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Youssef Benadada · Fatima-Zahra Mhada · Jaouad Boukachour · Fatima Ouzayd · Ahmed El Hilali Alaoui *Editors*

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Smart Sustainable and Green Logistics, Volume 1

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Artificial Intelligence and Emerging Technologies: Advancements and Applications

Digital Twins: Revolutionizing Automotive Supply Chains

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Abstract. This paper explores the transformative potential of Digital Twins (DTs) in the automotive sector, particularly in the context of the 4th industrial revolution. It delves into the evolution of DTs from their origins to their current applications to highlight the rapid technological advancement and the increasing influence DTs have on various industries and contexts. It discusses how DTs, powered by advanced technologies like IoT, Big Data analytics, and simulation techniques, are being adopted by automotive manufacturers to enhance the lifecycle management of vehicles and optimize supply chain processes. It examines the role of DTs in various stages of a vehicle's lifecycle, from its conceptualization and design to predictive maintenance and disposal to highlight the importance for interoperability and improved integration with other advanced technologies. Moreover, it identifies key research gaps that need to be addressed for further advancement in this field. It emphasizes the importance of fostering DT integration with other disruptive technologies and developing robust data management strategies. It calls for collaborative efforts in research and industry to bridge the existing gaps and fully unlock the potential of DTs in the automotive sector.

Keywords: Digital twins · automotive supply chains · Internet of Things · AI

1 Introduction

Over the course of the past decade, Digital Twin (DT) applications have seen a tremendous growth across a plethora of industries including the manufacturing, construction, healthcare, and automotive sectors. The remarkable acceleration in the adoption of DT has been fostered by the rapid advent of the 4th industrial revolution, especially since the onset of Covid-19 pandemic, that has propelled manufacturing operations and supply chains into an era of becoming 'smarter than ever'. According to a report by McKinsey [1], a DT is 'a virtual replica of a physical object, person, or process that can be used to simulate its behavior to better understand how it works in real life. DTs are linked to real data sources from the environment, which means that the twin updates in real-time to reflect the original version'. That provides DTs with the capability to represent complex, real-world systems with high accuracy helping designers to understand what is happening in real-time and optimize their physical counterpart, contrary to static simulations

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that typically do not interact with the real world in real-time but rely on historical data and assumptions and are used to test a wide number of possible scenarios in a rather time-consuming and expensive way.

IBM [2] classified DTs under 4 categories of twins according to their level of product magnification: (i) individual components or parts of a larger system (e.g. car engine or tires), (ii) a complete product or asset (e.g. an entire car or a manufacturing machine), (iii) a collection of assets that work together as a unit or system (e.g. an assembly line in a plant), and (iv) an entire process which may involve multiple systems or units (e.g. supply chain). Their development necessitates the integration of various resources (e.g. IoT devices, sensors, actuators, network devices, hardware components, and software systems). Despite this, the benefits they offer in terms of increased operational efficiency, improved product development, increased sales, reduced costs, faster turnaround times, and enhanced customer satisfaction make them a valuable investment for many different players. For example, the engineering sector uses DTs to enable real-time process insights and controls; the construction and the oil and gas sectors use them to optimize building processes and improve monitoring; the manufacturing industry to model real-time operations and leverage decision-making; the finance sector to mitigate financial fraud; the healthcare sector to personalize care provision; and the energy sector to optimize the use of assets and planning.

DTs' operation is underpinned by emerging technologies, such as IoT, 3D visualizations, simulation tools, and predictive analytics. On this basis, Ivanov [3] defined DTs as 'computerized models that represent the network state for any given moment in time and allow for complete end-to-end supply chain visibility to improve resilience and test contingency plans'. According to Tao et al. [4], in the automotive sector DTs offer a wide range of vehicle services including (i) real-time state monitoring, (ii) energy consumption analysis and forecast, (iii) user management and behavior analysis, (iv) user operation guides, (v) intelligent optimization and updates, (vi) product failure analysis and prediction, (vii) product maintenance strategy, (viii) product virtual maintenance, and (ix) product virtual operation. The evolution of DTs in the automotive industry has transformed most of these services into a vital component for enhancing automotive supply chain operations and has led leading market and technology trend researchers, such as Gartner, Forbes, and McKinsey, to recognize them as a top ten strategic technology trend since 2017 [5].

1.1 Research Objectives

This paper aims to explore the transformative potential of DTs within the automotive sector, particularly in the context of the 4th industrial revolution. More particularly, it will:

- Investigate the origins and evolution of the DT concept from its early inception to its current applications across various industries.
- Examine the role of enabling technologies and analytics capabilities in enhancing the value and impact of DTs across diverse industries.
- Examine the applications of the DT technology within the automotive sector.
- Determine the key challenges that affect data integration, security and interoperability of DTs across supply chains focusing on the automotive sector.

- Identify current research gaps and propose a set of actions to address them, thereby paving the way for further advancements in this field.

1.2 Research Methodology

The methodology starts with a broad analysis of the DTs concept within the manufacturing sector. It explores a wide range of industrial DT applications to highlight the rapid advancement of the technology. Subsequently, it focuses on the automotive industry and examines the varying applications of DT across different supply chain stages identifying several challenges affecting their performance. To this end, the study will adopt an interpretivism research philosophy using a deductive research approach, which entails a comprehensive review of published information concerning the chosen industrial case studies.

2 Digital Twin Background

2.1 Origins of the Digital Twin Concept

Although the concept of the digital twin (DT) is attributed to books of science fiction published in previous decades, its use technically dates back to the 1960s when NASA began to experiment with virtual models in the context of the Apollo program [6]. Yet, the DT idea was first mooted in the literature in 1991 through David Gelernter's publication, 'Mirror Worlds'. This marked the inaugural discourse on the potential of revolutionizing computing and transforming society by replacing reality with a sophisticated, high-tech and interactive software imitation [7]. Nonetheless, it was not until 2002 that Dr. Michael Grieves from the University of Michigan introduced this concept to the industry at a Society of Manufacturing Engineers conference in Troy, Michigan. In this presentation, he proposed the use of a conceptual model named 'Doubleganger' underlying product lifecycle management (PLM) [8]. Around the same time, Kary Främling introduced his work 'Product Agent' in which he also explored the integration of physical entities with their virtual equivalents in an Internet of Things (IoT) and PLM context [9]. Based on these works, John Vicker of NASA eventually coined the term 'digital twin' in a 2010 Roadmap Report describing the creation of full-scale digital simulations of space capsules with the aim to replicate the system, analyze the issues faced, and maximize their usage potential [10].

2.2 Evolution of the Digital Twin Concept and Applications

Since 2010, the concept of DTs has gained increasing prominence, with General Electric (GE) playing a pivotal role in popularizing it through their 'Industrial Internet' initiative. As part of it, GE examined the use of virtual doubles of wind turbines and jet engines animated with real-world data. By mounting numerous sensors on them, they were able to collect, transmit and store tremendous amounts of data using Industrial Internet of Things (IIoT) systems, and perform analytics to optimize asset performance and minimize unscheduled downtime [11]. These applications emphasized the adoption of DTs within industrial contexts, enabling the monitoring, optimization, and predictive analysis of machine and equipment performance [12]. Concurrently, Nasa advanced its existing DT systems to enhance the performance of their spacecraft and components through simulated scenarios; monitor and analyze the health and condition of spacecrafts in planetary environments; run diagnostics to detect anomalies and deviations from the expected behavior, and take proactive measures making necessary adjustments and repairs; and finally reduce costs and minimize the environmental impact of its operations by pinpointing areas where energy consumption could be optimized [13].

In 2019, the automotive sector began using DTs to simulate and monitor factory floors remotely, assess vehicle designs, and enable predictive maintenance, thereby diminishing the need for physical prototypes and optimizing product development. Soon, DTs gained momentum across various other industries, such as in urban planning where architects started using them to envision city blocks with precision before building them [14]; the energy sector where DTs were used to digitalize energy systems [15]; and the healthcare sector where several researchers started using DTs to model and simulate the human body to personalize medicine and optimize treatments [16]. These applications were further enabled by the advancement and integration of disruptive technologies, such as artificial intelligence (AI), machine learning (ML), 5G, and virtual reality (VR), facilitating better real-time decision making and predictive capabilities.

It was only in 2021 that Nvidia launched its 'Omniverse' engine, a real-time 3D graphics collaboration platform, that allows businesses to build 3D renderings of their own [17]. Omniverse is considered as a breakthrough innovation in DT technology, as it allows individual entities and teams to develop Universal Scene Description (OpenUSD)-based 3D workflows that enable improved collaboration among different teams while accelerating numerous manufacturing processes. Using ray tracing and AI technologies, it offers enhanced quality and realism of 3D simulations. Currently, many businesses, such as BMW, Ericsson Energy, and Lockheed Martin are using Omniverse to create complex and accurate virtual replicas of objects, processes, and environments, such as factories and planetary systems [18]. Using Omniverse, Siemens introduced 'MindSphere', a cloud-based, open IIoT as a service end-to-end solution, that enables businesses to connect their physical, web and enterprise-based systems in a central location [19]. Eventually, 'MindSphere', evolved into the 'Insights Hub', a cloud-based platform, which collects and analyses sensor data in real-time and makes them accessible through digital applications enabling manufacturers to optimize products, production assets, and manufacturing processes along the entire value chain [20]. Soon, Amazon launched 'AWS IoT TwinMaker', a competing service, that allows businesses to create a scalable and holistic digital representation of facilities and operations by integrating data from IoT equipment sensors, production lines and live video, while optimizing building operations, boosting production output, and optimizing equipment performance [21]. Currently, DTs undergo a continued expansion focusing on sustainability, resilience and interconnected systems playing a crucial role in energy transition, the development of smart cities, and the optimization of end-to-end supply chains. Such DT systems aim at identifying bottlenecks and resolving them with minor human intervention; providing real-time visibility of inventory levels across supply chains facilitating a more accurate and efficient inventory management; mapping transportation routes and optimizing logistics; planning and forecasting demand; understanding patterns and modelling the outcomes of modifications, among others [22].

3 Use of Digital Twins Across Automotive Supply Chains

The advent of the 4th industrial revolution marked a significant turning point for the DT concept within the automotive industry. This period witnessed a substantial transition from dedicated industrial automation mechanisms towards mechatronic and cyber-physical systems leveraging the capabilities of advanced computational and communication technologies [23]. During this time, many automotive manufacturers started adopting DT technologies harnessing the power of IoT, big data analytics, and simulation techniques, as a strategic approach to enhance lifecycle management of vehicles, optimize product quality, and effectively harness production and supply chain processes. For example, in 2019, Bentley Systems partnered with Siemens to launch the 'PlantSight' project which aimed to create a complete, up-to-date, as-operated DT of an entire plant by consolidating diverse data types from multiple physical and engineering sources into a unified source of truth facilitating ongoing change management, collaboration, cost reduction and operational efficiency [24].

The DT technology can significantly support automotive supply chains by monitoring the status of a vehicle across different product life cycle stages, such as its conceptualization and design; material and components' procurement; building and adding manufacturing capacity; product testing; employee training; storage; sales; predictive maintenance; after-sales services; and recycling. At each phase, there is an enormous amount of data generated. The goal is to leverage these data for the swift and cost-effective production of high-quality vehicles. DTs enable real-time monitoring of every component within the supply chain ensuring adherence to constraints while facilitating up-to-date end-to-end visibility for both suppliers and manufacturers. In addition, DTs unlock new possibilities in system automation and optimization through the integration of AI and ML solutions. Eventually, DTs can help automotive businesses to avoid inventory shortages or scraping through transparent stock level insights. Finally, DTs have the potential to optimize logistics through real-time shipment data leading to cost reductions and reduced environmental impacts.

3.1 Vehicle's Conceptualization and Design Phase

Vehicle design is an extremely complex, creative, and iterative process which requires numerous simulations, prototypes and test runs before transitioning to production. Design is required to define the physical appearance of both the interior and exterior features of a vehicle. DTs can be extremely useful in the design phase of a car, as they can be used to simulate the entire vehicle, including its mechanics, electronics, and physical behavior [25]. In addition, DTs can help manufacturers to cope with the increasing technological complexity of cars, the growing number of technical and regulatory requirements, and the constant design improvements [23]. Using the latest developments in computing, digital simulation, cloud technology, AI, and ML, designers can gain a realistic representation of a vehicle's shape, appearance, and performance by striking a balance between function, aesthetics, and physical constraints. For example, in Renault Group the designers are using DTs to achieve the best vehicle finish by testing different colors, textures, positions, and materials using its virtual model [26]. In addition, using real-time data from previous models, designers can get valuable insights into the performance of vehicle features, facilitating easier and faster design improvements [27].

Furthermore, the designers can review several vehicle design alternatives and make informed decisions by sharing the vehicle's virtual model with engineers [28]. Car manufacturer Maserati, for instance, has used DTs to optimize car body aerodynamics using virtual wind tunnel tests, a method that is typically complex and costly when conducted physically [29]. Mercedes-Benz has collaborated with Nvidia to leverage Nvidia's expertise in high performance computing graphics and bring AI and metaverse technologies to the design of a shared virtual model allowing designers and engineers to work together seamlessly [30]. The use of DTs has enabled Mercedes-Benz to explore different design options, test modifications and assess their impact; predict car performance accurately; identify potential issues and take appropriate actions to address them; and improve the car's safety and reliability; while minimizing reliance on physical prototypes [31]. Designers can also collaborate with operational teams and analysts to provide enhanced customization and personalized options to customers [32]. Using DTs to capture customer preferences allows designers to seamlessly integrate them into product design and development, streamlining the creation of customized products [33].

3.2 Materials Procurement and Suppliers Selection Phase

DTs can be a useful tool on resource management and production planning operations within the automotive supply chain. They can provide more accurate demand forecasts by analyzing real-time market trends, customer preferences and historical sales data. This, in turn, facilitates the procurement of materials in the right quantity at the right time. DTs can also be used to create virtual replicas of materials to assess their properties under various scenarios and conditions, aiding the selection of the highest quality materials. Xiang, Zhang, Zuo and Tao [34] used DTs to simulate the physical, cost, and environmental performance of different materials used in laptop shells to identify the most environmentally friendly option. Furthermore, DTs can enable the simulation of network movements of materials sourced from different locations allowing the prediction of material demand, consumption, and delivery times from different suppliers. Additionally, DTs can be used to simulate a factory floor and monitor production operations to identify potential bottlenecks, delays, and defects. Finally, DTs can be used to predict potential vehicle breakdowns, enabling adjustments to stock levels to support predictive maintenance effectively [35].

DTs are also instrumental in the strategic supplier selection process within the automotive sector. They can be used to capture and analyze the behavioral and operational data of different car parts and assess the impact of materials with different durability supplied by different vendors [32]. Considering potential changes on timelines, costs, and product quality, automotive businesses can make well informed supplier selection decisions [36]. For example, Tesla creates the virtual model of every one of its cars, analyzing data gathered from onboard sensors using AI algorithms to determine where faults and breakdowns are most likely to occur. This serves a dual purpose; aiding in preventive maintenance measures and assessing the quality of the parts provided by different suppliers [37]. Moreover, DTs can be used to simulate the impact of various contract terms on procurement costs and supply chain performance, facilitating negotiations for more favorable agreements with suppliers [25].

3.3 Vehicle Manufacturing Phase

Within a plant, a DT can be the virtual replica of the physical manufacturing facility, offering the capability to simulate and optimize the production processes [38]. DTs can model the assembly process and pre-emptively identify potential issues, resulting in cost, time, and resource savings by reducing the need for physical prototyping and testing [39]. In addition, DTs applied to machinery and manufacturing equipment contribute to determining plant maintenance requirements while boosting the efficiency of production lines. By predicting potential failures, the DT minimizes downtime by enabling preventive measures and facilitating maintenance. The use of DTs in factories is estimated to yield up to 30% improvement in product quality, 20% reduction in lead times, and a 40% increase in resource efficiency [40]. For example, BMW has created a 3D DT of its Regensburg factory in Germany. The virtual replica precisely mirrors the physical factory, providing real-time monitoring of every aspect, from the factory floor to the machinery. This enhances operational efficiency and promotes seamless collaboration between different factories. BMW has since digitized many of its factories and has introduced the iFactory tool that promotes inter-factory collaboration [41].

In addition, DTs used for layout planning can assess the impacts of installing new machines to increase manufacturing capacity [42]. DTs enable manufacturers to respond quickly to changes in demand, market trends, and customer preferences, enabling the customization of vehicles to suit individual customers' needs. Manufacturers can also develop their own DT systems by using existing open, scalable cloud-based platforms, such as the iTwin platform developed by Bentley Systems. This is designed to create, visualize, and analyze the DTs of various infrastructures, and test various activities conducted both in automotive and other production facilities [43].

Moreover, the use of in-line DTs allows operators to train on a virtual machine until they acquire the necessary skills and confidence to operate the actual equipment. This accelerates the learning process and reduces the potential for machine damage and human injury. Examples include Siemens' DT of their electric motor production process, which enables employees to acquire hands-on experience in assembly and troubleshooting processes without affecting actual operations [44]. Also, General Motors has collaborated with GE in using DT to replicate factory floors and test new equipment, providing employees with a risk-free virtual hands-on-experience [45].

3.4 Predictive Vehicle Maintenance Phase

Following the sale of a vehicle and while it is in operation, manufacturers can employ DTs to monitor the real-time condition and performance of vehicle components using data collected from sensors. This way, vehicle owners can repair, replace, or upgrade the components before failing. Consequently, DTs contribute to improving vehicle quality and reliability, while reducing repair costs, and optimizing maintenance schedules based on actual vehicle requirements. Volvo, for example, is using DTs of their vehicles to gather real-time performance, sensor and inspection data, their service history, and warranty data, and assess changes in their configuration and parts replacement. This allows Volvo to monitor the performance of various components, detect potential issues and take preventive action before they become critical [46].

3.5 Vehicle Disposal Phase

DTs also enable car producers and users to make more informed decisions about the fate of the cars and their components at the end of their lives. DTs can be used to simulate the wear and tear of different car parts and components allowing producers and users to predict their lifespan, assess their residual value, and plan for their replacement and recycling. For example, Ford has developed seven DTs for each model they manufacture, each corresponding to a different supply chain phase, including disposal. DTs can eventually help users to optimize the recycling process by simulating the separation, processing and reuse of different parts and materials, leading to more efficient disposal procedures and cost savings [29]. In their study, Wang and Wang [47] introduced a DT system for the recovery of electrical and electronic waste to support remanufacturing operations in accordance with international standards.

4 Conclusions and Recommendations

While the use of DTs undoubtedly allows for significant advancements in numerous areas across automotive supply chains, their implementation requires significant investment in both physical resources and expertise. The continuous increase of data sources, the generation and transmission of vast amounts of data at each phase of a vehicle's lifecycle, and the plethora of design options demand specialized technical knowledge and necessitate the implementation of robust data engineering capabilities that include cloud computing and IoT systems, human-computer visualization interfaces and powerful computing analytics to ensure the quality and usability of the gathered data. Despite the seemingly high investment costs, the establishment of high-performing computing infrastructure and advanced analytics can help users to optimize the real-time collection and transformation of data into a suitable format for analysis and eventually identify required process changes in a more cost-efficient, safe, and timely manner than traditional static simulations. Coupled to the increasing availability of tools and infrastructure and the improving system interoperability, DTs currently become increasingly accessible to businesses of any size and industry.

Yet, the lack of a unified and universally applicable ontology and taxonomy framework for DTs currently impedes software harmonization, data interoperability, collaboration and best practice sharing among diverse industries, applications, and processes. A starting point to overcome this is the current development of a DT Definition Language by Microsoft based on industry standards aiming to minimize reinvention and simplify solutions. The development of a unified taxonomy will reduce resources, time, and investment needed for conceptual modeling and system development by enabling resource sharing and learning from past experiences. It will not only enhance understanding within automotive companies but also accelerate the adoption of DTs, driving business value across the supply chain. Additionally, the development of standardized metrics and measures will help businesses to evaluate and improve the performance and interoperability of the DTs used.

While DTs enable the convergence of the physical and virtual versions of vehicle prototypes, factory floors, and vehicles on the road, most of the data generated at each supply chain stage tends to remain segregated and minimally integrated with the subsequent stages of the vehicle lifecycle. This not only leads to inefficiencies in the production process but also to missed opportunities for vehicle and process optimization. To manage the end-to-end process in a more effective way, it is essential to develop robust DT data management frameworks including improved tools, methodologies and systems for data collection, storage, visualization, analysis, and exchange. The aim is to make the data collected by IoT sensors, stored in log files, and analyzed using AI-powered analytics readily accessible by different supply chain stakeholders in order to support end-to-end optimization and informed decision-making.

However, the exchange of DT-generated sensitive information by many stakeholders may entail significant security and privacy concerns. Businesses can protect DT data by integrating cloud encryption, blockchain verification, and cloud retrieval to allow for their permanent, transparent, and immutable recording and distribution across value chains. Yet, it is crucial to acknowledge the dependence of DTs on various technologies, like cloud computing, blockchain, AI, and VR, which may have their own limitations. To mitigate this, automotive businesses should work with research institutions to enable the seamless integration of the different technologies and develop solutions supporting low latency, high reliability, and energy-efficient data processing. Despite the challenges, the potential benefits of DTs can surpass the existing limitations with the right blend of careful planning, prudent investment decisions, and strategic implementation, further solidifying the increasing prominence of DTs.

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Enhancing Battery Lifespan in Electric Vehicles: An Optimal Approach to Deploying Dynamic and Static Wireless Charging Infrastructure

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Abstract. The escalating global increase in greenhouse gas emissions demands immediate solutions to curb this environmental threat. Electric vehicles have emerged as a practical remedy, albeit with specific constraints aimed at promoting their widespread adoption. Introducing wireless charging for electric vehicles addresses the time constraints associated with their adoption, offering a contactless recharging technology between the power source and the vehicle. However, practical limitations may preclude the installation of induction charging technology in certain areas. To address this challenge, we examine two modes of electric vehicle charging: dynamic and static. We present a mathematical model designed to optimize the planning of charging infrastructure for both modes. This optimization encompasses the strategic placement of wireless charging systems for dynamic scenarios and stations for static modes to facilitate the mobility of a diverse fleet of vehicles with varying battery capacities within the network. Our objectives in this study revolve around minimizing the count of power transmitters, which directly impacts infrastructure costs, and maximizing the lifespan of electric vehicle batteries, given their pivotal role in vehicle performance.

Keywords: Optimization · mathematical modelling · electric vehicle · static and dynamic charging · heterogeneous fleet · battery life

1 Introduction

Human-generated greenhouse gas emissions (GHGs) have perturbed the Earth's climate equilibrium, giving rise to global warming, a matter of grave concern to the international community. As a response to the pressing necessity to address the growing average emissions, several nations have initiated actions within the transportation sector, a principal contributor to these emissions. The electrification of vehicles stands out as an effective solution to this problem, though it necessitates the optimisation of the technology underpinning electric vehicle (E.V.) network infrastructure.

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Wireless charging technology (W.C) is a method of recharging electric vehicles by efficiently converting significant amounts of energy within a short proximity, typically within tens of centimeters. It is worth noting that this approach poses no risk to human health. Within the realm of wireless charging, two distinct modes exist. The initial mode, referred to as static wireless charging (SWC), enables vehicles to recharge their batteries even while they are powered off. The time it takes to charge the vehicle using SWC is comparable to that of conventional charging cables, but it offers added convenience and enhanced safety. In practical terms, this means electric cars can be conveniently parked in designated areas like parking lots or garages equipped with static wireless charging systems (SWCS). The second mode is known as dynamic wireless charging (DWC), a system capable of recharging a vehicle in motion through the installation of a charging transmitter beneath the road surface. This technology often leads to discussions about the concept of electric roads. DWC has the potential to reduce the battery's capacity, subsequently lowering both its weight and cost. This particular charging approach eliminates the need for stationary charging, as the vehicle can be recharged while in motion. A DWC system (DWCS) comprises two key components: the electric vehicle (E.V.) and the power transmitter. Inverters play a critical role by converting direct current (D.C.) into high-frequency alternating current or voltage. Beneath the road's surface, underground power lines generate an alternating magnetic field, which is then received by a pickup coil mounted on the vehicle's floor [11]. The acquired power undergoes further processing through a rectifier and regulator before being directed to the vehicle's battery. In reality, the installation of dynamic charging systems on road networks isn't always feasible, whether due to the road's geometry or the challenges of electrifying the entire roadway. To address this limitation, the use of charging stations becomes necessary, where vehicles are charged in a static manner. Each of these stations is composed of a series of Static Wireless Charging Systems (SWCS). This introduces the concept of a road network with two distinct charging modes: a dynamic mode when a charging transmitter is incorporated into the road infrastructure, and a static mode employed in situations where the dynamic mode is not a viable option.

Vehicles using different battery types often exhibit varying characteristics, necessitating the consideration of these battery diversities when establishing network infrastructure. Notably, since the battery is a principal component of any vehicle, ensuring optimal battery life is an objective in work and offer cost-optimized solutions for the technology employed. To achieve this, we begin by reviewing existing works in the field and subsequently describe the specific problem addressed in this paper. In order to formulate the problem, we introduce a multi-objective mathematical model. To show the efficiency of our model we applied an exact method using Cplex optimizer.

2 State of the Art

The transportation industry, particularly in advanced economies, is undergoing a scientific transformation driven by extensive research endeavors focused on electric vehicles. This includes the studies highlighted within this section. In [3], Bolger introduced the concept of the first wireless electric vehicle, which has since seen significant technological progress, detailed in [8, 5]. KAIST's recent development, the Online Electric

Vehicle (OLEV) [20], employs a DWC system, with technical specifics available in [19, 4]. Sejong City, the newly designated South Korean capital, is preparing to implement a DWC-powered public transportation network to support its current bus routes [14]. Meanwhile, the European initiative UNPLUGGED has created an inductive fast-charging station for electric vehicles, exploring the enhancement of EV comfort and longevity through inductive loads in urban settings [1]. Ensuring the effective placement of these sites involves addressing location and traffic concerns. However, the installation of charging stations and DWC infrastructure poses unique challenges. Previous studies on charging station placement often assumed fixed points where vehicles stop to charge. But since DWC EVs can charge while moving, the power transmitters must be where the vehicles operate. Additionally, in DWC systems, the amount of charge needed depends on how fast the vehicle is going, which is different from traditional charging stations. Some research has been done on SWC at Auckland University [13]. Fisher et al. looked into the development of induction charging for EVs and the companies involved in DWC [9]. Ko and Jang introduced a model to minimize costs for installing power transmitters and determining battery size [12]. Kraxner et al. created a model to minimize annual costs and energy use in a mixed fleet of buses with different charging methods [22]. Liu and Song addressed location and battery size problems for DWC systems, considering uncertain factors in a two-step process [15]. Mouhrim et al. proposed a way to balance the cost of bus batteries and DWC systems on multiple routes [17]. Elbaz et al. looked into balancing infrastructure costs and battery capacity in different network setups [10, 7]. Among the exciting studies, we highlight the work of Sun Xiaotong et al. [21]. They explored two charging methods, DWC and SWC, to charge electric buses with the same type of battery while in service. This research focuses on the best use of both static and dynamic charging modes, considering the interaction between transportation and the power grid. Bourzik et al. [2, 16] presented the optimal deployment of the induction charging infrastructure for E.V.s with heterogeneous batteries; they conducted their study on the highway. To build the infrastructure, they considered that the road is subdivided into segments with the same length to find which segment would be occupied by the DWCS. When it comes to wireless charging for electric vehicles while considering battery lifetime, there's limited research available. For example, B. Pantic and colleagues [18] introduced a practical approach to determine the location of wireless charging infrastructure on the road. Their multi-objective model connects battery life to peak power output, recognizing that high peak power may harm the battery's lifetime. Similarly, Jeong et al. [9] presented a mathematical model to find the optimal battery size and power lane assignment for dynamically charged EVs on specific roads, taking quantitative battery life into account. The research cited in this section primarily focuses on electric vehicles (E.V.) with uniform batteries. However, it's important to note that E.Vs come with varying battery capacities, charge rates, discharge rates, and ranges, depending on the type of battery they use. This results in a mix of vehicles with different capabilities, making them heterogeneous. Our contribution to this field is centered on determining the best way to deploy electric vehicle infrastructure in complex transportation networks featuring both DWC and SWC charging modes. We take into account the diverse range of E.Vs with heterogeneous batteries. In our study, we aim to address battery degradation and optimize the lifespan of a vehicle's battery when traveling from one starting point in the network to a different endpoint along a specific route.

3 Problem Description

We are addressing transportation networks with vehicle fleets equipped with varying battery capacities. Our goal is to ensure that each vehicle type follows a specific route from its starting point to its destination while simultaneously optimizing battery life and minimizing costs related to installing dynamic charging transmitters and static charging stations. It's worth noting that the battery serves as the fundamental component of each vehicle and is also the most expensive one. By considering the infrastructure requirements for each vehicle individually, we increase the number of transmitters and charging stations, thereby increasing infrastructure costs. The network can be represented as a graph, denoted as G = (SA., SN.), where S.N. represents the set of nodes and S.A. represents the set of arcs. The network is comprised of two types of arcs: one for the installation of dynamic charging transmitters (denoted as SA.$'$ in red) and the other for static charging stations (SA.$''$ in green). Charging a vehicle at a station impacts its state of charge on other arcs in set SA$'$, where SA encompasses both SA$'$ and SA.$''$. It's important to note that all routes within the network may share the same arcs.

Our main objective is to determine the optimal placement of dynamic charging segments and static charging stations so that any vehicle can travel from its starting point to its destination in the network while minimizing infrastructure costs. It's worth noting that installing power segments throughout the entire network may not always be feasible, leading to the use of static charging for certain network sections.

Given the high cost of batteries and the central role of the battery as the primary component of an electric vehicle, we aim to maintain each battery's state of charge within a preferred range, which includes the preferred minimum charge (CMnP), for example, 20%, and the preferred maximum charge (CMxP), for example, 80% of the total battery capacity. By keeping the charge within these limits, we maximize the battery's lifespan, resulting in a higher number of charge cycles.

4 Mathematical Modelling

This research centers on the strategic planning of electric vehicle infrastructure, encompassing both static and dynamic charging modes. The primary objective is to reduce the expenses associated with the infrastructure's technology, which includes the inverter and power components, while simultaneously prolonging the battery lifespan as the core component of every vehicle.

4.1 Data and Model Parameters

- SN:: Set of nodes (vertices)
- SA: Set of arcs such as
- $SA = \mathrm{SA}' \cup \mathrm{SA}'' = \{(i,j)/i, j \epsilon SN\}$

- SP:Set of paths, composed of a subset of vertices S.N., and we denote the origin of the paths by $O\epsilon SN$
- P: Set of paths
- SVT: The set of vehicle types
- I_{max}^{β}: The maximum charge of the vehicle battery $\beta \in SVT$
- I_{min}^{β}: The minimum charge of the vehicle battery $\beta \in SVT$
- $I_{\mathrm{pmax}}^{\beta}$: The maximum preferable charge of the vehicle $\beta \in SVT$
- $I_{\mathrm{pmin}}^{\beta}$: The minimum preferable charge of the vehicle $\beta \in SVT$
- $DR^{\beta}(t)$: The discharging rate of the vehicle $\beta \in SVT$ at each instant t.
- DRS^{β} : The energy required for internal travel in a charging station by the vehicle β
- $CR^{\beta}(t)$: The charging rate of the vehicle β at time t in the DWC system
- CRS^{β}: The charging rate of the vehicle β in the SWC system
- $N_{(i,j)}$: The number of potential charging sites in the arc $(i, j)\epsilon SA$
- CI_m: The capacity of each inverter
- CI: The cost per inverter
- CA: The cost of an active segment without an inverter
- C.S.: the cost of a static charging station
- $V_{ij,kr}^{p}$: Equal 1 if the arc (i, j) is the follower arc of the arc (k, r) in the path p
- $E_{ij,g}^{\beta,p}$: If the battery charge is less than $I_{\mathrm{pmin}}^{\beta}$ of the vehicle $\beta \in SVT$ at the g^{th} segment of the arc (i, j) ϵSA during the trip p, we denote the difference by $E_{ij,g}^{\beta,p}$.
- $R_{ij,g}^{\beta,p}$: If the battery charge is greater than I_{pmax}^{β} of the vehicle $\beta \in SVT$ at the g^{th} segment of the arc (i, j) ϵA during the trip p, we denote the difference by $R_{ij,g}^{\beta,p}$.

4.2 Decision Variables

$$U_{ij}^{g} = \begin{cases} 1 \text{ if the potential charging sites g of the arc (i, j) is active} \\ 0 \qquad\qquad \text{otherwise} \end{cases}$$

$$W_{ij}^{g} = \begin{cases} 1 \ \text{ if the segment } g \text{ of the arc } (i, j) \in A \text{ has an inverter} \\ 0 \qquad\qquad \text{otherwise} \end{cases}$$

$$Y_{ij,g}^{\beta,p} = \begin{cases} 1 \ \text{ if the vehicle } \beta \text{ uses the g}^{\text{th}} \text{ potential site} \\ 0 \qquad\qquad \text{otherwise} \end{cases}$$

4.3 Constraints

As previously stated, each vehicle type starts its journey with a battery charge equal to its maximum preferred capacity. Consequently, at the origin point O of every path within the set P, the vehicle's initial load corresponds to the charge it had at the beginning of the first segment (designated as 0) of the path (o, i) on the trip within the set P. This initial load equals $I_{\max p}^{\beta}$ when the parameter λ is set to 1.

$$I^{\beta}\left(t_{oi,0}^{p}\right) = \lambda \times I_{pmax}^{\beta} \ \ \forall \beta = 0, \ldots, |SVT|, \forall p \in P, \forall (\mathrm{o, i}) \in \ \mathrm{SA} \tag{1}$$

The battery charge for each vehicle type at any given time must exceed the minimum required charge, a condition guaranteed by the following constraint:

$$I_{min}^{\beta} \leq I^{\beta}\left(t_{ij,g}^{p}\right) \ \forall g = 0, \ldots, N_{ij} - 1, \ \forall \beta = 0, \ldots, |SVT|, \ \forall (\mathrm{i, j}) \in \mathrm{SA} \tag{2}$$

The vehicle batteries are functional in such a way as not to exceed the maximum charge I_{max}^{β}, which is ensured by the following constraints:

$$I^{\beta}\left(t_{ij,g}^{p}\right) \leq I_{max}^{\beta} \ \ \forall g = 0, \ldots, N_{ij} - 1, \ \forall \beta = 0, \ldots, |SVT|, \ \forall (\mathrm{i, j}) \in \mathrm{SA} \tag{3}$$

The subsequent constraint pertains to the adjustment of the remaining energy as the dynamic segment progresses to $g + 1$. The initial component represents the vehicle's battery charge, denoted as β, at the commencement of segment g. The second component signifies the power consumption of the vehicle during the journey within segment g, while the final component reflects the power acquired from segment g when it is in operation. In cases where it is inactive ($Y_{ij,g}^{\beta,p} = 0$), the last component is set to zero.

$$\begin{aligned} & I^{\beta}\left(t_{ij,g+1}^{p}\right) = I^{\beta}\left(t_{ij,g}^{p}\right) + \int_{t_{ij,g}^{p}}^{t_{ij,g+1}^{p}} \left(-DR^{\beta}(t) + CR^{\beta}(t) \times Y_{ij,g}^{\beta,p}\right) dt \qquad , \\ & \forall \ \mathrm{p} \ \in P, \ \forall \beta = 0, \ldots, |SVT|, \ \forall (\mathrm{i, j}) \in \mathrm{SA}'', \ \forall g = 0, \ldots, N_{ij} - 1 \end{aligned} \tag{4}$$

The subsequent constraint pertains to the energy adjustment for each static segment g + 1. This adjustment is determined by the difference between the initial component, representing the vehicle's battery charge (β) at station g, and the second component, which accounts for the power consumption between stations g and g + 1 if station g is not in operation. In cases where station g is active $\left(Y_{ij,g}^{\beta,p} = 1\right)$, the second component is substituted with the power consumed during internal movement at station g, and the final term represents the electrical energy recharge at station g.

$$\begin{aligned} & I^{\beta}\left(t_{ij,g+1}^{p}\right) = I^{\beta}\left(t_{ij,g}^{p}\right) - \int_{t_{ij,g}^{p}}^{t_{ij,g+1}^{p}} DR^{\beta}(t) dt \left(1 - Y_{ij,g}^{\beta,p}\right) - Y_{ij,g}^{\beta,p} \times DRS^{\beta} + Y_{ij,g}^{\beta} \\ & \times CRS^{\beta} \times \left(t_{ij,g+1}^{p} - t_{ij,g}^{p}\right) \\ & \forall \ \mathrm{p} \ \in P, \ \forall \beta = 0, \ldots, |SVT|, \ \forall (\mathrm{i, j}) \in SA'', \ \forall g = 0, \ldots, N_{ij} - 1 \end{aligned} \tag{5}$$

Constraint (6) overrides constraint (5) when processing the origin of arcs. The battery load equals the first term of the addition if the arc is dynamic $\left((\mathrm{i, j}) \in SA'\right)$ and the arc (i, j) precedes the arc (j, k) in the path p $\left(\mathrm{V}_{\mathrm{ij,jk}}^{\mathrm{p}} = 1\right)$, or it will be equal to the second term of the addition if the arc (i, j) which precedes (j, k) is static $\left((i,j) \in SA''\right)$.

$$I^{\beta}\left(t^{p}_{ik,0}\right) = \sum_{\substack{\beta \epsilon SN \\ (i,j)\epsilon SA' - (k,j)}} \left(I^{\beta}\left(t^{p}_{ij,N_{ij}}\right) + \int_{t^{p}_{ij,N_{ij}}}^{t^{p}_{jk,0}} \left(-DR^{\beta}(t) + CR^{\beta}(t) \times Y^{\beta,p}_{ij,N_{ij}} dt\right)\right) \times V^{p}_{ij,jk} + \sum_{\substack{\beta \epsilon SN \\ (i,j)\epsilon SA'' - (k,j)}} \left(I^{\beta}\left(t^{p}_{ij,N_{ij}}\right) - \int_{t^{p}_{ij,N_{ij}}}^{t^{p}_{jk,0}} DR^{\beta}(t)dt\left(1 - Y^{\beta,p}_{ij,N_{ij}}\right) - Y^{\beta,p}_{ij,N_{ij}} \times DRS^{\beta} + Y^{\beta}_{ij,N_{ij}} \times CRS^{\beta} \times \left(t^{p}_{ij,N_{ij}} - t^{p}_{jk,0}\right)\right) \times V^{p}_{ij,jk} \forall j \epsilon SN - \{o\}, \forall (j,k) \epsilon SA, \forall g = 0, \dots, N_{ij} - 1, \forall \beta = 0, \dots, |SVT|, \forall \text{ p} \epsilon P \quad (6)$$

Site g is considered inactive when no vehicle type utilizes it, a condition guaranteed by the constraints (7).

$$U^{g}_{ij} \le \sum_{\beta \in SVT} \sum_{p \in P} Y^{\beta,p}_{ij,g} \quad \forall (i,j) \in SA', \forall g = 0, \dots, N_{ij} - 1, \ \forall \beta = 0, \dots, |SVT| \quad (7)$$

A potential site, denoted as g, is considered active if it is utilized by at least one of the vehicles, and this condition is ensured by the constraints (8).

$$Y^{\beta,p}_{ij,g} \le U^{g}_{ij} \quad \forall (i,j) \in SA', \forall g = 0, \dots, N_{ij} - 1, \ \forall \beta = 0, \dots, |SVT|, \forall \text{ p} \in P \quad (8)$$

Constraints (9) and (10) serve to secure the placement of a single inverter at the outset of every active series of dynamic recharge segments while ensuring that no inverter surpasses its active series capacity, denoted as CI_m.

$$W_{ij,g} = U^{g}_{ij} - \left[\sum_{k=1}^{N_{ij}-1} w^{g-k}_{ij} \times \prod_{j=1}^{k} U^{g-j}_{ij}\right] \forall g = N_{max} + 1, .., N_{ij}, \ \forall (i,j) \in SA' \quad (9)$$

$$V^{P}_{ij,jk}\left(\sum_{\text{g=z}}^{\text{N}_{\text{ij}}} U^{g}_{ij} + \sum_{\text{t=0}}^{N_{max}-(\text{N}_{\text{ij}}-\text{z})} \text{U}^{\text{t}}_{\text{jk}}\right) \le CI_m$$
$$\forall p \in \text{P} \ \forall (\text{i, j}) \in \text{SA} \ \forall (\text{j, k}) \in \text{A} \ \forall \text{ z} \in \left\{\text{N}_{\text{ij}} - CI_m, \dots, \ \text{N}_{\text{ij}}\right\} \quad (10)$$

The constraints (11) establish the quantity of energy that surpasses the minimum preferred battery charge for each vehicle type throughout the journey. It is equal to the difference between the minimum preferable battery charge $\left(I^{\beta}_{\text{pmin}}\right)$ and the battery charge $\left(I^{\beta}\left(t^{p}_{ab,g}\right)\right)$, if the vehicle does not exceed its minimum preferable charge, the difference $\left(I^{\beta}_{\text{pmin}} - I^{\beta}\left(t^{p}_{ij,g}\right)\right)$, in this case, is negative, and the quantity $E^{\beta,p}_{ij,g}$ will be equal 0.

$$E^{\beta,p}_{ij,g} = \max\left(0, I^{\beta}_{pmin} - I^{\beta}\left(t^{p}_{ij,g}\right)\right), \forall (\text{i, j}) \in \text{SA}, \forall g = 0, \dots, N_{ij} - 1,$$
$$\forall \beta = 0, \dots, |SVT|, \forall \text{ p} \in P \quad (11)$$

Constraints (12) compute the energy surplus beyond the maximum preferred battery capacity for each vehicle type.

$$R^{\beta,p}_{ij,g} = \max\left(0, I^{\beta}\left(t^{p}_{ij,g}\right) - I^{\beta}_{pmax}\right) \forall (\text{i, j}) \in \text{SA}, \forall g = 0, \dots, N_{ij} - 1,$$
$$\forall \beta = 0, \dots, |SVT|, \forall \text{ p} \in P \quad (12)$$

4.4 Objective Function

Our modeling aims to maximize battery lifetime on the one hand and minimize infrastructure costs on the other, including inverters and induction cables for dynamic charging cases and charging stations for static charging. For this, we have two objective functions. The first goal is to minimize infrastructure costs. The first term defines the total cost of static stations, the second term represents the installation of induction cables on the road, and the last term represents the cost of inverters.

$$Min\left(\mathrm{CS}\times\sum_{(i,j)\in \mathrm{SA}''}\sum_{g=0}^{N_{ij}}\left(U_{ij}^{g}\right)+\mathrm{CA}\times\sum_{(i,j)\in \mathrm{SA}'}\sum_{g=0}^{N_{ij}}\left(U_{ij}^{g}\right)+\mathrm{CI}\times\sum_{(a,b)\in \mathrm{SA}}\sum_{g=0}^{N_{ab}}(W_{ab}^{g})\right)$$

The second goal is to maximize battery lifetime by keeping the maximum possible charge variation between the minimum and maximum preferable values.

$$Min\left(\sum_{\beta\in SVT}\sum_{p\in P}\sum_{(i,j)\in SA}\sum_{g=0}^{N_{ij}}\left(E_{ij,g}^{\beta,p}+R_{ij,g}^{\beta,p}\right)\right)$$

5 Problem Solving

We focus on the mathematical model (MM) validation in this subsection, from which we will check the constraints of our model. To validate the MM, we use the.

In this section, our central focus is on the validation of the mathematical model (MM), during which we will assess the model's adherence to its constraints.

To carry out this validation, we employ the CPLEX optimizer [6], a solver with the capability to effectively solve linear (or quadratic) single-objective models, owing to its syntax closely aligned with mathematical formulations. For the validation of our mathematical model using the CPLEX optimizer, we examine a network consisting of 6 nodes and 11 arcs. Each of these arcs is subdivided into discrete potential charging sites, each segment being 50 m in length.

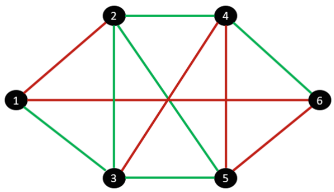

Fig. 1. The network of the example

In Fig. 1, we present the network under consideration in our example. The red arcs depict dynamic arcs, while the static arcs are represented in green. You can find detailed information about each arc's length in meters and the number of its potential charging sites (PCS) in Table 1.

Table 1. The discretization of the network

Arcs	(1, 2)	(1, 3)	(1, 6)	(2, 3)	(2, 4)	(2, 5)	(3, 4)	(3, 5)	(4, 5)	(4, 6)	(5, 6)
Length	1000	1200	1800	1100	600	1300	1300	500	800	1000	700
PCS No	20	24	36	22	12	26	26	10	16	20	14

In order to validate our mathematical model, we explore the utilization of four different vehicle types traversing various paths within the network. As previously mentioned, the CPLEX optimizer is limited to solving a single-objective mathematical model for this task. In this subsection, we carry out the validation of our MM for each of the specified objectives. Initially, our primary objective revolves around determining the optimal infrastructure cost, ensuring the successful journey of each vehicle type along their respective paths within the network. Subsequently, we address the problem with an objective of maximizing the battery lifetime for each vehicle type, accomplished by maintaining the largest possible charge variation within the defined minimum and maximum preferable values. For comprehensive details regarding the energy supply rate, energy consumption rate for each vehicle type, and additional data, please refer to Tables 2 and 3.

Table 2. Vehicles data

	The minimum charge	The maximum charge	The maximum preferable charge	The minimum preferable charge	The energy supply rate in DWC (kw)	The energy consumption rate in DWC ($kw/100km$)	The energy supply rate in SWC (kw/h)	The energy consumption rate for internal travel in SWC
V 1	1,76	7,04	6,5	2	4.2	25,2	8	1,25
V 2	6,44	25,76	24	7,5	3	19,6	10,5	0,5
V 3	3,68	14,72	13,5	4,2	5	19,5	7	0,8
V 4	5	20	18,5	5,8	5.5	34,7	9,5	1.8

The objective is to get the optimal number of stations, power segments, and inverters that allow each type of vehicle to move in the network between any two points. To test our model, since the resolution with CPLEX is based on an objective, we fix one objective each time, and we minimize the other. The following tables show the results found (Table 4):