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APPLICATION OF MACHINE LEARNING DURING MAINTENANCE AND EXPLOITATION OF ELECTRIC VEHICLES

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Abstract:
In the era of increasing demand for sources of renewable and cleaner energy, electric vehicles offer possible solutions in order to maintain and improve the mobility of transport systems. In parallel, the application of machine learning for digital twin technology greatly contributes to the development and optimization of vehicles and systems, saving time and resources, as well as material resources. In terms of electric vehicle components, electric batteries represent the most expensive elements where machine learning can help to optimize characteristics during exploitation and to predict maintenance time and their lifetime. This article related to the possible areas of future research, which, by intensifying the digitalization and machine learning for digital twin technology, will affect the improvement of the application and disposal of components, but the complete system of electric vehicles, during the entire life cycle, including the recycling.

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1. INTRODUCTION

In an era when economies around the world are faced with increasing costs of production and exploitation of vehicles with internal combustion engines, as well as with requirements to reduce the emission of pollutants produced by this type of vehicle, the concept of further development of vehicles is being questioned. Vehicles with partial or full electric drive are potential candidates for solving most of these problems.

Electric vehicles (EV) powered by an electric aggregate, that do not produce emissions at the point of use, can reduce environmental pollution by decreasing the reliance on vehicles with internal combustion (IC) engines [1]. When designing and operating electric vehicles, it is necessary to ensure the efficient and safe functioning of the EV charging network, the optimal characteristics of EV, from the aspect of volume and mass of the vehicle to the volume and mass of batteries for EV, and the quality of management of all dynamic characteristics of EV.

To this end, a simulation platform was developed to simulate the EV charging network, as well as the simulation of EV components and their mutual interactions [2]. Machine learning (ML) processes were simulated with a digital twin (DT) concept, which provides an excellent ability to simulate and predict the behavior of a real-world model or object in a suitable industrial environment. In this way, by applying machine learning tools, a physical image of a vehicle or equipment is formed in a digital environment [2,3].

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Machine learning can be applied across all stages of EV development and its use in transportation, including road traffic monitoring. Mobile battery chargers for EV on roads in traffic are also included in the monitoring [4].

In this way, the application of ML and the DT concept greatly contributes to the development and implementation of autonomous vehicles (vehicles without drivers) in traffic, especially as road networks become increasingly congested due to the rising number of vehicles still powered by conventional fuels [5].

Many authors and researchers have studied the application of DT technology in different modes of transportation, including various types of vehicles and both hybrid and electric vehicles [6].

By placing sensors on the vehicle and using appropriate modeling, it is possible to calculate the time between charges. Artificial intelligence (AI) can also help with the optimization regarding the time during hybrid or electric mode use in traffic [6].

In the context of the above, a very useful review paper regarding ML for the DT concept in the domain of EV can be found in the literature [7]. This paper addresses various categories within smart vehicle systems, including navigation control, electronic assistance systems, vehicle condition monitoring, and powertrain systems. It also explores the impact of EV and DT technologies and discusses future directions for their development.

The authors in one of the studies [8] developed a simulation model that calculates the appropriate vehicle characteristics in real time.

In summary, DT technology uses data collected from traffic signs, surveillance cameras, and other sources to provide a comprehensive view of city traffic. This information helps optimize driving routes, improve road infrastructure, and enhance overall traffic efficiency in urban areas. The use of ML in transportation digitalization can improve decision-making, increase safety, enhance vehicle stability, and accelerate the development of software-supported autonomous driving systems [2,7].

Fast and reliable charging, ideally supported by some degree of automation, is crucial. There are several options for automatic EV charging: parking the vehicle so that the charging connector automatically aligns with the charging cable, manually plugging it into the charger, or using wireless charging technology [2].

Some authors [9] have used ML techniques to predict fuel consumption and driving ergonomics. These parameters are integrated into the vehicle's physical model to simulate performance, including an electronic control unit prototype that regulates the simulation environment. The authors also developed a system that enables rapid EV charging while the vehicle is parked.

2. BASIC CONCEPTS ABOUT MACHINE LEARNING TECHNOLOGY

Digital Twin technology as an important process, involves the creation of a virtual model (i.e. a twin) of any physical object, for the purpose of its rationalization, optimization, and maintenance of the basic physical process and machine learning. The concept of DT technology was theoretically introduced in 2002 by Grieves [10] during a special meeting on product life cycle management at Michigan Lurie University Engineering Center.

In his subsequent article [11], the same author further defined DT technology as a combination of three primary components: 1) a virtual twin; 2) a corresponding physical twin (a physical object that can be a product, system, model, or any other component such as a vehicle, energy turbine, human, hospital, robot, etc.); and 3) a data part that provides data from the physical twin to its virtual twin and reverse. A virtual twin is an algorithm or replica regarding the behavior (in whole or in part) of its corresponding physical counterpart, with the same output as the physical object given input values.

Digital twin technology was first adopted by a group of researchers [12] to digitally reconstruct the aircraft structure. Initially, DT technology was used as a diagnostic tool for continuous monitoring of aircraft systems. Later, the model was developed into a replica (an exact twin) to simulate the entire life cycle of the aircraft and predict its performance [12].

Researchers define DT technology in several ways. The pioneers in domain od of DT technologies [13] define this technology as a base of virtual information consisting from micro to macro-geometrical levels.

As illustrated in Fig. 1, DT technology as a process involves the creation of: 1) a cyber twin that digitally represents a living or non-living physical entity or system; and 2) physical links that enable failure diagnostics, early predictions, and continuous monitoring of the physical twin's condition [6].

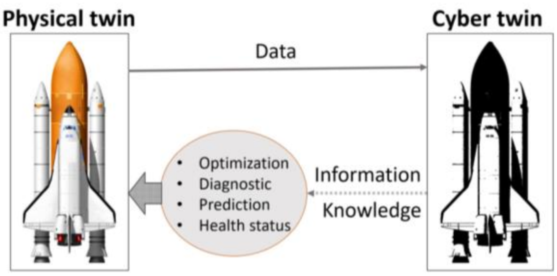
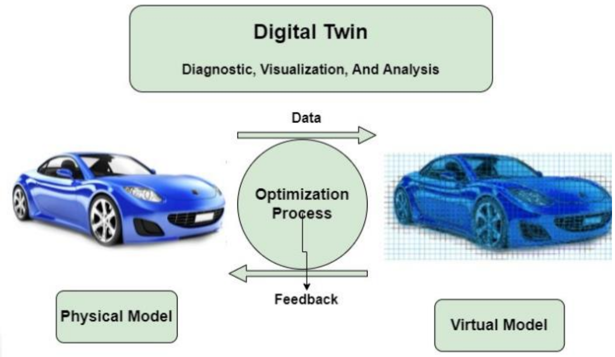


Fig. 1. The concept of ML process for DT technology [6]

However, there are some DT that mirror processes (physical environment), such as DT of mobile computing systems (MEC) [14], human protein-protein interaction (PPI) [15], supply chain [16], assembly of components in the production unit, and the schedule of operations and activities in the production process [17].

3. APPLICATION OF MACHINE LEARNING ON THE TWIN TECHNOLOGY EXAMPLE IN THE DEVELOPMENT OF ELECTRIC VEHICLES

Machine learning and DT technology can also be successfully applied in the sectors of vehicle production and their applications in the traffic and transport sectors (see Figs. 2a and 2b).



a)

b)

Fig. 2. DT technology as ML method for vehicle and transport

Machine learning and DT technology in the production and exploitation sectors contribute to the optimization of these processes and enable significant savings in time and resources.

This includes recharging EV batteries at home or public chargers (via a cable) or wireless charging. Like EV, driverless cars and automated driving are becoming more common, and physical charging of vehicles may become unfeasible, where specific charging systems are needed. There are also two options for charging, as explained above [9].

The Digital Twin Network (DTN) is the next generation of DT technology. Inside DTN, which represents different groups of physical objects integrated inside a virtual system, the DT of any physical object is the first cell. DTN enables a very successful exchange between DT and physical objects [17]. The DTN architecture shown in Fig. 3 was analyzed, consisting of three integrated layers: network, physical, and virtual layers [3].

The physical level consists of EVs, mobile EV chargers, roads, and objects. Navigation and sensors connect the system components, transmitting data about vehicle speeds and positions, road traffic congestion, and the availability of EV chargers, among other things.

The entire network level receives information from the physical level of communication services, provided via 5G or Wi-Fi connecting technologies. This layer sends information and data to the virtual layer as part of the DT technology network and servers. At the virtual level, DTs are connected to resolve the execution of simulation and computational tasks with new technologies, which enable decision-making, analysis, and issues related to maintenance [3].

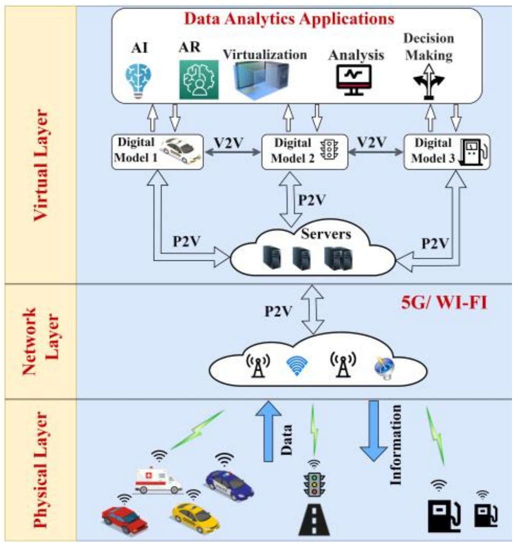


Fig. 3. Example of DTN cell architecture applied to EV in traffic [3]

Some authors [18] proposed a DTN model for building the network and its integration with the IoT network consisting of sensors and specific software (without the obligatory human intervention). The adopted system has significantly solved many problems, in business, transport, etc.

However, the main concept and basic architecture of DT are common in all these technologies. Fig. 4 shows the crucial technology that will be used with DT for electromobility. Internet applications are obligatory, as are virtual sensors, Bluetooth, 5G, satellite, data analytics, and autonomous vehicles. The proposed framework enables a real-time security tracking mechanism to detect invariant behavior and self-learning genetic positions to recognize EV exploitation conditions that deviate from normal and obtain the exact location of the vehicle in traffic. Furthermore, DT enables functions such as predictive maintenance, network analysis, energy efficiency optimization, and real-time network monitoring. In addition, seamless interactions between different network devices have been achieved, as their digital counterparts are platform-independent and can be managed using standardized methods, regardless of the specific technical details of devices [19].

Generally, through a communication tool, the physical model is converted into a digital one with mutual communication in both directions.

Altogether, it represents a base for AI, which should additionally enable the practical application of modern technologies and knowledge in the future. In this way, optimization is simplified in every field of application.

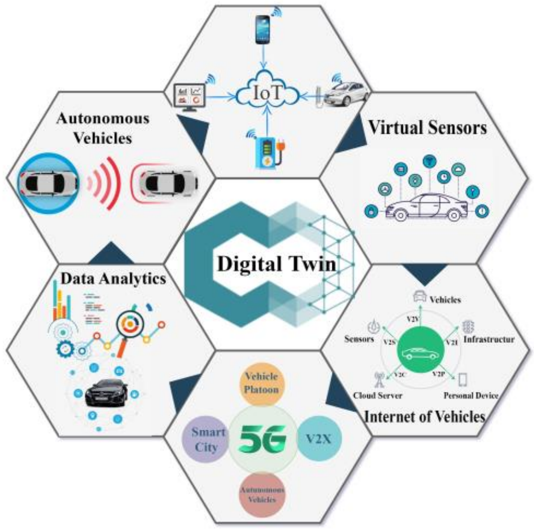


Fig.4. Key ML for DT technologies regarding the application for EV in traffic

4. APPLICATION OF TWIN TECHNOLOGY IN THE SELECTION AND OPERATION OF EV BATTERIES

In recent years, battery research has become more extensive and advanced, with many problems that need to be solved. To solve the problem of condition estimation and prediction of the characteristics of lithium-ion batteries, a model is usually used to describe the voltage response, capacity, and internal resistance curves [20]. Due to the large non-linearity and connection of battery characteristics, the challenge is to define a specific model of a lithium-ion battery [21].

It is also possible to take advantage of DTs in their correlation with complex systems inside EV. In this manner, it is possible to establish a DT framework for battery applications, for example in EVs, as shown in Fig. 5.

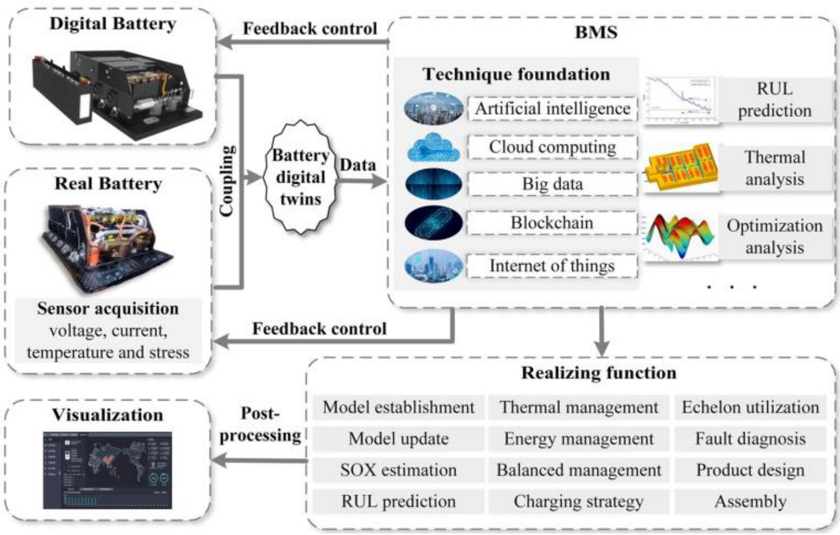


Fig. 5. Machine learning framework for DT technology in the domain of intelligent battery management systems

According to Fig. 5, the sensors are used to receive data about battery voltage, current, and temperature generated in the actual battery. A battery model is then established in geometric proportion that simulates a real battery in a virtual environment. Machine learning for Battery DT is obtained by merging real battery data with a virtual model [22].

By applying ML procedures for DT technology for application on EV batteries, the visualization of battery information can also be realized and make the characteristics of the battery much clearer and more transparent.

Some researchers have also provided a brief concept of development in the field of lithium-ion batteries, focusing on the use of DT to establish high model accuracy, mainly in assessing the state of charge of the battery and the state of the battery's service life [23-26].

5. APPLICATION OF DT TECHNOLOGIES IN THE DOMAIN OF ELECTRONIC COMPOUNDS FOR EV

When talking about the application of DT and reverse engineering technologies in the field of electronic components and systems on EVs, there are also specific requirements.

Modern vehicles, both EVs and classic vehicles powered by gasoline, diesel, or gaseous fuel, are equipped with electronic systems that communicate with each other via a given network called CAN-bus. A closed network with a central computer or electronic control unit (ECU) is connected to this network.

The electronic control unit on modern vehicles receives every second a large amount of information from sensors on the vehicle and transmits impulses in the reverse direction to the executive devices of the on-board system, Fig. 6. The system also stores codes that indicate the occurrence of an error. In parallel, diagnostic systems were developed for decoding and loading data into the vehicle's ECU [11].

Thanks to the progress of electronics and mechatronics, there has been an intensive development of vehicles, which has resulted in increased safety, reduced fuel consumption, cheaper maintenance, and an increased percentage of recycling.

Also, in the future, the application of AI should contribute to more intensive development and application of new technology, which should primarily affect the preservation of a clean environment and resources, i.e., reserves of raw materials.

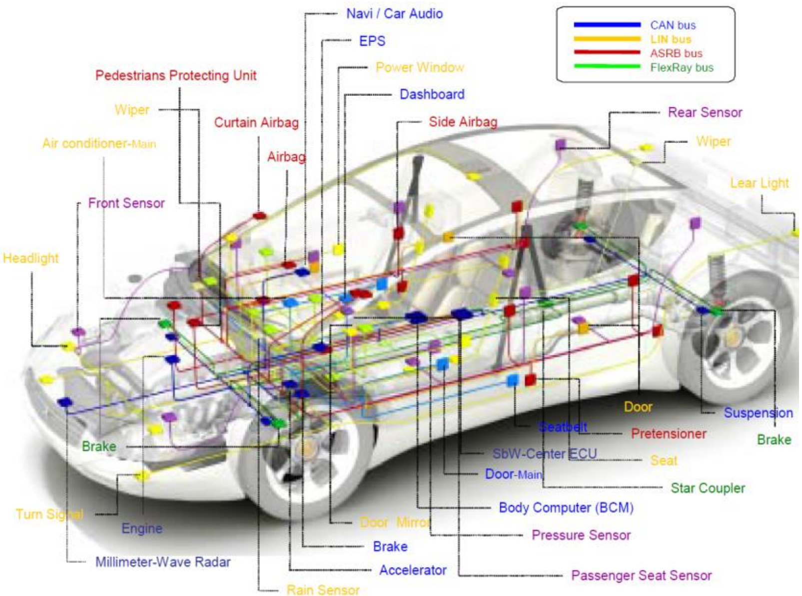


Fig. 6. CAN-bus architecture inside a modern vehicle

By applying ML and DT technologies, reverse engineering in the field of electronic components is approached. First, the wiring, pins, and component positions are recorded.

In the second step, physical damage to the parts is removed and mandatory cleaning of the computer memory is performed. There may also be residual recorded errors in memory that can be a problem when loading new data and reusing it.

In the third step, control and sorting of parts of electronic equipment is carried out. For this purpose, appropriate test benches are used to simulate the operation of the vehicle system (for example, an electronically controlled steering system with servo amplification), the operation of sensors, and the ECU, after which the correctness of the refurbished equipment is verified.

In the next step, when it is known within which system the equipment will be used, the software is loaded, the parts are assembled, and the final functionality is tested.

The complete procedure, starting from the dismantling of sensitive electronic components from the vehicle to their reuse, is very complex and responsible. Therefore, it is necessary to follow the procedures that must be included in the quality system.

Only in this way is it possible to form a suitable database to which AI methods can be applied in the future.

At the same time, it should be emphasized that the most important database in the reverse engineering system in this case is represented by recorded diagrams of connecting parts of the electrical installation, which were obtained based on the physical condition of the vehicle and the application of ML for DT technology.

In this way, by applying reverse engineering in the framework of electronic and electrical systems on vehicles, sustainability can be additionally contributed to. If we look at production and service, i.e., procurement of spare parts and equipment for vehicles, the presented methods also contribute to better treatment at the end of the vehicle's service life and disassembly; resources are saved due to the reuse of more and more parts; and also, a new business is started.

Reverse engineering is also of great importance when disassembling vehicles and separating rare metals used in electronic and electrical components of EVs and hybrid vehicles. One of the rare metals or magnets is neodymium used in electromagnetic components of vehicles.

As an example of the application of ML and reverse engineering, Fig. 7 shows a sketch of a recycling plant for dismantling EVs, extracting rare metal magnets, revitalizing them, and reusing them [27].

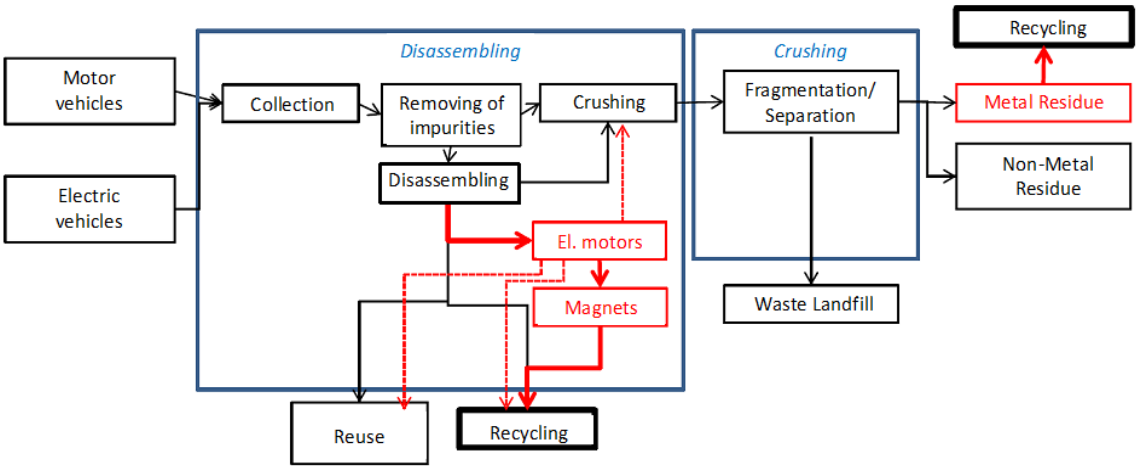


Fig. 7. Application of ML within a facility for recycling and reuse of rare magnets inside EV

In this way, smart management of EV disassembly and recycling processes, which contributes to the preservation of rare magnet reserves, additionally contributes to increasing sustainability in traffic and transport.

On the other hand, with smart management and the application of ML, it is possible to satisfy the increasingly strict regulations in this area, which are put before manufacturers, users, and service centers that deal with EV maintenance.

By preserving rare magnets and reusing them, a significant contribution is made to the development of EVs, whose mass and more affordable production is today the task of almost all vehicle manufacturers.

In this way, the results of the application of ML and DT technologies in the field of EV recycling represent a significant contribution due to the formation of a generally accepted database, which is a significant input for the future application of AI in this field.

6. CONCLUSION

This survey shows that there is still a lot to develop in the application of Digital Twin technology in the industry of hybrid and EV.

During this research, it was observed that this area is insufficiently researched, primarily because it is an advanced segment of engineering that has not yet found its application in practical solutions for hybrid and EV. This is highly important from the aspect of vehicle reliability but also of certain key assemblies, units, and systems on vehicles, such as electric batteries for application in electric or hybrid vehicles [4,28].

Applying the ML process for detailed analyses and models based on the DT technology enables the assessment of the functionality of the battery up to a certain period in operation on EV, which can prevent sudden failures [7,29].

The findings of the research have a wider applicability when designing hybrid and EV, because certain insufficiencies can be observed on the model itself, which can at the very beginning bring into question the concept, but also the economy and reliability of the electric and hybrid vehicle [30,31]. The application of such a model is significantly cheaper than the production of a vehicle prototype, where there exists the possibility for final correction and adjustment of certain operating parameters even before the production of the physical model itself [32].

Future research should be directed towards researching the machine learning for the models of the electric batteries themselves on electric and hybrid vehicles. This is important because these assemblies directly affect the autonomy and reliability of these types of vehicles, and in the case of certain models, they dominate the cost of making the entire vehicle [33-35].

The paper also pointed out the importance of recycling and reuse of electronic and electrical components on EVs. This primarily refers to the disassembly, proper separation, and reuse of rare magnets that are used for the production of EV parts whose raw materials are limited and come from distant countries.

The application of AI and ML in this area contributes to sustainable development, the preservation of the human environment through the preservation of raw materials and resources, and the parallel accelerated development of EVs.

Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

[1] X. Lü, Y. Wu, J. Lian, Y. Zhang, C. Chen, P. Wang, L. Meng, Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm. *Energy Conversion and Management*, 205, 2020: 112474. https://doi.org/10.1016/j.enconman.2020.112474

[2] W.A. Ali, M. Roccotelli, M.P. Fanti, Digital Twin in Intelligent Transportation Systems: a Review. *2022 8th International Conference on Control, Decision and Information Technologies (CoDIT)*, 17-20 May 2022, Istanbul, Turkey, pp.576-581. https://doi.org/10.1109/CoDIT55151.2022.9804017

[3] W.A. Ali, M.P. Fanti, M. Roccotelli, L. Ranieri, A Review of Digital Twin Technology for Electric and Autonomous Vehicles. *Applied Sciences*, 13(10), 2023: 5871. https://doi.org/10.3390/app13105871

[4] A. Rassõlkin, T. Vaimann, A. Kallaste, V. Kuts, Digital twin for propulsion drive of autonomous electric vehicle. *2019 IEEE 60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*, 07-09 October 2019, Riga, Latvia, pp.1-4. https://doi.org/10.1109/RTUCON48111.2019.8982326

[5] D.M. Botín-Sanabria, A.-S. Mihaita, R.E. Peimbert-García, M.A. Ramírez-Moreno, R.A. Ramírez-Mendoza, J.d.J. Lozoya-Santos, Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote Sensing,* 14(6), 2022: 1335. https://doi.org/10.3390/rs14061335

[6] M.M. Rathore, S.A. Shah, D. Shukla, E. Bentafat, S. Bakiras, The role of AI, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities. *IEEE Access*, 9, 2021: 32030-32052. https://doi.org/10.1109/ACCESS.2021.3060863

[7] G. Bhatti, H. Mohan, R.R. Singh, Towards the future of ssmart electric vehicles: Digital twin technology. *Renewable and Sustainable Energy Reviews*, 141, 2021: 110801. https://doi.org/10.1016/j.rser.2021.110801

[8] M. Aslani, M.S. Mesgari, M. Wiering, Adaptive traffic signal control with actor-critic methods in a real-world traffic network with different traffic disruption events. *Transportation Research Part C: Emerging Technologies*, 85, 2017: 732-752. https://doi.org/10.1016/j.trc.2017.09.020

[9] H. Shikata, T. Yamashita, K. Arai, T. Nakano, K. Hatanaka, H. Fujikawa, Digital twin environment to integrate vehicle simulation and physical verification. *SEI Technical Review*, (88), 18-21.

[10] M.W. Grieves, Virtually intelligent product systems: Digital and physical twins. *Complex Systems Engineering: Theory and Practice*, 2019: 175-200. https://doi.org/10.2514/5.9781624105654.0175.0200

[11] R. Steinhilper, S. Freiberger, M. Albrecht, J. Käufl, E. Binder, C. Brückner, New Technologies for Remanufacturing of Automotive Systems Communicating via CAN Bus. *Glocalized Solutions for Sustainability in Manufacturing*, 2011: 90-95. https://doi.org/10.1007/978-3-642-19692-8_16

[12] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a digital twin. *International Journal of Aerospace Engineering*, 2011, 2011: 154798. https://doi.org/10.1155/2011/154798

[13] M. Grieves, J. Vickers, Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. *Transdisciplinary Perspectives on Complex Systems*, 2017: 85-113. https://doi.org/10.1007/978-3-319-38756-7_4

[14] R. Dong, C. She, W., Hardjawana, Y. Li, B. Vucetic, Deep learning for hybrid 5G services in mobile edge computing systems: Learn from a digital twin. *IEEE Transactions on Wireless Communications*, 18(10), 2019: 4692-4707. https://doi.org/10.1109/TWC.2019.2927312

[15] B. Björnsson, C. Borrebaeck, N. Elander, T. Gasslander, D.R. Gawel, M. Gustafsson, et al., Swedish Digital Twin Consortium. (2020). Digital twins to personalize medicine. *Genome Medicine*, 12, 2020: 4. https://doi.org/10.1186/s13073-019-0701-3

[16] J.A. Marmolejo-Saucedo, Design and development of digital twins: A case study in supply chains. *Mobile Networks and Applications*, 25, 2020: 2141-2160. https://doi.org/10.1007/s11036-020-01557-9

[17] C. Zhuang, J. Liu, H. Xiong, Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *The International Journal of Advanced Manufacturing Technology*, 96, 2018: 1149-1163. https://doi.org/10.1007/s00170-018-1617-6

[18] Y. Dai, K. Zhang, S. Maharjan, Y. Zhang, Deep reinforcement learning for stochastic computation offloading in digital twin networks. *IEEE Transactions on Industrial Informatics*, 17(7), 2020: 4968-4977. https://doi.org/10.1109/TII.2020.3016320

[19] M. Kherbache, M. Maimour, E. Rondeau, Network digital twin for the Industrial Internet of Things. *2022 IEEE 23rd International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, Belfast, United Kingdom, 2022, pp. 573-578. https://doi.org/10.1109/WoWMoM54355.2022.00089

[20] B. Dudić, Global Development and Sustainability of Lithium-Ion Batteries in Electric Vehicles. *Advanced Engineering Letters*, 3(2), 2024: 83-90. https://doi.org/10.46793/adeletters.2024.3.2.5

[21] Y. Ma, X. Li, G. Li, Y. Hu, Q. Bai, SOC oriented electrochemical-thermal coupled modeling for lithium-ion battery. *IEEE Access*, 7, 2019: 156136-156149. https://doi.org/10.1109/ACCESS.2019.2949357

[22] B.M. Sopha, D.M. Purnamasari, S. Ma'mun, Barriers and enablers of circular economy implementation for electric-vehicle batteries: from systematic literature review to conceptual framework. *Sustainability*, 14(10), 2022: 6359. https://doi.org/10.3390/su14106359

[23] B. Wu, W.D. Widanage, S. Yang, X. Liu, Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy and AI*, 1, 2020: 100016. https://doi.org/10.1016/j.egyai.2020.100016

[24] X. Qu, Y. Song, D. Liu, X. Cui, Y. Peng, Lithium-ion battery performance degradation evaluation in dynamic operating conditions based on a digital twin model. *Microelectronics Reliability*, 114, 2020: 113857. https://doi.org/10.1016/j.microrel.2020.113857

[25] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, D.U. Sauer, Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-

health estimation. *Journal of energy storage*, 30, 2020: 101557. https://doi.org/10.1016/j.est.2020.101557

[26] R. Gilbert Zequera, A. Rassõlkin, T. Vaimann, A. Kallaste, Overview of battery energy storage systems readiness for digital twin of electric vehicles. *IET Smart Grid*, 6(1), 2023: 5-16. https://doi.org/10.1049/stg2.12101

[27] S. Milojević, I. Miletić, B. Stojanović, I. Milojević, M. Miletić, Logistics of Electric Drive Motor Vehicles Recycling. *Mobility & Vehicle Mechanics (MVM)*, 2020: 46(2), 33-43. https://doi.org/10.24874/mvm.2020.46.02.03

[28] A.H. Azadnia, G. Onofrei, P. Ghadimi, Electric vehicles lithium-ion batteries reverse logistics implementation barriers analysis: A TISM-MICMAC approach. *Resources, Conservation and Recycling,* 174, 2021: 105751. https://doi.org/10.1016/j.resconrec.2021.105751

[29] Z. Lv, Y. Li, H. Feng, H. Lv, Deep learning for security in digital twins of cooperative intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems,* 23(9), 2021: 16666-16675. https://doi.org/10.1109/TITS.2021.3113779

[30] T. Skrúcaný, M. Kendra, O. Stopka, S. Milojević, T. Figlus, C. Csiszár, Impact of the electric mobility implementation on the greenhouse gases production in central European countries. *Sustainability*, 11(18), 2019: 4948. https://doi.org/10.3390/su11184948

[31] T. Skrucany, S. Semanova, S. Milojević, A. Ašonja, New Technologies Improving Aerodynamic Properties of Freight Vehicles. *Applied Engineering Letters*, 4(2), 2019: 48-54. https://doi.org/10.18485/aeletters.2019.4.2.2

[32] S. Milojević, Sustainable application of natural gas as engine fuel in city buses: Benefit and restrictions. *Journal of Applied Engineering Science*, 15(1), 2017: 81-88. https://doi.org/10.5937/jaes15-12268

[33] T. Kathmann, D. Reh, J.C. Arlinghaus, Exploiting the technological capabilities of autonomous vehicles as assembly items to improve assembly performance. *Advances in Industrial and Manufacturing Engineering*, 6, 2023: 100111. https://doi.org/10.1016/j.aime.2022.100111

[34] S. Gajević, A. Marković, S. Milojević, A. Ašonja, L. Ivanović, B. Stojanović, Multi-Objective Optimization of Tribological Characteristics for Aluminum Composite Using Taguchi Grey and TOPSIS Approaches. *Lubricants*, 12(5), 2024: 171. https://doi.org/10.3390/lubricants12050171

[35] S. Milićević, I. Blagojević, S. Milojević, M. Bukvić, B. Stojanović, Numerical Analysis of Optimal Hybridization in Parallel Hybrid Electric Powertrains for Tracked Vehicles. *Energies*, 17(14), 2024: 3531. https://doi.org/10.3390/en17143531