation of lateral force at high slip angles.

TABLE II. LINEAR TIRE MODEL VS. NON-LINEAR PACEJKA TIRE MODEL

Tire Slip Angle, α , [deg]	**2.5°**	**5 °**	**7 °**
Lateral Force difference between Linear and Non-Linear Tire Pacejka ‘89’ Model	4%	33%	65%
Lateral Force difference between Linear and Non-Linear Tire Pacejka ‘94’ Model	14%	25%	40%

In contrast, the nonlinear Pacejka model accounts for tire saturation, capturing the peak lateral force and the subsequent reduction in force beyond this point. This distinction is critical for accurately predicting vehicle behavior in high-speed maneuvers, limit-handling conditions, and dynamic stability analysis.

The peak lateral force generated by a tire is influenced by both slip angle and normal load. However, as the normal load increases, a saturation point is reached beyond which additional load no longer results in a proportional increase in lateral force.

 ISBN: 978-1-68558-233-3

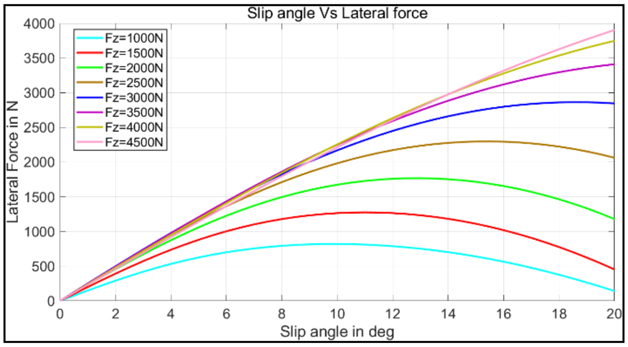


Figure 7. Non-Linear Tire Model with Varying Normal Forces.

This nonlinear relationship, depicted in Figure 7, highlights how both cornering stiffness and peak lateral force vary with changes in normal load. In the Pacejka tire model, the primary inputs are the tire slip angle and normal force, while the output is the resulting lateral force. The model captures the nonlinear behavior of tire forces, showing that while an increase in normal load initially enhances lateral grip, excessive loading can lead to diminishing returns due to tire deformation and structural limitations. Understanding this interaction is crucial for optimizing vehicle dynamics, particularly in suspension tuning and load transfer management.

IV. VIRTUAL VEHICLE MODEL AND SIMULATION

A three-wheeled MBD flexible model, as shown in Figure 8, has been developed using ADAMS CAR. The system is represented as two primary subsystems: Rear frame: Includes the rider, engine, chassis, body, seat, and rear wheels. Front frame: Comprises the front fork, handlebar, and front wheel.

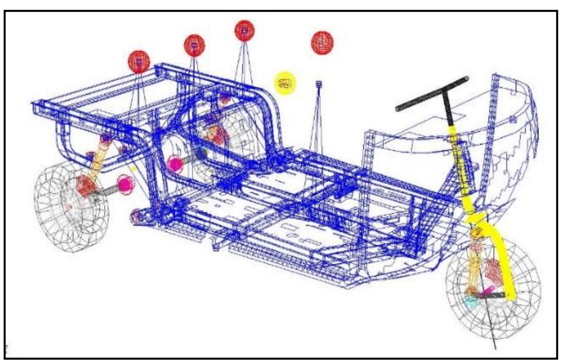


Figure 8. Three-Wheeler MBD Model.

The rear and front frames are connected at the steering axis via a revolute joint, allowing relative rotation between the two sections. During motion, the tires are free to sideslip, generating lateral forces that depend on sideslip and camber angles. These lateral forces, from a dynamic perspective, act as restoring forces similar to those produced by springs, influencing vehicle stability and handling behavior. To enhance model accuracy, key parameters, such as mass properties, inertia, hard point locations, suspension characteristics (spring/damper properties, jounce, and rebound characteristics), and tire properties are updated based on experimental data. A complete vehicle model is constructed using modular templates with user-defined input data.

For tire modeling, both the Pacejka '89 and '94 handling models are developed, with the Pacejka '94 model being implemented in simulations due to its improved accuracy in capturing tire behavior under dynamic conditions [5]. The use of this detailed MBD model allows for a comprehensive analysis of three-wheeled vehicle dynamics, particularly in evaluating stability, ride quality, and handling performance.

A. *MBD Simulation*

A full-vehicle MBD simulation has been conducted to analyze the handling characteristics of a three-wheeled vehicle. The simulations were performed using ADAMS/Car, which provides a driving machine module capable of executing various handling maneuvers [3]. These maneuvers are broadly classified into: Open-loop steering maneuvers: Driver-independent inputs, useful for evaluating fundamental vehicle dynamics. Closed-loop maneuvers: Driver-in-the-loop simulations, considering control feedback mechanisms. In this research, the following handling analyses were performed, and their results were evaluated:

Step Steer Maneuver – A sudden steering input is applied to examine the transient response of the vehicle, focusing on yaw rate, lateral acceleration, and roll stability.

Constant Radius Cornering (CRC) – The vehicle is driven in a steady-state circular path to assess lateral grip, understeer/oversteer characteristics, and roll behavior at different speeds. This is shown in Figure 9.

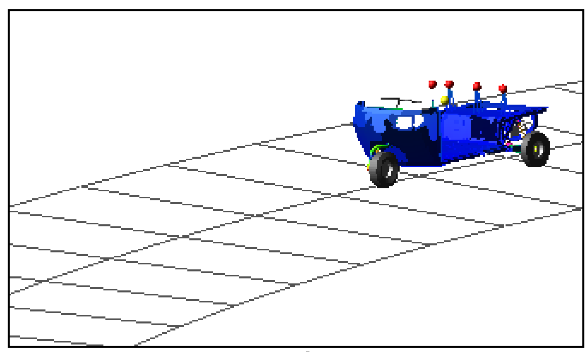


Figure 9. CRC – MBD Simulation in ADAMS.

These simulations provide critical insights into the stability, responsiveness, and overall handling performance of the three-wheeled vehicle under dynamic conditions.

a) Step Steer maneuver

A step steer analysis yields time-domain transient-response metrics. During a step steer analysis, ADAMS/Car increases the steering input from an initial value to a final value over a specified time. The most important quantities measured are shown in Figure 10.

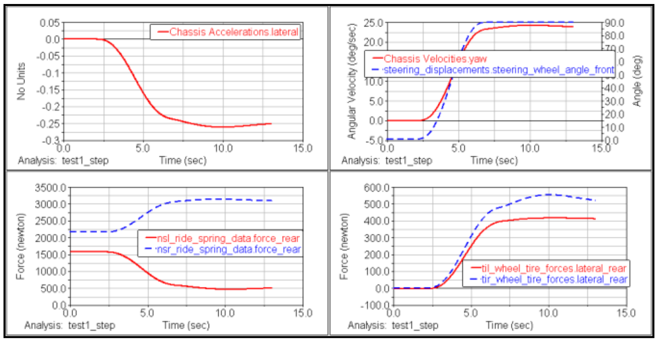


Figure 10. Vehicle lateral acceleration, yaw rate, steering angle input, rear (left/right) spring forces, tire lateral forces.

b) Constant radius cornering

For constant-radius cornering analysis, the Driving Machine drives full vehicle down a straight road, turns onto a skidpad, and then gradually increases velocity to build up lateral acceleration. One common use for a constant radius cornering analysis is to determine the understeer characteristics of the full vehicle [2].

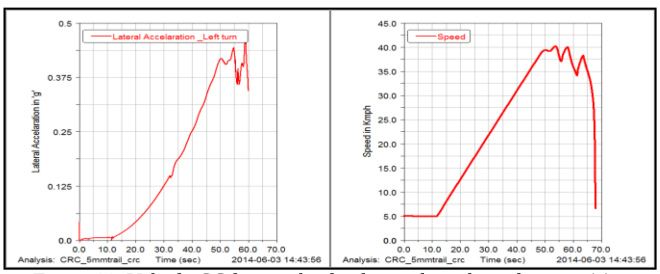


Figure 11. Vehicle CG longitudinal velocity, lateral acceleration (g).

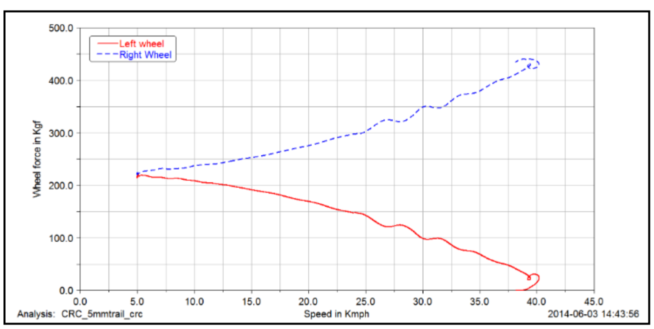


Figure 12. Rear Tire (left and right) normal forces.

It is also useful to find out vehicle velocity at which roll-over instability starts. From the Figure 10 and Figure 11 given below, it was observed that the vehicle stars to roll when its velocity reaches around 38 kmph for 30m radius.

V. Experimental Validation of Simulation Results

An experimental study was conducted to validate the vehicle dynamics simulation results by performing real-world tests on a controlled test track shown in Figure 12. The test vehicle was driven in a steady-state circular maneuver on a track with a 30 m radius. The objective was to assess lateral acceleration, roll angle, and yaw velocity under varying speed conditions and determine the threshold at which wheel lift-off occurs [8].

The test was conducted across a range of speeds, beginning from the lowest feasible velocity and gradually increasing to the maximum possible speed before instability. The speed increment strategy was designed to ensure a systematic variation in lateral acceleration:

- Up to 28 km/h, the speed was increased in steps that corresponded to an approximate lateral acceleration increment of 0.05 g.
- Beyond 28 km/h, the speed was increased in fixed increments of 2 km/h until wheel lift-off was observed.

The RT1003 Inertial Measurement Unit (IMU) and Steering Sensor is a high-precision system designed for vehicle dynamics analysis, capturing yaw, pitch, and roll rates using advanced gyroscopes, along with linear accelerations via high-accuracy accelerometers shown in Fig.13. It provides real-time roll and slip angle estimation, essential for stability control and performance evaluation. Integrated with a high-resolution steering angle sensor and torque measurement capability, it enables detailed analysis of steering response and driver input [9].

Figure 12. Constant Radius Cornering at Test rack.

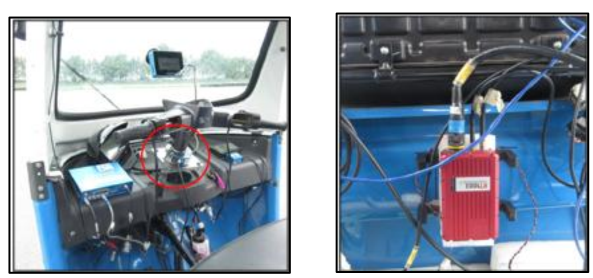
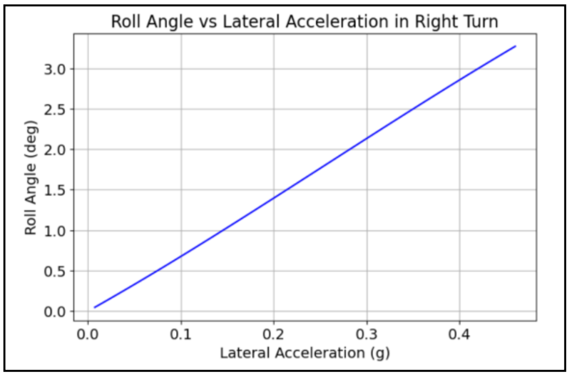


Figure 13. RT1003 IMU and Steering sensor for Vehicle dynamics Parameter Measurement.

From the experimental results, it was observed that the onset of wheel lift-off occurred at approximately 40.38 km/h, indicating the point of critical lateral acceleration at which the vehicle's roll stability limit was exceeded. The findings are graphically represented in Figure 14, illustrating the relationship between speed, lateral acceleration, and roll angle leading to the instability condition.

 ISBN: 978-1-68558-233-3

The test results provide valuable insight into the real-world validation of vehicle stability limits and rollover tendencies, offering a critical comparison with the simulated predictions. These findings contribute to improving vehicle safety analysis and the refinement of suspension and stability control systems.



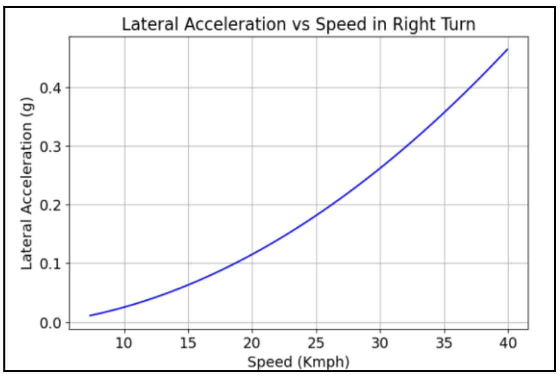


Figure 14. Lateral accelerations, Speed and Roll angle.

VI. CONCLUSION

This study presents the development and validation of a 12-Degrees-Of-Freedom (DOF) vehicle model to analyze ride and handling dynamics under various driving conditions. The integration of both linear and nonlinear (Magic Formula) tire models allowed for comparative analysis against Automated Dynamic Analysis of Mechanical Systems (ADAMS) simulation results, with the nonlinear model demonstrating superior alignment.

The validation process included MBD simulations and experimental tests, focusing on key handling aspects, such as yaw rate, lateral acceleration, and roll stability. The results showed that the vehicle exhibited roll instability at approximately 38 km/h in simulations, closely aligning with the experimentally observed wheel lift-off at 40.38 km/h.

The findings highlight the importance of incorporating high-fidelity tire models and validating vehicle dynamics through real-world testing to ensure accuracy. This research provides valuable insights into vehicle stability and rollover tendencies, which are crucial for improving suspension and stability control systems.

VII. FUTURE WORK

Future research can be extended to a wider range of road conditions, including asphalt, pave, and Belgian blocks, under varying friction (μ) levels to better understand their impact on vehicle dynamics. Additionally, investigations into diverse vehicle configurations, such as three-wheeled and unconventional architectures, will enable a more comprehensive assessment of dynamic behavior under real-world operating conditions. This will facilitate the refinement of suspension kinematics, steering response, and stability control strategies, ultimately enhancing vehicle safety, ride comfort, and performance.

Furthermore, the current model will be improved by incorporating a higher Degrees-Of-Freedom (DOF) and integrating structural compliances to better capture real-world dynamic behavior. Advanced analyses will be performed by incorporating roll stability detection and control. Wheel Force Transducer (WFT) data acquired from Road Load Data Acquisition (RLDA) to quantify component-level excitations. These excitations directly influence key vehicle dynamics parameters, including ride quality, handling characteristics, and structural durability, enabling a more precise evaluation of system-level interactions and optimization of vehicle performance.

REFERENCES

[1] T. Gawade, S. Mukherjee, and D. Mohan, "Six degrees-of-freedom three-wheeled vehicle model validation", Proceedings of the Institution of Mechanical Engineers, 219, D4, pp.487-498, 2005.

[2] T. D. Gellespe, "Fundamental of Vehicle Dynamics", SAE,Inc., Warrendale, pp.117,1992.

[3] J. C Huston, B. J. Graves, and D. B. Johnson, "Three wheeled vehicle dynamics", SAE Paper 820139, 1982.

[4] M. K .Naidu, S. Srinivasa Rao, and T. Tejesh, "Ride analysis of three wheeled vehicle using MATLAB/Simulink". Proc. of Int. Conf. on Advances in Mechanical Engineering, paper no.1058, 93(4), 52- 56, 2012.

[5] H. B. Pacejka, "Tire and Vehicle Dynamics," 2nd Edition, Elsevier, 2005.

[6] M. A. Saeddi and R. Kazemi, "stability of Three – wheeled vehicles with and without control systems", International Journal of Automotive Engineering, Vol. 3, No.1, 343-355, 2013.

[7] K . Ramji, V. K. Goel, and V. H. Saran, "Stiffness Properties of small sized pneumatic tyres", Instn. Mech. Engrs., Automobile Engg., 216, D2, pp.107-114, 2001.

[8] T. E Tan and J. C Huston, "Rigid Rider System, Part I: Modeling and Parameter Values", SAE Paper 841058, Section 4, 93, 1984, pp 4.806-4.817, 1984a.

[9] T. E Tan and J. C Huston, "Three-wheeled ATV—a No-Suspension Rigid Rider System, Part II: Applications-Handling and Ride". SAE 841059, Section 4, 93, 1984, pp. 4.818-4.824, 1984b.